Polish-Japanese Academy of Information Technology
Faculty of New Media Arts

# WHAT IS MY ARTWORK WORTH IN THE 21st CENTURY?

# APPLYING COMPUTATIONAL TECHNIQUES TO THE PROBLEM OF CONTEMPORARY VISUAL ARTS EVALUATION: RECOMMENDER SYSTEM FOR ART PRICING

Doctoral Dissertation

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# ABSTRACT

ANNA GELICH. 'What is my Artwork Worth in the 21st Century?' Applying Computational Techniques to the Problem of Contemporary Visual Arts Evaluation: Recommender System for Art Pricing. (Under the direction of Dr hab. Anna Klimczak and Auxiliary Supervisor: Prof. Dr hab. Zbigniew W. Ras)

'What is my Artwork Worth in the 21st Century?' is the question equal to 'What is my Art Worth in the Computer Age?'. The Computer Age we live in now where every aspect of our lives is encouraged by computers was difficult to imagine half a century ago. In the art world it presents a particular challenge even though the contemporary art market became a large sector of the global economy and keeps growing. With the increased information available on the Internet, artists and customers are challenged with the digital environment filled in with the information that tells them not much about pricing the work of art they want to sell or to purchase. It creates a challenge for potential customers that are not educated in art sales and who do not know the points of quality and validity of the prices.

This research discusses the problems of contemporary visual arts evaluation in the computer age and sheds light on the opportunities of applying computer science techniques to develop a recommender system for the effective fine art pricing. In terms of visual arts, in this study, I focus on the experiment only with fine art. I touch on the state of the contemporary art market, historical changes in art form, mediums, art perception, and art pricing. I review the studies on recommender systems and art analytics and discuss how computer techniques in the 21st century can be applied to build effective decision-making support art pricing tool. I discuss the development of the datasets and features to build the recommender system for contemporary visual arts pricing. Contemporary artists who do not have significant sales records often use simple metrics to evaluate their works of art

such as artwork dimensions, time and material cost. In order to move forward, I must consider features which are less obvious. This study explores the features which were developed during my earlier research based on contemporary fine art items [77], proposes a new set of features, methods of clustering data, and new datasets to be used to build an effective recommender system for contemporary fine art pricing.

The important aspect of this work is a multidisciplinary approach. In the computer age and in the Internet era, the problem of contemporary art pricing cannot be solved without a multidisciplinary approach.

Finally, one of the important parts of my study is an Art Experiment which explores a set of new mediums and computational tools, nowadays widely used in artistic practices. My Art Exhibition “ZOOM IT IN -VIRTUAL CONTINUUM” explores the integration of animated real-life virtual elements into a hybrid architectural spatial environment through the generation of kinetic perception produced with the help of digital mechanisms, fabricated color wheel and human body. Technological mechanisms, virtual reality and speed change our perception of the spatial environment giving the opportunity of a new artistic vision of space and artistic explorations. Constructing optic-based visual artistic animations was a chance to look into the virtual and physical worlds united in the single virtual continuum. It provided me with the opportunity to translate my emotional and physical conditions during the university pandemic lockdown into artistically articulated hybrid space to develop new artistic language and art mediums and to explore materiality, texture, forms. One of the parts of my art exhibition also explores social narratives and communications inside of the new hybrid spatial environment.

# ABSTRAKT

"Jaka jest wartość mojego dzieła sztuki w XXI wieku?" - Zastosowanie technik informatycznych do problemu wartościowania współczesnej sztuki wizualnej: System rekomendacji cen dzieł sztuki. (Pod kierunkiem Dr hab. Anny Klimczak i Prof. Dr hab. Zbigniewa W. Rasia). "Jaka jest wartość mojego dzieła sztuki w XXI wieku?'' jest pytaniem podobnym do: "Jaka jest wartość mojego dzieła sztuki w erze komputerów?". Epokę komputerową, w której dziś żyjemy, gdzie prawie każdy aspekt naszego życia jest wspierany przez komputery, trudno było sobie wyobrazić pół wieku temu. W świecie współczesnej sztuki jest to szczególne wyzwanie, jako że jej rynek stał się dużym sektorem globalnej gospodarki i stale rośnie. Wraz ze wzrostem ilości informacji dostępnych w Internecie, artyści i klienci stają przed wyzwaniem związanym ze środowiskiem cyfrowym wypełnionym informacjami, które niewiele im mówią na temat cen dzieł, jakie chcieliby sprzedać lub zakupić. Stwarza to wyzwanie potencjalnym klientom, którzy nie są doświadczeni i zorientowani w sprzedaży dzieł sztuki, nie znają aspektów jej jakości i aktualnych cen.

Moja praca omawia problemy współczesnej oceny dzieł sztuki w społeczeństwie ery komputerów i rzuca światło na możliwości zastosowania technik informatycznych do opracowania systemu rekomendacyjnego wartości dzieł sztuki. W badaniach poruszam tematykę stanu rynku sztuki współczesnej, historycznych zmian w jej formie, estetyce, mediach i cenie dzieł. Dokonuję przeglądu badań dotyczących systemów rekomendacyjnych i analityki dzieł sztuki oraz omawiam, w jaki sposób techniki komputerowe w XXI wieku można zastosować do zbudowania skutecznego narzędzia wyceny dzieł sztuki, ważnego przy podejmowaniu decyzji jej sprzedaży lub kupna. Omawiam tworzenie zbiorów danych i opisujących je atrybutów, które umożliwiają zbudowanie systemu rekomendującego dla współczesnych cen dzieł sztuki. Współcześni artyści, którzy nie mają znaczących wyników sprzedaży, często używają prostych

wskaźników do oceny swoich dzieł, takich jak ich wymiary, poświęcony czas tworzenia i koszt materiałów. Aby pójść dalej, muszę wziąć pod uwagę mniej oczywiste cechy istotne do opisu dzieł sztuki. Niniejsza praca zgłębia cechy, które zostały opracowane podczas moich wcześniejszych badań opartych na współczesnych dziełach sztuki [77]. Proponuję nowe metody grupowania danych, które mają być wykorzystane do zbudowania skutecznego systemu rekomendacyjnego w zakresie wyceny współczesnych dzieł sztuki.

Ważnym aspektem tej pracy jest podejście multidyscyplinarne. W dobie komputerów i w dobie Internetu nie da się rozwiązać problemu wyceny dzieł sztuki współczesnej bez potraktowania tematu multidyscyplinarnie.

Wreszcie, jedną z ważnych części moich badań jest eksperyment artystyczny, którego celem jest wdrożenie nowych mediów i narzędzi obliczeniowych, obecnie szeroko stosowanych w praktykach artystycznych. Moja wystawa pt.: 'ZOOM IT IN - VIRTUAL CONTINUUM' ("POWIĘKSZENIE - WIRTUALNE KONTINUUM") bada integrację animowanych, rzeczywistych i wirtualnych elementów z hybrydowym architektonicznym środowiskiem przestrzennym, poprzez generowanie percepcji kinetycznej wytworzonej za pomocą mechanizmów cyfrowych, sfabrykowanego koła kolorów i ludzkiego ciała. Mechanizmy technologiczne, wirtualna rzeczywistość i prędkość zmieniają nasze postrzeganie środowiska przestrzennego dając szansę nowej artystycznej wizji przestrzeni i artystycznych poszukiwań. Tworzenie opartych na optyce animacji artystycznych było szansą na wejrzenie w świat wirtualny i fizyczny zjednoczony w pojedynczą ciągłość. Dało mi to szansę na przełożenie moich stanów emocjonalnych i fizycznych (podczas przymusowego zamknięcia uczelni w okresie pandemii) na artystycznie wyartykułowaną przestrzeń hybrydową, którą stworzyłam w celu opracowania nowego języka wizualnego oraz zbadania materialności, tekstury i form. Jedna z części mojej wystawy bada również narracje społeczne i komunikację w nowym, hybrydowym środowisku przestrzennym.

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# Chapter 1: Introduction

## 1.1 Background

The computer age we now live in was difficult to imagine even half a century ago when the access to the Internet and digital gadgets were not this ubiquitous. Nowadays, almost every aspect of our lives is controlled by computers or combined with machines. Theorist J. Hillis Miller points out that the “new technologies invade the home and the nation [1]”. Philosopher Bernard Siegler states that “decision making is combined with machines [1].”

In the art world like in other areas the shift to digitalization presents a particular challenge on various levels. Friedrich Kettler argues that the concept of medium is getting eliminated. “Modulation, transformation, synchronization: delay, storage, transposition; scrambling, scanning, mapping – a total media link on a digital base will erase the very concept of medium [1].” There are already types of art, including Cybernetic, Kinetic, Robotic, Telematic, Computer Art that require an unconventional and new approach in medium articulation as well as price evaluation in the growing contemporary visual art economy.

The art market, including the online art market, became a significant sector of the global economy. According to the 2021 Hiscox art trade report, online art market is estimated to grow by 72% to $13.59 billion [2]. The same report states that 84% of the art customers believe that due to the pandemic online purchasing became a continuing method to acquire art [2].

The current computer era allows the art customers and artists to reach out each other more easily.

However, with the enormous information stored online, stakeholders in the art market are challenged with the net filled in with the data that in practice tells them not a lot about the artwork price. Overwhelming information and the amount of art they can find online make a challenge for future customers that are not familiar with the art sales and do not know the points of quality and the art price validity. Consumer insecurity over prices limits the development of the art economy. Hiscox art trade report states that 41% of art customers don't purchase art online due to "lack of transparency and objective guidance [2]." The same report shows that customers are unsure about "the 'right' price" [2] and that 33% of art customers are uncomfortable that they may pay "larger sums of money online [2]."

This research explores 'pains and gains' the contemporary art market and art evaluation problem in the digital age in the $21^{st}$ century. It explores the opportunities of applying computational techniques to art pricing as well as the challenges of developing an effective art pricing model. The important part of this study is a parallel artistic research expressed through a solo exhibition, in which I address the problem of the novel artistic forms, mediums, spatial environment and explore the mechanisms and computational tools that can be applied to the problem of contemporary art process and evaluation.

As soon as artwork leaves an artist's studio it immediately becomes not only the subject of economic evaluation but a subject of the cultural evaluation [3]. Understanding pricing models and set of features in terms of current economic reality of contemporary fine art pricing seems rather difficult without at least providing brief context in terms of the historical and technological changes in the $20^{th}$ -$21^{st}$ century. To better understand the pricing model and to provide enough context, this work included the parts which shed light on the historic, cultural, economic, social and aesthetic aspects of art evaluation and art evolution.

Thus, In Chapter 1, I will touch on the historical and technological changes in art form, medium, various art movements, the state of the contemporary art market, art aesthetics, art trends and pricing challenge. In the Chapter 2, I will talk about Recommender Systems including different methods of recommendation and discuss the prototype of Recommender System Artist (Art-Innovative Systems for Value Tagging which was proposed as the result of I-Corps program funded by National Science Foundation (NSF). I will discuss the personalized models based on clustering artists and placing their artworks into the relevant pricing category in order to build a recommender system for art pricing and to provide stakeholders in the art market with the decision support system for secure art purchasing. In the Chapter 3, I will discuss computer science techniques which can be applied for features development including text analysis and image processing to create Recommender Systems for art pricing. Chapter 4 will discuss the experiment on development of datasets and construction of features. In the Chapter 5, I will present the experiment focused on action rules discovery for pricing art systems. Finally, in Chapter 6, I will present my artistic research, where I investigated modern computational tools and techniques in terms of hybrid spatial environment that was boosted by pandemic lockdowns. I explored that the spatial environment can become a hybrid space that includes elements of virtual and physical attributes. I discovered that inside of hybrid space people are able to communicate easier and that their perception of space is altered. I tended to explore people's emotional state and their movement circulation inside of the boundaries to discover the artistic and architectural elements that can be applied to improve their communication. I learned that hybrid space environment increases people's freedom of movement and flexibility and it generates the conditions for better creative self-expression process.

My artistic experiment tends to establish the criteria for better articulation of artistic processes and artistic outcomes as well as qualities of spatiality and dimensionality. It based on an implementation of computational tools in order to explore the nature of spatial environment. It articulates the spatial environment not as vacuum but as superficial hyperspace layers that generate hybrid active environment based on the concept of relationship between all entities inside of the environment which became more transparent and digitalized during the pandemic lockdown. The conceptualization and articulation of new hybrid environment we now live in, provides us with the opportunities to explore novel sensations which are rendered into a motion of viewers' interactions and communications which tend to improve the individual artistic process and imagination.

## 1.2 Related Work

Related works on art trends and changes in the 20th century [1], including suprematismmovement are presented in [4], [5], [6], the post second world war technical development in [1], [7], [8], [9], [10], [11], [12], [13], [14], [15], conceptualism movement in [3], [6], [8], [16], [17], [18], [19], [20], [21], world wide web development in [1], [3], [7], [22], artificial intelligence and data development [7], [8], [23]; on evolution of art form and mediums, changed perception and aesthetics of art and art techniques in [5], [7], [22], [24], [25], [26], [27]. State of contemporary art market discussed in [2], [28], [6], [7], [10], [29], [30], [31], [9], [36], [32], [33], including economic reports. Emerging NFTs marketplaces and online trade challenges discussed in [2], [10], [39], [34], [35], [36], [43], [37], [38], [39], [40], [41], [42], [50]. New mediums, computational tools, new conditions related to art labor, authorship and marketing are explored in [7], [8] and art pricing problem in terms of the contemporary works of visual art is discussed in [2], [23], [6], [10], [9], [36], [8], [11], [43], [13], [14], [15], [16], [17], [44], [45].

### 1.2.1 Method

I used available online resources for collecting and analyzing data related to art area. I conducted online and in-person interviews with the stakeholders in the art market in 2017-2020, being supported by National Science Foundation (NSF) grant: NSF I-Corps program [46].

During NSF I-Corps program, I offered stakeholders in the art market to respond to questionnaire (see, APPENDIX A) in order to understand the controlling mechanism of the art market, quantify and justify related hypotheses, generate insights. Brief interviews were also conducted during art fairs and art exhibition. Geography of my research project included major American cities and art centers such as NYC, San Francisco, Atlanta, Houston, Boston, Miami as well as European cities (Warsaw, London). The primary goal for the interviews was to develop an understanding of the complex landscape of the contemporary art market, to explore the art market and its customer segments. Art market is the opaque structure. It takes time and special approach to quantify and justify various hypotheses. Interviews helped to specify the art market ecosystem which include emerging and established artists, auction house specialists, gallery directors, art dealers and art collectors. More than 155 participants were interviewed between 2017-2020. For this research, Customer Segments such as Art Collectors, Auction House Specialists, Insurance Company Specialists, Banking Specialists, and others were determined.

Activities, which I also conducted with a group of researchers included:

1. Building the right team
2. Building communication skills

3. Building the skills for the Art Market analysis and its validation through the interviews
4. Developing insights and hypotheses based on the information received during the interviews
5. Testing our hypotheses
6. Improving Data collecting techniques
7. Building and presenting the recommender system prototype
8. Conducting interviews
9. Visiting art commercial events

Activities were repeated using iteration techniques. To explore the contemporary visual art market, I visited major trade art fairs such as The Art Basel Miami Art Fair, The Armory Show, The Spring/Break Art Show. The major art platforms such as Artsy, Artnet, Saatchi Art were explored and interviews with their representatives were conducted.

The prototype of primary innovation of the resulted technology such as the development of a crowd of personalized knowledge-based recommender systems based on the concept of actionability was built.

## 1.3 Trends and Changes in the 21st century

### 1.3.1 Suprematism

Art in the 20th century was enlarged by multiple art movements, including The Avant-garde movement. That created a significant evolution (revolution) of art form and art mediums. It also changed the perception of art and art techniques, increasing the complexity of art evaluation. Having my personal background connected to the cities which at the beginning of the 20th century became the linchpins of the Avant-Garde movement and other visual art manifestations, for example, in Saint-Petersburg, I saw the reconstruction of the first Malevich's exhibition, which inspired a lot of thoughts about this movement since I was a teenager. This is one of the reasons why I started this study by investigating new steps in the art world starting from the time of 'Black Square'. Kazimierz Malewicz, Russian artist of Polish origin, began to work on the painting in 1913 and showed his painting at the exhibition in 1915. This work was promoted by the painter as the art of the suprematism movement. With the development of the suprematism movement, the art world moved towards non-objective art. Kazimir Malevich thought that it was the end of the era of realistic painting, as well as the starting point for "art of the coming age". New art which would not have frameworks and established laws [4]. His first pre-suprematist, non-objective drawings, and canvases depicting complex, multi-elements groups of geometric elements appeared already in Spring 1915 [4]. The word 'Suprematism' had its roots in Malevich's native language, Polish, to which it came from Latin. In Catholic liturgy, 'supremacia' meant 'superiority' or 'dominance'. For Malevich, the initial stage of 'Suprematism' was establishing the supremacy of color energy in painting [4].

Suprematism was expressed or articulated in the application of simple geometric forms - squares and circles. They became a fundamental part of the program. White space also played a leading role and brought “the unity of space and time”. The tension of color and space, as well as the manifestation of new geometry, were all visible results of this novel approach. These concepts led to the destruction of the traditional boundaries or limitations in visual art, and to the expansion of visual language. Suprematism influenced all the Avant-Garde movements in the 20th century. The birth of ‘Black Square’ and geometric abstraction became known as a profound “revolutionary act”, which “closed the epoch of the immediate perception of reality and its mimetic-realistic reflection and heralded the beginning of a new era of civilization, with its all-powerful virtual reality subject only to the conceptual constructions of human speculation [4].” One of the most influential art critics, Clement Greenberg, in "Towards a Newer Laocoon" characterized the Avant-Garde period as "an historical apology for abstract art [5]." Some later artists such as Barnett Newman, John Cage, and Donald Judd still considered Malevich as their unacknowledged predecessor, others, like Yves Klein, used a notion of Suprematist paintings in their work [4]. An ex director at London's Tate Gallery, Will Gompertz in [47] argues referring to occasional audience's narrative that nowadays everyone could produce this kind of Black Square. He states that the modern art is strongly tied with the values of innovation and imagination, and it was novelty that made “Black Square” extremely valuable including financial value. “Financial value we place on rarity in our capitalist society, where the laws of supply and demand rule. Put all three together -originality, authenticity, rarity - and you have the reason why a Malevich Black Square is worth a million dollars and a version by you or me not [47].”

### 1.3.2 Post Second World War Development

Major step of digital art development is tied to the Post Second World War, including the Cold War, technological changes and computer development [1]. As it is pointed out in [48] computer and telematic culture emerged out of military development and remained still connected to it.

There were multiple experiments with computer-generated art conducted by musicians and artists. In the United States, in the 1950s the first electronic artworks were made by Ben Laposky, John Whitney and others. In Europe, these types of experiments were conducted multiple artists including Pierre Boulez, Edgar Varese. Karlheinz Stockhausen experimented with electronics. Artists Jean Tinguely, Pol Bury, Nicolas Schöffer, Otto Piene, Julio le Parc and groups including Le Mouvement, The 'New Tendency', and others started testing the directions of kineticism and cybernetics [1]. For example, Nicolas Shoffer, in Paris in the 1950s, developed first autonomous cybernetic sculptures and sculptural kinetic concepts which he named spatiodynamism, luminodynamism, chronodynamism. He invented the CYSP (Cybernetic Spatiodynamism) spatiodynamic sculpture, which was equipped with an 'electronic brain' - analogue circuit [49]. Another artist Edward Ihnatowicz, who described himself as a Cybernetic Sculpture artist, created Sound Activated Mobile (SAM) which consisted of parabolic reflectors shaped as flower and it had an articulated neck [49].

In 1965 and 1966 the first exhibitions of computer art were held at Stuttgart University Art Gallery and at the Howard Wise Art Gallery (NYC). Emerging ideas of theorists like Marshall McLuhan and Buckminster Fuller provided the conceptual background for the development of digital art practices [1]. Computers have widely become a tool "to put things to perform usefully" [50] but at the same time the artist's knowledge remained the valuable entity.

"Computer technology has already moved in the direction of doing more with less. The cost of the modern computer would scarcely be affected if it were made of the most precious metals, for material-wise there is not very much to a computer. What counts is the knowledge of how to put things to perform usefully [50]."

Part of this postwar conceptual background was the idea that amalgamation of new technologies and system ideas would make a better world. Such approach opened the doors for endless enthusiasm which from the economic point of view included certain amount of free labor applied to this area. "Artists, composers, filmmakers, scientists, architects and designers all seized upon the possibilities of new technologies and ideas to produce work that either involved such technology or alluded to the world it was helping to bring about [1]." Artists enthusiastically worked in different fields and countries kept employing these ideas and creating the foundation for the implementation of the computer graphics into the art world, among them Roy Ascott, David Medalla, and Gordon Pask in Britain, Lilian Schwartz, Edward Csuri, Ken Knowlton, Michael Noll, who developed computer graphics in the USA, Manfred Mohr and others -in Germany [1]. Ideas of combination of art and technology were thriving, helping to create new mediums. Michael Noll remembers in his interview referring to his early computer experiments. "In the early 1960s I used programmed randomness along with mathematical order to program a digital computer to produce images—they were called "patterns"—although I considered them abstract computer art [51]." Other artists in the 1960s used digital computers to generate patterns to help creators in the future may to use new artistic medium [51]. He mentions that "one of his objectives was to 'to educate artists and others about the possibilities of digital computers as a new medium in the visual arts [51].

Many artists utilized new mediums differently. So called Fluxus members, Wolf Vostell and Nam June Paik, were among those who first started using televisions in their artwork. The works of Paik also included other technologies, for example, tape. He also started to use portable video cameras and produced video art. Video art was a practice which started to use younger artists such as Les Levine and Bruce Nauman. Electronics, lasers, and light systems were also explored by artists, including Vladimir Bonacic, Otto Piene, Dan Flavin [1]. One of the crucial developments during this time became the development of large-scale multimedia environments which was crossed with psychedelic music and underground entertainment.

In 1966 EAT ('Experiments in Art and Technology') group established by Billy Klüver and Robert Rauschenberg had its famous show "9 Evenings" in NYC, which involved both artists and engineers [1]. Other exhibitions including "The Machine as Seen at the End of the Mechanical Age" (MOMA), were also held in the following years. The legendary exhibition "Cybernetic Serendipity", which was curated by Jasia Reichardt, took place at the ICA in London in 1968. Jack Burnham, critic and theorist, organized "Software: Information Technology, its meaning for art" exhibition in 1970 in NYC. It showed the works of scientists, computer theorists, artists "with little regard for any disciplinary demarcations" and with a notion of techno-utopianism [1]. Multiple articles and books were published during these times, including "Science and Technology in Art Today" by Jonathan Benthall [52], "Art and the Future" [12], "Science & Technology in the Arts: a Tour Through the Realm of Science / Art " by Stewart Kranz [53].

The late 1970s together with the development of computer-generated art, 'computerization of society' and the advent of 'telematics' was declared meaning the combination of computers and telecommunications [1]. Artists who were creating during this period included Douglas Davis, Harold Cohen, Jeffrey Shaw, Lilian Schwartz, Robert Adrian X and others. Terminology such as Poststructuralism and Postmodernism started emerging during this time, as a critical response to the spread of information technologies and communications networks. Philosophers such as Derrida, Baudrillard, Deleuze implied a critique of communications theories and systems [1]. The first "Ars Electronica" – a new type of festival took place in Austria in 1979 [54]. It focused on studying the development of computers and electronic technologies [1] [54].

In 1983, device AARON produced by Harold Cohen was shown. It was an artificial-intelligence program that could paint and draw [1] [55] [49]. A prototypal painting system was presented back in 1971. When in 1973, AARON program was born, it was not an AI program though as we understand nowadays. Today it is able to learn from different sets of data because of neural networks implementation. Harold Cohen's first robot looked like the "turtle" and its larger successor, which was equipped with a robotic arm, could draw on paper. However, AARON machine was more of a proof of concept than a working device [55]. Cohen major achievement was codification of his own drawings where AARON were

of art without the artist's intervention [49].

Centers for the promotion and distribution of digital media art, like Zentrum für Kunst und Medientechnologie (ZKM) in Germany, were founded at this time. The first International Symposium on the Electronic Arts (ISEA) took place [1]. Among artists who were involved in these processes were Robert Rauschenberg, Robert Whitman, LaMonte and Zazeela Young, groups such as USCO and Pulsa. Many of these artists were later considered to become part of Conceptual Art [1].

### 1.3.3 Conceptual Art

In the 1960s a critical concept of emerging ideas and process rather than ensuring art objects was the key point of the work of art. One of the artists who brought art into the next stage of the discussion through the articulation of “conceptual language” was Sol LeWitt. He did not invent the term “conceptual art,” but he was one of the first artists who identified himself as a “conceptual artist” and articulated its meaning in his work “Paragraphs on Conceptual Art” in 1967 where he became an advocate for conceptual art. “In conceptual art the idea or concept is the most important aspect of the work… [56].”

This term is usually related to the artworks produced in the middle of 1960s to the middle of 1970s even though Marcel Duchamp with his “readymade” Fountain from 1917 and revolutionary “readymades” introduced the way to the conceptual thinking [57]. He set “a new vocabulary” for art creation by taking his “readymade” objects and exhibiting them [18]. Before Duchamp provocation, art was something man-made typically framed and hung on a wall. Duchamp claimed that artists should not be restricted by mediums to express themselves arguing that concepts should come first and then realized through any medium that artist chooses. It was not anymore about ‘beauty’ but about ‘ideas’ [47]. It could even be an artist's body and performance. “Artists used a range of media and processes adopting a ‘do-it-yourself’ attitude to creative activity, often staging random performances and using whatever materials were at hand to make art [20].” For example, Henry Flynt in 1961 described his performances as ‘concept art’.

The process of some conceptual artwork generation can also be described as an algorithmic workflow as described below. “Wall Drawing #815 harkens back to one of the earliest Wall Drawings - Wall Drawing #51 (All architectural points connected by straight lines) which were made with blue snap lines. Like its predecessor, Wall Drawing #815 can be installed on any size wall, but #815 consists of thirty randomly placed points marked by nails, connected to one another via white string, all on a black wall [19].” The process also can include the specific instructions given to people as it was done in 1959 by Allan Kaprow in his performance when he gave specific instructions to the audience on a piece of card [47].

The range of these types of approaches basically meant that artists did not intend their works to be physical objects as well as to be easily “bought or sold”. Artists were not supposed to be engaged with the typical sales. Artists questioned the structures of the world of art and often produced work with socio-political context showing frustration with governmental policy. One example is Joseph Beuys’s social art where the medium was no longer a traditional medium but reflects a complexity of the social idea when he created artwork out of a van or made artwork "using dead animals and filthy rags as the juxtaposition to the sterile uniformity promoted by Nazis [47]." Projects of the artists belonged to Fluxus (‘flow’) movement (1961) tended to expand the boundaries of art merging it with life, involving social critique and reaching out a broad audience [128]. Thus, conceptual art could include different ways of expression but as Sol LeWitt pointed out, “Conceptual art is good only when the idea is good [47].” That brings us again to the evaluation the quality of concepts and if we can price them appropriately. However, for example, some Fluxus artists did not want even to sell their art pieces stating that "art was life and not a commodity" [128]. Artists during that time widely experimented with new mediums, emerging art performances and conceptual projects attempting to redefine the meaning of the works of art, involving the strong narrative of anti-commercialism [128].

The conceptual art movement continued in the twenty-first century in the work of Martin Creed, Simon Starling and others [21]. However, even though the anti-commercialism was a strong element of this movement, there were attempts to introduce projects to the market via exhibitions organized by the art dealers (not by the museums). For example, Seth Siegelaub organized a series of exhibitions in New York in 1969 [21]. In 1973 records of the conceptual art movement appeared in the Six Years book, by the American critic Lucy Lippard. The subtitle was ‘so-called conceptual or information or idea art’. Thus, the language and direction were formally articulated. During 1966–1972 the movement received a rather strong theoretical and public approach and other trends emerged [21].

Among other values the systems and conceptual art were concepts of autonomy and signature. The origin of these concepts roots again in Malevich and Klee art as well as other artists who often claimed that the creative process and the work by itself often dictates the point when the work is considered complete [49]. By using industrial material, adopting structural content, artists attempted to eliminate the personality engaged in the creation of the art object - “that were considered both university and personality free [49].”

Starting from the Duchamp's “readymade” objects and their acceptance into the museums there was an argument that the art market opens its doors for conceptualization and commodification of everything [3]. The system of pricing art became rather ambiguous without clear points for evaluation.

### 1.3.4 World Wide Web

At the beginning of the 1990s the World Wide Web (WWW) became available. It was initially founded for the science laboratories in the context of research and educational institutions. It was created as a result of the ideas of Tim Berners-Lee, and the European Nuclear Research Centre (CERN) in Switzerland where Hypertext Markup Language or HTML was developed that would allow later the creation of texts, pictures and to embed links [1]. In 1994, the first user-friendly web browser Mosaic and Netscape were developed.

As noticed in [22], the Internet radically changed the place of computers in visual art and the life of society. The Web became used as a medium by a number of artists who were producing their artwork under the term 'net.art'- the work that only could be shown on-line. Among artists who were creating art using web space were Vuk Cosic, Alexei Shulgin, Olia Lialina, Heath Bunting, Natalie Bookchin and others [1]. The network made it possible to connect visuals and text [48] as well as environments which were previously separated by physical space even though much of the public is still not familiar with majority artists' web projects. A lot of artists moved to academia. There, many of them considered 'biotech' and 'nanotech' as the future step for research. The labs were utilized as a new context. "The World Wide Web took the notion of connectivity to new levels [48]." As a result of this change, programming languages and techniques connected with the internet development and research, appeared as one of the mediums which artists have been used to produce the work of art. Such spaces also became a crucial part of the artist's self-expression. There are multiple languages and programs which artists currently use in their art practice, among them TouchDesigner, P5.js editor, Photoshop, Illustrator, Maya, 3D Max, Blender, Dynamo, Houdini, Rhinoceros, Python, Java Script and more. Usually, they have different or similar interfaces and include elements of coding or programming. For example, one of the popular web tools artists use to produce the works of art is P5.js (created by the Processing Foundation). It uses a JavaScript library for creative coding which is available for free to everyone. Through the setting of functions and variables artists create interactive paintings and animations. The art is highly interactive, abstract, often it has educational and political functions or gaming. It might include text and represent different aesthetics. Sometimes, it is just reproduction of sounds or all possible features together as it can be seen in the P5.js showcase [58]. For example, Roni Cantor, the author of Programmed Plotter Drawings [59] used p5.js to produce and display some visuals in the p5.js editor. Then, after exporting programmed graphics into SVG file, created a physical drawing with the help of plotter AxiDraw V3 [60], [61]. We can see the new way of artwork producing ( Figure 1, Figure 2).

It is obvious that the method to price similar works of art should be determined. Currently, the works of art which were produced implementing similar methods are on display during the different art fairs and online with the intention to be sold. The highly interactive nature of digital art, various opportunities for artistic expression, complexity of that expression and complexity of the programming make digital art an attractive medium for artwork in the future. Here, we define digital technologies as a medium which implies the art, which is produced, stored, presented using digital format. Whereas digital art which uses digital technologies as medium can be anything from the installation to the ‘browser-based’ art only.

Web development brought the tendency of using media “toward immaterial virtuality [48].”

Figure 1. Programmed Plotter Drawings. Roni Cantor

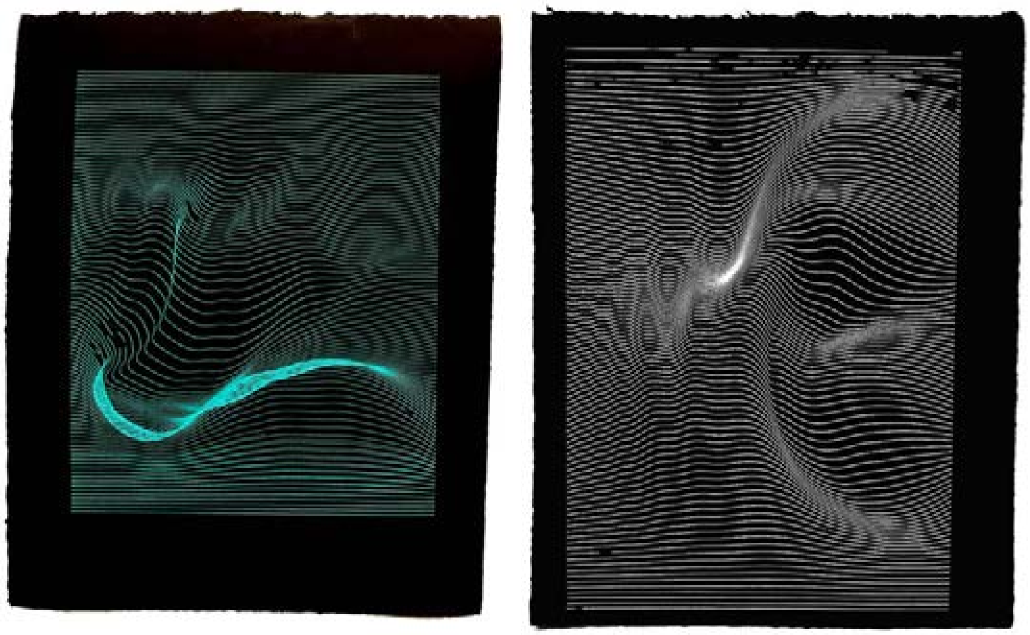
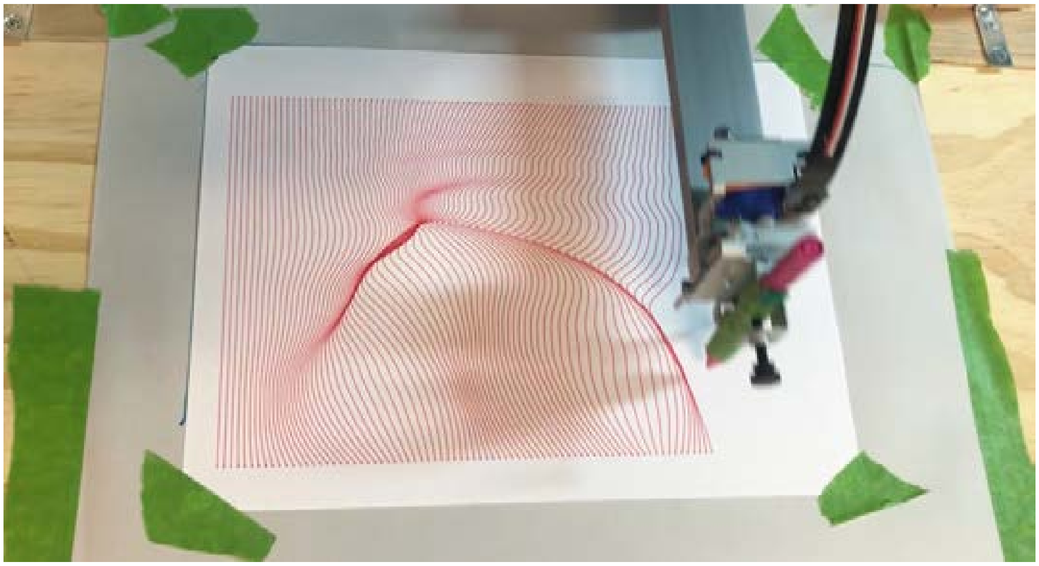


Figure 2. Programmed Graphic. AxiDraw V3 Plotter. Roni Cantor



The potential of digital artwork often calls for collaboration between multiple disciplines. However, interactive work of art changes the roles of the artists and viewers. It requires the understanding of the interface mechanisms of the work [48]. The process of how we experience virtual art is different from our traditional artwork viewing experience. “The interface of the interactive works reflects a constantly shifting context that is dependent on the navigational choices we make [48].” Often artists who work with digital virtual technologies generate situations where content and context are interchangeable. The Internet also allows us to re-contextualize the information and clone everything [48]. For example, “When Documenta X decided to “close down” its website after the end of the physical exhibition, the artist Vuk Cosic cloned the site, which remains available online until today [48].”

The development of the Internet net brought one of the inevitable consequences - the art distribution went beyond local geographies and made the artists a global participant. From the economic point of view the Web made the art transactions and art communications faster and increased visibility of the art market [3] bringing certain changes to the democratic exchange even though not all communities and countries still have unlimited access to the Internet.

### 1.3.5 Artificial Intelligence

The development of the World Wide Web triggered the development of datasets and AI techniques. In 1956, J. McCarthy and M.Minsky organized the first workshops to articulate new directions on the development of AI, the term they introduced a year earlier. They offered to use the new digital computers to explore the conception of intelligence. It drove the rise of the studies of machine intelligence and logic-based programming becoming influential in psychology, cognitive science and AI robotics with biologically inspired approaches. That brought AI closer to neuroscience inspiring artificial evolution and neural networks as well as new collaborations between scientists and artists bringing new joined projects to life [49]. During 2000s, such collaboration was the DrawBots project. One of the project's goals was to understand creativity and cognition in artwork creation in terms of implications of artificial life for the theories of aesthetics and creativity. The main question to answer was whether autonomous machines like DrawBot can create artwork independently [49]. It again raises the question of the evaluation of the drawings which was done by robots or with the help of mathematical algorithms. How can we price them?

AI techniques have influenced art practice enormously and currently their role in the art practice is growing, becoming a new medium for the art. “There is a human in the loop, asking questions, and the machine is giving answers. That whole thing is the art, not just the picture that comes out at the end. You could say that at this point it is a collaboration between two artists — one human, one a machine. And that leads…to think about the future in which AI will become a new medium for art [23].”

AI can become not only a new medium but the work of art which was produced using AI algorithms was even sold for $432,500 [23]. The Edmond Belamy portrait sold for this amount in 2018 was created by Gan (Generative Adversarial Network)-an algorithm which was defined by formula [23]. The formula which contains a lot of parentheses is written in the corner of the painting. The algorithm was composed by feeding the system with data of 15,000 portraits which were composed during the period $14^{th}$-$20^{th}$ century [23]. One of the ideas of this invention was to prove that algorithms can ‘emulate creativity’ [23]. The portrait indeed contains creative elements- see Figure 3 [23].

AI is just one of new technologies that can strongly influence the art market in the future. The method of evaluation and pricing such art pieces and mediums is still uncertain

Figure 3. E. Belamy's Portrait created with GAN

## 1.3.6 Data

Because of the computers capacity to process various information as data objects many media artists develop their artwork around the immense database capability [48]. It creates not only a potential for multidisciplinary directions for the artist's work but involves meaningful large social, philosophical concepts rather than individual “objects” like the work of Andreja Kuluncic and collaborators “Distributed Justice” (2002). Their net project which deals with ethical reasoning and political philosophy consists of the virtual game where online visitors building a society with the narrative of the dynamic social changes and exhibition space filled with theoretical and practical activities. Later all parts of the project were stored in a Web portal and the project was developed into an open forum [48]. Data can be stored, archived, called up for multiple uses within different contexts, especially in terms of long-distance collaborations. Nowadays, people even make their data available on social platforms following the paradigm "Broadcast Yourself". Stakeholders in the art market use databases to evaluate the works of art (we will discuss it more carefully later in our study). Studies, including our research, would not be possible without ubiquitous in the computer age databases. This data availability changes the working process approach, art form and function narratives. Artwork not only became interactive and immaterial, but it can be seen by a mass audience at the same time and in different locations. It brought a loss not only of traditional objects as art but a problem of the loss of artist full authorship control in terms of digital artwork [48].

One of the important aspects of the data for art practice is data visualization - creating visuals from the sets of data because data sets exist initially as processes which are not necessarily visible [48]. Utilizing data helps the artist to enhance the level of visualization to represent spatial environments. It enhances the viewer's new ways of seeing and understanding the world.

It also raises the question whether data or artificial intelligence could be considered as new medium in the artistic practice [49], [23]. How this kind of art might be priced and who is the author - artists, scientists or machines [23]?

### 1.3.7 Art Perception

The last that I like to point out in the part of Trends and Changes is some changes in terms of art perception as well as art aesthetics.

Numerous art critiques and philosophies discussed art perception and art aesthetics in the 20th-21st century that brought new questions including what could be considered as art in the 20th century and how it could be evaluated. For instance, in the book “After the End of Art”, art critic Arthur Danto argues that Brillo Box sculptures by Andy Warhol shown at the Stable Gallery in April of 1964 was the work of art.” Author points out differences between “reality and art”—that what Warhol had done was not really art. However, the author was convinced that these objects were art. “Wherein the difference lies between them and the Brillo cartons of the supermarket storeroom, when none of the differences between them can explain the difference between reality and art [5].”

Exploring the philosophical categories of art, Danto states that the philosophical challenge now is “to explain why they are works of art.” His main conclusion was that in the twentieth century art can be “anything artists and patrons want it to be [5].” The author quotes A. Warhol and states that there is the “end of art” meaning the end of narratives at a certain period. “It does not entail that all art is equal and indifferently good. It just means that goodness and badness are not matters of belonging to the right style or falling under the right manifesto [5].” “The sixties were a paroxysm of styles" meaning that “anything could be a work of art [5].”

Thus, the threshold of art aesthetics for entering the art world was expanded to allow every possible piece of art to enter the art world. It created additional conditions for the art market and art pricing.

In [5] author states that "the end of art—a somewhat dramatic way of declaring that the great master narratives which first defined traditional art, and then modernist art, have not only come to an end, but that contemporary art no longer allows itself to be represented by master narratives at all [5]." Artists liberated from history are free to make art in whatever way they wish. Nowadays, compared to modernism, there is no contemporary style [24].

In recent years, describing some computer art related exhibitions, art critics argue that "computer art *is* art, and that its examples are not just historical artifacts but aesthetic objects [22]." They argue that computer artwork is not just a technical presentation but an artist's judgment which includes the choice of materials as well as the choice of the results that must be displayed or must be thrown away by artists themselves. Seeing computers as tools cannot prevent us from experiencing the results of experiments as art objects [22].

In [25], H. Hagtvedt , R. Hagtvedt and V. M. Patrick studied psychological and aesthetic perception of visual art and attempted to build a model for the visual art perception and evaluation. They incorporated cognitive and emotional components into their study. They characterized the formation of the evaluation of art as organization of cognitive and affective elements stimulated by the work of art which generate a rank of emotions and perceived features which influence evaluation and perception of the work of art. The topic of the aesthetics of art appreciation which included emotional and cognitive factors examination were also discussed in [26] where H. Leder, G. Gerger, D. Brieber and N. Schwarz evaluated viewers' emotional responses to the contemporary works of art.

In [27], D. M. Kohinoor and E. S. Cross attempted to explore a visual aesthetic experience in terms of multicultural universal fine art appreciation. They studied to which level cultural background forms the art preferences. They combined multicultural examples (Anglo-European and Indian) for this examination. The study stated that despite common features (symmetry, contrast, color, brightness, proportions, complexity) which influence the art perception, human perception of art is still subjective and based on the individual aesthetic preferences. Visual art rating is also highly unique and depends on the depicted subject. Even though the article explores the universal differences in perception of art, it is interesting that the painting depicting the representational subjects such as people, landscapes, and still life are assigned with higher ranking compared to artworks which depict non-figurative abstract content. That may be connected to the human preference for meaningful associations even though the ratings for abstract art are higher among those who have professional art knowledge [27].

In terms of the altered interaction between art object and audience and emerging so-called interactive artworks, N.Bourriaud introduced the phrase “relational aesthetics” which describes a process model of approach to audience/artwork [48]. Even though the aesthetic perception of art was changed during the 21st century and expanded its borders widely stimulating computational imagination, aesthetic preferences remain subjective and individual where overall the representational subjects are rated higher in terms Modern computational imagination and computational aesthetic perception expands our understanding of digital art where evaluation categories include “creativity” and “judgment” and make the “beauty” the unstable category to evaluate the art piece [22]. Nowadays, computational imagination has engaged us into the new discourse which challenges our art aesthetic and art perception. It is "an evolving paradigm that engages but also challenges our persistent oil-on-canvas aesthetics, line by line and bit by bit [22]."

## 1.4 State of Contemporary Art Practices and Art Markets

### 1.4.1 Online Art Trade

In this part of the study, I discuss the state of the contemporary art market in terms of online art trade, and I focus on the challenges occurring within the virtual art trade.

Being a large area of the global economy, the contemporary art market, especially the online art market has great potential for unlimited growth. The online art trade was thriving recently due to the pandemic lockdown. Having a great potential for financial returns [28], art and the art market became a significant area in the globalized economy embedded into economic globalization and the World Wide Web [6]. Globally, the art market was estimated at $63.7 billion with the auction turnover of $ 8.45 billion in 2017 [28], [7]. However, collector surveys state that 40% of art collectors never sold any artwork and they were not certain about the total value of their collectibles [28].

The art trade by itself has been changing and the traditional art market became mixed with the online trade. In 2018 more art galleries became closed than opened [7]. Many small size galleries struggle to survive [10]. On the contrary, online sales made up 29% of gallery transactions which was a dramatic increase in 2013 and online art transactions in the first part of the 2021 were $6.8 billion and raised by $13.5 billion by the end of 2021 [2]. The combined art value was increasing more rapidly than the volume.

China gained a crucial role in the art market and became relative to the American and European markets [29]. Historically, the art market concentrated to some level in terms of value in the main centers like the USA and Europe.

“Paris had a temporary revival as a world art center during the 1950s and 1960s; however, over the 1960s, New York and London dominated, largely due to their established bases of wealth and economic power and to the introduction of a new system of taxes on art sales and other regulatory deterrents in France. During these years, the major auction houses of Christie’s, Sotheby’s, and Parke-Bernet in New York thrived and began to attract a wider interest from wealthy collectors and investors, particularly for Modern art sales [30].”

Nowadays, online trade has all potential to become a major commercial tool in the nearest future. In a recent art trade report, 56% of art consumers stated that the switch towards digital trade, which had a trend over the pandemic lockdowns, would become permanent [2]. However, even though the pandemic shifted art sales into virtual reality, where online transactions became the primary way of communication and in-person events where sales occurred, including multiple art fairs, were canceled, there are still obstacles to global adoption of online sales. For instance, there are buyers that prefer interaction with the artistic communities which cannot be achieved online [31]. Another obstacle is concerns over prices, including price transparency. Survey showed that 90% of new customers and 92% of small volume customers pointed out that price transparency was a crucial aspect when they buy art online [28].

An art buyer without an art expert has little information on an artwork especially when purchasing online. In this case, the reputation of the artist is an important factor that makes buyers feel more secure about their purchase and assures art quality [9]. This brings the question of how an uninformed customer can decide on purchasing art in a complex virtual art market.

The average consumer with enough income while purchasing original artwork would be at a loss to justify why one watercolor which has the same size, materials, shape and visual features is worth $300, another watercolor is worth $3,000, or $30,000. None of them would have the auction record to set the investment value. How can customers understand why a large watercolor which depicts flowers in a vase on the table is $25,000 while the almost similar work on paper is at one-tenth the price [62]?

Adding to the problem, gallery sales or auction records do not give customers enough knowledge to understand art pricing [32]. Even with the auctions with the prices which were set by professional, unpredicted price fluctuation happens frequently. These fluctuations are connected to sale rates. They may be used to evaluate changes in the art market [33]. All that makes the conditions even more complex for the art buyer. In the digital age, sales information became largely available. However, using simple “thin” methods of valuation creates problems between buyers who use such methods and other participants in the art market who tend to use “thick” compound methods of evaluation [32].

There are also concerns that the rigidity of utilizing of simple metrics, for example, auction sales results, may create issues due to the trend driven nature of the auctions [32].

### 1.4.2 Emerging NFTs marketplaces

Another phenomenon of the online art trade became NFTs marketplaces. During recent years, the number of NFTs platforms and marketplaces dramatically increased, contributing to the online art trade [2] where NFTs took over the world and exploded in the art market space.

Recently, Christie's auction house sold the NFT collection of digital art for $69 million [63]. Non-fungible tokens (NFTs) give the person who purchases them ownership of online art collectibles. "Non-fungible" means that they are unique assets. They carry a unique digital identification with the proof of ownership and can be exchanged between stakeholders on a public blockchain. NFT art can come in various forms, including static and dynamic images where every item has a unique trackable history and provenance [34]. There are fees for every transaction. Fee structure of every marketplace is different [34]. Sometimes NFT marketplaces hold real time auctions.

Another important NFT's feature is royalties that reward artists for every sale. It can positively change the art industry and artist marketing experience [35]. Traditional art market does not always provide artists with royalties. One of the important aspects of NFT items is a proof of provenance [36] which is currently a reliable part of NFTs platforms.

Among emerging popular NFTs platforms are Nifty Gateway [64], ArtSquare [37], OpenSea [38], Metapurse [39]. NFTs are considered as 'the gateway to new digital canvas' [40]. One of the popular NFTs platforms is Tezos. Tezos [40] - 'a blockchain designed to evolve' [36]. The goal of Tezos platform as the most 'eco-friendly' and algorithm efficient platform is to create a place where 'users can directly and frictionlessly interface with each other over a decentralized network' [36]. Artists of this digital platform can connect with fans and sell art, collectors can buy and sell art. All stakeholders of this virtual space can interact with different applications, and they do not need intermediary. It stated that more and more people join NFTs daily [36]. NFT platforms can be a 'user-governed and user-centric movement', providing participants with security, collaboration, energy-efficient algorithms and smart contracts [36], forming the generation of crypto collectors [41] and large ecosystem [34].

NFT platforms are becoming a space which can eliminate concerns of price transparency and provenance. The trade report on the market stated that even though the art collectors used to non-transparency in the art market, 90% of new buyers as well as 92% of smaller spenders argue that "price transparency was a key consideration when buying art online [42]." The multiple art platforms allow stakeholders in the art market to reach each other out to complete transactions. However, there is still an uncertainty about provenance of the work of art and the price validity, problems of buyer insecurity and building trust challenges. Building trust became one of the challenges pointed out by 50% of art platforms [2]. Increasing price transparency and reducing provenance concerns, NFTs marketplaces are still unable to be reliable platforms to justify the price validity as well as to solve the other art marketing issues. Many of the art buyers still consider them as an unknown platform even though authors in [65] argue that for the artists it is a way of economic stability and democracy. There is also a historic similarity between the current NFTs debates and the conceptual art debates back to 1960s.

"Artists were attempting to circumvent the market and the systems of inequities that they recognized and did not want to participate in. They began creating work that could not be acquired and objectified. Now we are echoing those conversations some 50 years later in service of the same ideals and motivations [65]."

As part of the art and technology discussion, there is still a fear of computers, artificial intelligence and new mediums. There are different types of arguments. But as artist A. Michael Noll noticed.

"A fear of computers and artificial intelligence goes way back to the 1950s and 1960s—and more recently extends to the Y2K bug, NFTs, virtual reality, and the metaverse. I would have hoped that by now some critics had gotten over their distrust and fear of new media, new technologies, and new tendencies. The use of digital computers should not be an excuse for "bad" art or an end in itself. The "art"—not the medium—is what should matter [51]."

### 1.4.3 Labor and Marketing

As I mentioned above, digital technologies have not only altered artistic production but also changed the economic model of art marketing. Economy moved from "material" goods to "immaterial" information goods where virtual goods fit into the physical world and artists fit into the category of immaterial labor that produces informational content of a commodity including an element of free labor such as voluntary modification of websites [48]. One of the platforms which questioned the value of labor as well as artistic production became Aaron Koblin's interactive application "The Sheep Market" (2006) which generated a vivid online discussion. "The Sheep Market deliberately makes no claims for participatory art: people are hired to perform a creative task for an extremely low wage and the artist, in one section of the Website, provocatively sells blocks of sheep drawings for $20 as adhesive stamps with a certificate of authenticity [48]." That questions the commodification of human network intelligence as well as cultural commodity [48]. Some of the art projects include free labor which does not gain any immediate profit. Other art projects create byproducts of their processes and play with the capitalist model of digital economy by adopting models of the capitalist market such as artist group etoy in the etoy. ART-COLLECTION. It intended to reinvest all financial earnings in art [48]. Contemporary art cannot avoid referring to the context of the cultural production in the information age [48]. Media art faces economic challenges such as instability.

The nature of digital information and art contributes to this instability. Behind the media art there is an idea of interactivity which became the marketing trend of Silicon Valley in the 1990s and has been described as “consumer commodity economics” [48]. “Since much of the extensive, heterogeneous history of interactive art has pursued a decidedly anti-commercial direction, we pose the rhetorical question: In what ways does such commercial saturation of interactive multimedia challenge its ability to resonate with artistic meaning [48]?”

Artists developed interactivity as a social base for art but in many cases, art served as the popularization of commercial products. In the 1990s, sometimes art was difficult to distinguish from advertisements [48]. The Web also gave to the artists new opportunities in terms of marketing but also raised for them new questions.

How to evaluate new media or interactive art in terms of art aesthetics? Are we looking at art or just technological effect or advertisement? Another question is whether art net projects without a special promotion attract the Internet surfer? Are there the best ways for artists to reach out a targeted audience and customers via the Internet?

### 1.4.4 Authorship

The technological changes shifted the conventional idea from the art as an object to the rise of the idea of dynamic and interactive art forms where the audience can be a valuable participant. This change challenged the artist authorship as well as relations between artists and viewers [48]. Signature, which refers to authorship is a unique autograph by the artist. Usually, it is an identifier which influences the artwork price. In [49], the author gives an example of Francis Bacon’s painting which was sold for $86 million because it ‘bears the attribute of the unique signature style [49].

On the contrary, in the 1960s the movement against 'signature' took place. It had several reasons, one of them was artists' reaction against art world economics which they saw as exploitation of their work. It was also a rejection of the galleries which were focused on unique signed objects when artists were concerned with the process and concept [49].

The question is how the artist's signature should be evaluated and whether the presence of the artist's signature should increase the price of the artwork is still relevant. That must be addressing in the art pricing system.

### 1.4.5 Artists with New Mediums and Computational Tools

As I discussed already in the part devoted to the World Wide Web development, as a result of all technological developments and changes, the artists working environment and culture as well as models of practice became a part of computer-mediated culture where many artists can use digital tools to create the artwork, or to use digital space as an art medium. More often the individual practice is extended and works of art become results of collaboration and partnership with scientists, programmers, engineers, and designers that forms multidisciplinary teams and cross-collaboration with cross-disciplinary environments. The production boundaries have become blurred too. Technologies that shape computational culture allow experimentation in a vast range of media [49]. Boundaries between art, science, technology, design are collapsed and artists by themself, like Stanza or Mick Grierson, often become brilliant programmers using and constructing new creative tools and software [49]. For more than two decades, one could roughly distinguish the spectrum between opposite ends of software (virtuality) and hardware (physicality).

Within the range of digital technologies used, there are three groups of artists which can be identified. Artists who use new media as a medium. They create work of arts using new media as a medium using its medium' characteristics. Another group is artists who utilize art media as a tool to generate more conventional art forms. Finally, artists who integrate all means of media, including video, performance, robotics, and the Internet to generate interdisciplinary works of art [48]. In the part devoted to World Wide Web development we already showed the example of using programming languages as new mediums and technologies as new ways of production.

Some challenges of this change and new practices is to adjust terminology for new types of art [49] as well as the new relations between artist and the audience. For example, we call some works artists currently producing 'interactive artworks' where 'interactivity' is a term that can be used to describe anything from point-click navigation to opening the system that has a fully collaborative dialogue interface. It is known that dialogism in electronic media is interactive, but it should not be mixed up with the global network exchange provided by telecommunications. The generation of digital works of art is tied to the desire for collaborative exchange with the audience, often to gain new insights [48]. As pointed out in [48] because "digital media are often literally dialogic (as opposed to a dialogue that configures itself as a mental event), the position of "making" and the relations between artist and audience are altered", "the experience of the traditional art object is in transposition from the look of the eye to the eye of the mind". In this type of process, the work of art is incomplete without audience participation [48]. Thus, digital technologies changed the nature of interaction between artists and audiences as well as the nature of the working environment, including the evaluation of these processes.

"Digital functionality - such as algorithmic calculations, databases, and telecommunications - transform a work of art into a dynamic environment [48]." The changes in this area are so fast that new media technologies change the narrative ways of expression, developing the way of dynamic experimentation [48]. "What we might call computational culture, is drifting and expanding as fast as expanding definitions of art are being challenged: terminals are no longer fixed, art comes at you from many directions and at the speed of light, distributed media pervade our everyday existence [49]."

Artist's conventional role is shifted, some authors see artist in the computational era as an artist-researcher. In the 21st century it is not sufficient for artists just to utilize new computer tools. Artists have to be at the forefront of research and the technological developments [49] to be able to sustain the sense of novelty in their art. For instance, the author describes transformations in terms of textile works of art and the new technologies' influence on the art practice which allows to offer new view into the realm of virtual textile [49]. "The resulting work incorporates cutting-edge digital technology to transform the virtual warp and weft of mutating textile patterns into sonic improvisation, creating an environmental installation where the immediate haptic and abstract aural qualities of the material are made available for multi-sensorial experience [49]." Another example is the work by British artist Stanza, who used traffic, security data for his work and research. His research studies are an example of how computer art as well as its distribution may keep up with fast developing technology [49].

One of the other important questions to point out which is partly related to our current research, is how the institutions (art galleries, museum, appraisal agencies, auction houses and other art institutions) can be adaptive to the twenty-first century artistic practices which are not only limited nowadays to visual arts but getting rapidly expanded with the development of computational environment and culture [49]. In this technological rapidly changing space, some artists already perceive their works as ephemeral, they see digital technologies 'inherently unstable' [49]. That brings us to the question on how artists' ways of evaluating, pricing and marketing their art must be adjusted in the 21st century.

## 1.5 Art Pricing Problem

This part specifically addresses the challenge of pricing a work of fine art and more broadly the ecosystem of the art market -the complexity and subjectiveness of contemporary art marketing.

The factors that shape the art pricing are compound. Attempts at quantifying art have been challenging for many researchers and art dealers due to the essence of art which is often considered as non-commodifiable. Auction plays a crucial role in shaping the price. There are also some models which explain customer behavior. Since we became surrounded by technology, there have been attempts to connect art to the different areas of computing and economy.

A certain number of studies related to topics such as categorizing works of art by period or building theories on the basis of visual attributes. These studies focused mainly on works of 'old masters' or popular artists, but not on the contemporary fine art pieces. There is a difference in terms of pricing of ‘old masters’ and contemporary artworks. This study focuses particularly on contemporary fine artworks done by artists who were born after the 1940s. As I mentioned, there is a system of auction records which are useful to assign a price for art of ‘old masters’. This type of work has enough records for evaluation. There can also be available records of similar artists to set up a foundation for the art evaluation. The prices of works of the secondary as well as tertiary markets are also often shaped by the importance of the historical period or provenance.

Stakeholders of the primary market are often challenged with the overwhelming information which does not tell them enough to assign the valid price. As it was already noticed, online marketplace recently grew. Hiscox trade report [2] reveals that online art market sales are estimated to dramatical rise by 72.2% to $13.59 billion in 2021. That growth permitted new potential customers with different backgrounds and often without art expertise to access the market. Report indicates that 41% of new customers in the art market prefer to buy art online and nearly 19%, compared to 13% in the previous year, purchased more than $50 000 worth of art on the Internet. 58% of art customers spent more than $5 000 to buy online [2]. However, the majority of customers who are not educated in the art area are uncertain about the price validity and quality of the artwork. 51% of customers have concerns about the art quality. 70% of art customers would like to have more background information about the artist or item they buy online. 89% - indicate a provenance tracking as a service which would help them to buy more art. 65% of customers indicate that the pricing tool would make them more confident to buy art and collectibles online [2]. In the art market there is an opposition between commercial and artistic values. There is no ‘commodify goods’ with the essence which tend to be ‘non-commodifiable’.

Stakeholders in the art market share non-economic value through economically valuable pricing [8]. How to price the non-commodifiable art is still the subject of many discussions and has been described as an exception to established economic theories [8], [9]. Even though many stakeholders in the art market tend to say that it might be scarcely possible, and others prefer not to discuss it at all, still the bottom line of this discussion is the argument whether art is a part of cultural significance or a commodity of the global economy [6].

In [8], the author argues that prices are a part of cultural information. Prices indicate how artists, consumers and art dealers see their roles. Author describes his experience with the art dealer who characterizes his relationship with artists as a “family and community” and refuses to “talk numbers” in terms of setting the price. In many cases art dealers and gallerists tend to characterize their relationship with art and artists using the word “love”. “It is all about love! Can you sell or buy love?”. At the same time the described art dealer tends to remember how much it was paid for the works of art being proud that “the value of his collection surpassed the past acquisition prices dramatically [8].” It gives the idea what price must be from the artist/dealer point of view rather than economic perspectives [8].

From the perspective of directors, managers of small and mid-sized galleries, artists do not know how to evaluate their work of art. One of the business models is based on “spreading the word about the artists”. Prices are often assigned by examining what comparable works are sold for by making predictions based on personal knowledge. This can be very difficult for less established artists who do not have developed sale history. There is a very large risk for artists evaluating their art pieces too low or too high. This can harm their careers, damage the investment value, and make art dealers lose money. It also makes prices arbitrary, which can make investment in art unattractive, especially when investing in artists without a proven sales record. In some places, it also takes approximately 30 minutes to determine a starting estimate for an original work by an emerging artist. Prints or works by more established artists take closer to 10 minutes. The main challenge is to maintain regular sales. Finding new buyers is another most pressing challenge.

Majority of artists do not have commercial success and just make art to prove their artistic identity. High price often indicates elite value rather than high demand [62]. In the standard markets which manufacture other commodities, for example, the consumer understands the difference between Mercedes costs and Mercury. They think about better engineering, materials. Consumer's risk is normal [62].

Art only gained attention as an investment just recently [11]. Although like other assets, the art market can be analyzed [43], the researchers found that art has the worst 'risk-return profile'. They stated that the fluctuations of the art market are very difficult to model. Again, the fundamental value of art is hard to understand. This uncertainty can be called "unjustified optimism" related to future values when the art will be sold again [11].

Starting in the 1940s, the contemporary art market became an unpredictable business roller coaster with the uncertain regulations [10]. But, for the owner of the work of art, its value means more than just an investment potential. It is also a pleasure to have it [13]. It is a passionate adventure [10]. It states that there are several types of art consumers. 'Collectors' who are willing to purchase it for a large amount and usually do not want to resale it. 'Flippers' who are unwilling to buy it for a high price. They often resell their collections without waiting for the best economic conditions. 'Investors' who resell their artworks when the economic conditions are the best [13]. Some collectors' practices, for example, 'flipping' a collection have adverse reaction from other stakeholders in the art market [14].

So-called ‘superstar artists’ from whom a great amount of sales comes have another strong impact on pricing. In [15], it is pointed out that inexperienced buyers tend to search for the works of art of the artists with the well-known names from the established galleries to eliminate the risk of purchase. The dealers, who often call themselves “market makers”, as much as their artists become brands and art became the symbol of status [10]. That leads to the small part of the popular artists whose prices rise increasingly. Author in [16], states that there are small variations in the artist's talents and that the quality is enlarged compared to the price of their works of art.

Adding to these issues, online auctions experience unique ways of selling. The amount of the artworks available online has increased enormously during the last decade. For instance, in 2000, within the art category, eBay had more than 14,000 auctions, and in 2020 -35,000 [17], with at least 600,000 pieces for sale [44]. In the ‘art painting’ category there were at least 725,000 artworks offered for sale [44]. The authors of [17] even discussed the factors impacting the auction results. The factors such as reserved prices impact the result. The seller reputation and the reviews on shipping have no impact on the auction outcome [17]. But the authors in [45] argue that shipping charges do influence the auction outcome.

Thus, there is not just one consolidated art pricing model. We are dealing with disputable theories where various factors influence the artwork pricing and the stakeholders in the art market determine prices by themselves. Their agreements on art prices are depended on a system of assumption [6].

Another question which relates to the pricing is what can we call an art piece? The art market consists of many uncontrollable elements, and it challenged it [6]. How to separate commercial mass production from fine art. Contemporary artists often do not have a consequential sales record and just use basic metrics - the dimension of the artwork and the material cost- to price their artworks. There is not enough understanding of how to explain the emotional factors which drive the art consumers' preferences.

This research examines the challenge of generating an effective pricing strategy. In the next chapter, devoted to recommender systems, I will discuss the studies on the evaluation of art and art analytics to identify computer science techniques which can be applied potentially to solve this problem. One of the challenges is developing the recommender system as a pricing tool and generating a meaningful set of attributes.

## 1.6 Chapter 1 Conclusions

In Chapter 1, I discussed art trends, movements, and technological innovations in 20th -21st centuries that shaped the evolution of art form, mediums, aesthetics and art techniques and increased the complexity of art pricing. One of the first notable movements was the Suprematism movement which influenced the major art movements of the 20th century. The "Black Square" geometric abstraction was a 'revolutionary act' which enlarged the boundaries of art perception and complexity of art pricing. I argue that the novelty in terms of art style or art approach has a huge financial value.

Digital art development was connected to the Post Second War technological changes and computer development. These changes boosted the new art styles and mediums such as computer graphics. It influenced the art ecosystem - social and cultural movements, and experiments related to art innovations. Artists' enthusiasm, utilization of new mediums and educational efforts made computer-generated art a strong part of the visual arts environment. The first prototype of technological drawing system opened the doors for the implementation of robotic research into the art area.

One of the crucial aspects of this art evolution became the Conceptual Art movement. Through the articulation of the conceptual language and commands as well as new art theories, later, the implementation of programming languages into the creative visual art environment became widely acceptable. It also enlarged the thresholds of entering the art world and the art market. After the revolutionary act of “readymade art” everything could be called “art” and potentially to be sold. That significantly complicated the art pricing process. Art was not anymore just about ‘beauty’, the ‘ideas’ became new objectives for art evaluation bringing the additional complexity to the art market. Evaluation of the quality of ‘concepts’ became a next challenge for the art consumers. The concept of art autonomy and signature expanded the complexity of evaluation as well.

The Internet transformed the role of contemporary art and the ways of its distribution. The development of the Internet made the art distribution go beyond local geographies and made the artists global participants involved in the global online art trade.

Virtual trade became an essential part of the art market during the pandemic. It made the economic art transactions and art communications faster. It increased visibility of the art market bringing certain changes to the democratic values and increasing the number of diverse art trade participants. The artists working ecosystem, culture and models of practice have changed. Digital space and the Internet became a new medium for many artists and after merging with new technologies such as plotters became a contributor to the new methods of physical art production. Multiple languages, programs, and computational tools which artists currently use in their art practice became ubiquitous and widely accepted.

These technological changes brought the development of multidisciplinary teams and approaches inside of art practices. They changed the nature of artist-audience interaction and the role of artists. One of the examples of new ways of marketing and interactions became emerging NFT marketplaces which can be also classified as those that use eco-friendly algorithms and those that do not. Nowadays, artists have to be pioneers of research and technologies to be able to perform novelties in their art practice like it was during the Suprematism and other art movements. Currently, NFT platforms support this need. These marketplaces also support the need of the art market transparency, the proof of art provenance and artist royalties. However, NFTs marketplaces as well as other marketplaces increased due to development of virtual art trade are still unable to be reliable platforms to justify the price validity.

Art that relies on the Internet and that is produced with the help of plotters or other new technologies requires reliable methods of evaluation as well as adjusting the terminology. Internet infrastructure development boosted the development of the various datasets, mediums and AI techniques, including neural networks. That boosted not only new technologies such as DrawBots, the device which can create an artwork, but made AI, the ‘artist’, creating pictures that can be sold for almost half a million dollars. AI is one of new technologies that can influence the art market in the future. The method of evaluating and pricing AI art pieces is still uncertain.

Data is an essential element in the computing age. Not only artists can use data as a creative medium, but stakeholders in the art market can also use databases to create a system for the art pricing. With the help of databases, a mass audience can experience the same art object, at the same time but in different locations. One of the ways of artistic creativity became data visualization practice that enhances the viewer's opportunity of seeing and understanding the world because datasets by itself often do not contain elements of visual representation.

In terms of art aesthetics and perception, we can conclude that in the 21st century it is widely accepted that art can be anything that artists or patrons want it to be. There is also no contemporary style. Interestingly, that computer art is not just a technical representation but an artist's judgment on choice of materials, or results to display. Some studies conclude that in the 21st century aesthetic perception remains subjective and individual where representational subjects are rated higher compared to abstract art.

Art institutions should find a way to keep pace with the art changing environment and evaluate new types of art to distinguish the art from just new technological effects or advertisements including questions on the presence of an artist's signature. New art pricing methods have to address these historical, technological, cultural and economic changes to have a reliable price validation system.

Lastly, I discussed the state of the contemporary fine art market and the challenge to price contemporary visual art. The factors that shape art pricing seem complex in the 21st century. The question whether art has commodifiable or non-commodifiable nature is challenging for many researchers and stakeholders in the art market. In the art market there is a paradox between commercial and artistic values. Artists often do not know how to price their works of art and other stakeholders in the art market often use 'the word of mouse' about artists to set pricing and it is challenging for less established artists and can harm their career path. Thus, some of the artists do not have commercial success and cannot sustain themselves via their art sales.

The art investment has the worst 'risk-return profit'. There are different types of stakeholders in the art market and different types of artists including 'superstar artists' who have significant impact on pricing. Currently, auctions play a crucial role in price shaping, but they mainly refer to the “old master” artworks which have some number of auction records. There are not enough sales records for the art in the primary art market.

Although the art market has been growing and indicates that the number of customers who prefer to buy art online is increasing, a high percentage of the customers have concerns in terms of art quality and price validity while buying virtually.

The fundamental value of art is challenging to comprehend. Thus, there is no consolidated art pricing model and art prices are often just set in the system of acceptance.

# Chapter 2: About Recommender Systems

## 2.1 Introduction

This chapter reviews the works on recommender systems, methods of recommendations and building the personalized recommender models based on the clustering artists with the similar characteristics and placing them into the relevant price category.

## 2.2 Related Work

Methods of recommendation discussed in [66], [67], [68], [69], including collaborative, content, demographic filtering [66], [67], [68], [70], [71], [72]. Knowledge based recommender system, hybrid recommender systems and recommender systems for art pricing are explored in [67], [71], [72], [73], [74], [75], [76], [77], [78], [79], [80], [81], [82], [83], [84], [85], [86], [87], [88]. Studies on art analytics and computer science techniques are presented in [89], [90], [91], [92], [93], [94], [95], [96]. Text analytics, document vectors, sentiment analysis and image processing are explored in [97], [98], [99], [100], [96], [101], [102], [103], [104], [105], [106], [107], [108], [109], [110], [111], [112], [113], [114] and action rules development and feature studies - in [115], [116], [117] [118], [119], [120].

### 2.2.1 Method

Activities related to development of the prototype of the recommender system for art pricing included the following.

Major resources and activities in the art market were identified. The simulation of the system business model was built. It was considering to GET Customers: Earned + Paid Media (Google AdWords, Facebook Advertising, Instagram, email newsletters). To KEEP Customers and reduce churn: Loyalty Program. One free usage after 5 purchases for customers without license, Free Product Updates for customers buying either basic or premium product, Elite Club for Wealthy customers; to GROW Customers: sell existing customers premium product (if they use basic product for minimum one year -> offer the update to premium with 20% of the regular price, Referral (two free usages for successful referral of one new customer).

A list of Value Propositions for customers and the channels how to reach them were considered - directly via the website or indirectly via Art Technology Platform like Artsy through licensing. The crucial costs, computer resource costs, customer education, database purchases, and Revenue Streams were identified. Determined objectives were to specify Key Resources and Key Activities, to consider following Key Activities: Database Construction and Management, Application and Website Development, Minimum Viable Product Development, Customer Need Discovery, Market Development, Partnership Relationship Maintenance, Web Mining, to identify the critical component of our Key Resources as the Dataset of Paintings and Artists.

A major technical objective for the building of a primitive prototype was to collect a small sample of 20,543 most popular oil, watercolor, and acrylic paintings from one of the websites used for artwork sales. With every painting, to extract additional information attached to that painting either directly or indirectly (for instance information about the artist who can be found on a different website). The Art-Dataset, built for our preliminary research, describes artworks in terms of features having impact on their prices (features we are aware of were dimensions, medium, brightness, subject; features we may not be aware of: style, color, type of scenery, number of views, number of favorites, and multimedia type of features which can be extracted from art pieces by dedicated multimedia software). The total number of created features exceeds 120. The price range of paintings in the testing Art-Dataset was $100 - $39,000. To discretize the price attribute, there were chosen cuts in places where there is a gap in price attribute and the neighborhood was characterized by a relatively low density.

Then, these cuts were tuned a little bit by observing the classifier performance. Values (480, 1020, 2335, 5100, 10650, 19500) showed the resulting discretization cuts. WEKA was utilized to extract classifiers from the Art-Dataset with the price attribute being discretized. Random Forest had the best performance. One of the discoveries was a confusion matrix that showed that paintings are overpriced which means the classifiers trained on that dataset assign too high price tags to new pieces of art.

## 2.3 Background and Different Methods of Recommendation

Recommender systems are systems that are used to create a relation between a user and preferable items [66]. Users express their preferences in different ways. Directly- by using ratings when saying what they like or dislike, or indirectly- through their consuming preferences and behavior [66], [67]. During the last decade, the web has been generating a huge amount of data which can help to assess customer's habits [67]. That provides users with the information about products which can be targeted because in many cases users are overwhelmed with the amount of available options [68]. Thus, automated systems with different filters can provide consumers with better decisions.

Majority of recommender systems are built to satisfy the needs of the individual consumer. However, they were designed to be helpful for a group of individuals. Recommendation algorithms can be applied to a collective environment. There are various applications for the recommender system where recommendation algorithms, for instance, collaborative filtering which can be applied to a group domain [69].

Methods of deriving a recommendation depend on the type of information and strategy which is used to generate recommendations. One of the methods to classify the recommender systems is by assuming how they generate recommendations. There are five main methods for deriving the recommendations for consumers such as collaborative filtering, content filtering, demographic filtering, knowledge based recommender systems and hybrid recommender systems.

The earliest type of recommender systems is *Collaborative Filtering* [70]. The initial recommender systems used this method to create recommendations [68]. The basic explanation for this method is that, for example, if two consumers like similar items in the past, then, if one enjoys something new, the other consumer will probably like the same [71]. One of the restrictions of this method is that without ratings recommendations are not possible [68]. It can cause confusion if a new unique item is added to the filtering. This problem to create any suggestion without ratings is known as the 'coldstart' problem [68]. This method also tends to highly rate pieces that have been stored in the system longer. Such items are more likely to be interacted with for a longer period of time that generates popularity for them [68].

*Content Filtering* is a recommender system that filters the content. It makes suggestions based on the similarity to the pieces which consumers interacted with in the past [71]. It analyzes the content to make recommendations [68]. It works very well for recommending text content with a vast quantity of contextual information [66]. One of the obvious advantages of these systems is the consumer independence that allows the consumer with an expanded profile to be provided with recommendations without references to the other active consumers. However, the system tends to place consumers, without complete profiles, into the interests which are only shown in their profiles [68].

*Demographic Filtering* relies on demographic data to make recommendations for the users [71]. This method is based on the idea that consumers of the similar nationality, sex, or age have the same preferences about pieces they want to buy [66]. This system is less useful than other systems, however, it can be combined with other recommender systems to increase performance by improving context [67]. One of the arguments is that this type of systems is subset for collaborative system [72].

*Knowledge Based Recommender System* uses domain knowledge in a certain area to generate recommendations [71]. It has a unique advantage to other systems in terms of working in a very complex environment with the different conditions which can be changed over time [67]. With idiosyncratic high pricing items with complex rules of characteristics it can be problematic [67]. Consumers may be also willing to have explicit, complex requirements [67], [72]. A main difference between knowledge-based recommender systems and other systems is that they are based more on direct requests from consumers [67]. They are often more efficient than other methods earlier in their life cycle. However, systems can lose functionality when the learning component is not getting developed [71].

Constraint Based Systems and Similarity-Based Systems are two main types of knowledge-based systems [67], [72]. The couple of primary techniques for building a knowledge-based system- ‘case based’ and ‘constraint based’ techniques [67], [72]. In ‘constraint based’ system consumers can outline constraints where often some of them are relied on domain-oriented rules [67]. On the contrary, a ‘case based’ system relies on similar results to those which are defined by consumers [67], [72]. Both systems attempt to fulfill the requirements. The user must modify specifications interactively if requirements cannot be defined [67], [72].

*Hybrid Recommender Systems* is a combination of different techniques to create a new system which can be more efficient than others which are used alone [71]. For instance, a system with combinations of collaborative filtering with content-based filtering is a good example of a system which can eliminate some defects of both systems. It often aggregates the different type techniques, but the same type can be combined as well [67]. Hybrid recommender systems can be different in design. Some of them contain numerous models combining them into the one model which is sometimes defined as a monolithic system [67], [72]. Other methods of construction can be ‘parallel’ or ‘sequential’ methods which can be named ‘pipeline’. Parallel method has multiple independent merged systems. A sequential method has one feeding which is put in order into another [67], [72]. Hybrid recommendations can represent numerous outputs for the consumers more than combining them to generate a mixed systems [67].

## 2.4 Recommender Systems for Art and for Pricing

Finally, I will discuss recommender systems for art pricing. Currently, there is only a small number of systems developed so far which target problems and challenges within the art domain. However, there is a good potential for the construction of new systems in this area. Authors of [73] discussed these problems. They tried to categorize the works of art based on the genre, artist and style [73]. The raw image features were extracted and then utilized to train the system. It was later used for classification [73].

The problem of recommending art items to users was discussed in [74]. Utilizing a dataset of purchased art items, authors tried to predict purchases with the help of features that were developed [74]. They did experiments with metadata which was composed from the manually chosen tags, visual features, including those which were extracted using neural networks. They concluded that metadata was not this useful to predict sales. On the contrary, visual features derived from neural networks had the best performance [74]. In [75], the authors continued to explore the challenge of feature engineering for art item purchase prediction.

Authors in [76] built a system to predict which artwork users would choose to interact with on a website. The website presents both artists and users that leads to the specific user behavior because users, by interacting with artworks they support, may change their preferences [76]. The researchers extracted temporal, visual and social features to create their model for user behavior prediction and the results were positive.

A system for pricing contemporary art items was explored in [77]. It was based on a restricted dataset containing 20,000 best-selling art items. The system has large pricing intervals and its recommendations are limited to utilizing only dimensions and mediums as predictors. This system had influence on the methods we discuss later.

Existing art pricing systems use human experts rather than data analytics to evaluate works of fine art. Some of them like MutualArt [78] have the large database of past sales, however, the number of attributes describing sales is rather small. It assigns prices to new works of art by comparing them with similar items in their datasets. It charges $49 for a one-time service. It asks to provide the information about the art piece with some details and the valuation report is produced in 72 hours.

Another system - FindArtInfo [79]- is a free art appraisal website which is based on information about 441,107 artists and 3,837,892 prices on different fine art (antique and contemporary art). This appraisal tool is based on comparing new items with recent auction prices of similar artworks. Auction sales occurred over the recent years. Database also contains more than 369,596 signatures and 2,310,465 photos of artwork as well as artist names. This online platform [80] offers art expertise for 24/48 hours and price starts from $28. Among multiple art categories there is a section of Contemporary Art.

Platform [81] offers free art appraisal but only for the art collectors. There is a platform's statement: "If you're an artist, I'm sorry, but I can't help you appraise or sell your work". System [82] proposes to chat with "Thousands of highly rated, verified Art Appraisers" for only $60 per month.

Some websites like WikiHow [83] provide free appraisal hints helping to evaluate artwork. It includes multiple steps including the investigation of the market demand, knowledge of the marketability, market trends, previous sales of the similar pieces. There are also professional art appraisers. The cost of the professional art appraiser is starting from $300 for a single service in the USA [84].

Some recommender systems attempted to integrate business objectives. For instance, the system in [85] can take into consideration consumer price preferences to maximize the successful sale. Purchase-oriented information can be integrated into the recommendation algorithms to create “price- and profit- aware recommender systems”. Authors also conclude that price and profit awareness is a promising research direction for recommender systems [85].

In [86] system tends to delete human involvement into price settings, but it has certain disadvantages. Paper discusses some problems which can happen if there is no user involvement. Authors splitted algorithms into the ‘first generation’ algorithms which utilize rules and the ‘second generation’ which do not utilize rules. ‘First generation’ algorithms are rather simple and set pricing without competitors whereas “second generation” are focused on maximizing benefit and adaptation to “learn” [86]. In [87], authors built a recommender system that would estimate a customer’s WTP (willingness to pay) for the product to suggest them items. Researchers analyzed half a year transactional data from the popular eBay platform to model customer’s WTP (willingness to pay) emphasizing that a seller’s reputation may improve the recommender system accuracy and exploring the impact of review score on customer’s WTP. The study of WTP was developed in [88]. The authors explored the situation when the reviews may not impact the customer’s WTP. They wanted to understand the relation between online customers reviews and price distribution. They argued that the understanding of this relationship can improve the market management which became customer-centric due to the information technology. Research sheds light on how to use seller reviews proactively in order to extract customer risk precedents to understand how customers use seller reviews in order to evaluate the seller risks and to create personalized recommendations to customers. The data was selected from the Ebay platform assuming that it was a risky market, and it had a review mechanism. However, this study has some limitations and data issues [88].

### 2.4.1 Recommender System ArtIST

The prototype of the Recommender System ArtIST (Art-Innovative Systems for Value Tagging) was proposed as the result of, funded by National Science Foundation (NSF) and VentureWell, I-Corps ArtIST project which took place between 2017-2020. It was developed in the KDD laboratory (UNC, Charlotte) by the author of the current thesis. I argue that it is the first recommender system for art pricing which tends to use deep analytics and data driven techniques in order to provide the stakeholders in the art market with the tool needed to secure the pricing of the works of contemporary fine art.

The recommender system for art pricing will be a web-based personalized recommender systems for evaluating and making recommendations for the pricing of fine art. Development of the complete version of such a system would require construction of multiple datasets describing artworks and artists, construction of related features in those datasets, development of a variety of rule-based classifiers and system engine development.

As it was mentioned above, currently, there are no recommender systems available on the market which utilize action recommendations. The ultimate plan is to build an interactive software system for artists which would include an art inventory tool to use in managing prices of artworks, art sales, and for saving time. The system could be used to help in making investment decisions, to boost artist's self-confidence, to save artist's time in evaluation of work of art, to identify best buyers and the proper market to increase sales as well as identify the best assets for investment. The creation of such software systems will help stakeholders in the art market understand the value of the art objects and help them to make better decisions around investments into the works of art, to make better returns and develop the new business model for the art market, which helps to increase the amount of the new customers and mitigate the market risk. As I discussed above, currently, the art market does not have reliable methodology in evaluation. This system could be attractive to a variety of stakeholders in the art market including artists, art dealers, art collectors, insurance companies, art galleries, shipping companies, banks, estate lawyers, interior design companies, architects, federal fraud investigators, charities for assessing donations, tax accountants, and divorce attorneys.

The system will provide a new method of addressing domains where classification seems arbitrary and is highly connected to personal opinions. Prices are often driven by personal factors, such as memberships in various communities. This can introduce personal biases and excludes artists with non-traditional backgrounds. By providing an objective measure for prices, this can diminish some of the biases that may harm the careers of artists. This will encourage art investment and career development for less established artists. Because the art is overpriced, and art market is rather opaque. This system will provide stakeholders in the art market with a web-based valuation methodology that increases transparency, reduces risk, provides them with better information, and helps facilitate trust from all parties. The system may help to predict the value of art investments, to provide an objective value of art for taxation, court cases, or insurance purposes, to give banks an objective value of art for when it is used as collateral, to support the financial stability of galleries through better decisions about promotion of artists and exhibitions, to improve the trust of collectors in their investments and their dealers, and to help artists maintain control of the commercial aspects of their work built.

Later, I will discuss more carefully the study done in order to develop the set of features from the visual characteristics of the images, including colors, number of edges and sentiment analysis. I will combine the results in the final conclusion.

# Chapter 3: Computer Science Techniques Applied for Features Development

## 3.1 Introduction

This part provides information in art analytics and computing, and touches on some of the methods which were used later. It reviews how some techniques could be applied in the content of our art pricing problem. One obvious challenge in developing a model for pricing the works of art is to construct a set of classification features. Artists without a developed sale history often use simple metrics, such as the dimensions of the work, the cost of materials, and the time. The features that are less obvious have to be considered to move forward.

Nowadays, it is common practice for artists to provide biographical information, work descriptions, work titles and so on in the virtual world. There are opportunities to use this information as a source for the setting up of an additional feature. I discuss the features that were developed and propose other sets of features.

## 3.2 Studies in Art Analytics

A large number of studies were conducted in the area of classifying images or works of art automatically. Some of these strategies consider the automated tagging of the artwork, while others focus on the problem of developing features.

Interesting classification method was developed using the online Rijksmuseum collection. Authors offered the automated system that could classify by creation year, artist, material and categorization into types (prints or painting) to help museums with automatic labeling and to encourage visitors to explore the collection online. The dataset consisted of 112,039 various artwork digitized reproductions. Authors introduced a feature vector from the art image to describe the item for classification [89]. Tagging fine art collections using automated strategies has received attention in recent years. Different approaches and objectives have been studied. Image retrieval based on emotion, similarity and artistic description have been addressed. Authors in [90] built a works of art retrieval system which was based on the artistic color concepts assuming that color (color temperature, color palette and color contrast) always played an important role in artwork. Authors can extract images of such categories as ‘Painting in warm colors’, ‘Temperature contrast in the center’ [90] allowing the retrieved works description in artistic terminology [90]. They evaluated 1000 paintings of different styles and color concepts to test their method [90]. Research was based on Itten's color theory whose color circle consisted of “primary”, “complementary” and “tertiary” colors and 180 colors organized as the chromatic sphere with the different intensity and saturation. One of the parts of the experiment was to extract color concept values from certain areas and combine them into the sum of the artistic color concepts and the geometrical properties of the areas to index images

[90]. Authors were able to work with queries related to color temperature, color palette, color contrast which can be used for the classification purpose in their future work [90].

Some authors ([91], [92], [93], [94]) have explored a method of categorizing paintings in various styles and artistic periods. In [91], the image dataset was represented by three schools of art - surrealism, impressionism, and abstract expressionism that included nine artists. The method could classify paintings, find similarities and associate them by artists and schools of art. Study [93] focuses on comparison of qualitative color attributes to quantitative to investigate an issue of accuracy. Authors based their research on the three art styles - the Baroque, Impressionism, Post-Impressionism to automate the color classification in these styles [93]. The authors of [94] expanded the number of styles to eight -Renaissance, Baroque, Realism, Romanticism, Impressionism, Post-Impressionism, Art Nouveau, Expressionism in order to categorize painting style using SVM (Support Vector Machines). The features which were used had wide variation from the color focused domain-oriented strategy [93] that emphasizes that the reasoning of the system has to be understandable to humans. System built by [94] does not utilize prior domain knowledge. While strategies differed, the stress on transformation of visual features of an image for the automated classification is constant.

One of the developed topics is the area of automatically tagging works of art with emotional labels. There are multiple strategies considered. Authors in [95], mapped images to one of the emotional categories, classifying images and abstract paintings based on the following eight emotions -anger, disgust, fear, sad, amusement, awe, contentment, excitement. Researchers stated that images influence emotional human level. They attempt to create methods to retrieve and combine features which target the emotional level in order to employ them for image emotion categorization. Authors extracted a set of visual attributes from the image, for example, the brightness, color, texture, compositional and content features. They used three datasets including artistic photography, abstract paintings as well as IAPS (the International Affective Picture System) for this research [95]. On the contrary, the authors of [96] proposed to use color only to classify images based on their related emotions. They referred to psychological theories to tie certain colors to emotions and to apply them to the works of art in the collection.

## 3.3 Text Analytics

Text analytics or text mining is the extraction of the helpful insights from the text sample using different statistical algorithms' [97]. Text analytics has several challenges.

### 3.3.1 Document Vectors and Sentiment Analysis

A text document transformed into a representative vector with the help of the Paragraph2Vec algorithm [98]. That is called "Distributed Memory Model of Paragraph Vectors" (PV-DM) as well as Paragraph Vector. It was built to expand on the initial Word2Vec algorithm presented in [99]. Paragraph2Vec is similar to Word2Vec. It extends the original concept of Word2Vec. It adds another component that functions as a tag for the paragraph subject [98]. Paragraph Vector takes any length document and returns it as a fixed length vector representation making it useful, for example, to determine document similarity. Algorithms utilizes trained neural networks to generate vector representation of text. One method of doing that is to convert the documents into vectors and to measure their proximity in terms of multi-dimensional space. The advantage of Paragraph Vector is that they are capable of learning from data which is unlabeled [98]. That was utilized to build classification text features in the next chapter.

The initial Word2Vec algorithm developed in [99] used neural networks and relied on the Skip-gram model. The Skip-gram model developed in [100] can predict the next word which has to appear in a sequence of words. The objective of the Skip-gram model is to discover word representations that can be used to predict the surrounding [99]. "Skip-gram predicts surrounding words given the current word" unlike the most common vector representation for text CBOW (Continuous Bag of Words) which predicts a word based on the surrounding words and context [100]. The training goal of the Skip- Gram technique is 'to learn word vector representations that are good at predicting the nearby words'', "to find word representations that are useful for predicting the surrounding words in a sentence or a document [99]." Skip-Gram is 'efficient method for learning high quality vector representations of words from large amounts of unstructured text data [99]."

The Internet provides us with the platform to express our opinions and sentiments, for example product reviews, it might contain valuable information which is expressed not only in numerical categories [97]. *Sentiment Analysis* refers to natural language processing which deals with "sentiment detection and classification from texts [121]." Sentiment analysis or 'opinion mining' extracts the consumer's opinion on some subject, especially from settings where numerical ratings are not available [97]. Opinion mining techniques can analyze the text from social media, blogs, review boards and other platforms where users post their opinions about entities, events. It is defined as computational analytics [97]. Opinion mining provides researchers with more subjective detailed information that can be additional to the recommender system prediction. It also refers to finding positive and negative user statements with the help of text processing [97].

Attempts to evaluate the opinion of the consumer is a frequent challenge in sentiment analysis. Determining the polarity of the sentiment is one of the popular methods. The text is placed into positive or negative, or into positive, negative and neutral category [121]. Vader, which stands for ‘Valence Aware Dictionary for sentiment Reasoning’ is a rule-based sentiment analyzer that assigns polarity for the given text using a combination of rules and lexical features-words.

## 3.4 Image Processing

Some features exploration was based on the notable visual characteristics in the work of art. They are mainly centered on the use of colors, edges, and the connectivity between light and dark areas of the image. It helps to understand the perception of the artwork by the audience. Below, there are three image compositions to illustrate the function of these techniques – Figure 4, Figure 5, Figure 6.

### 3.4.1 Emotions and Colors

In this work, the concept of basic universal colors was studied in order to quantify the colors we discussed. Originally this idea was developed in the monograph ‘’Basic Color Terms: Their Universality and Evolution’’ [101] where authors used the World Color Survey (WCS) in order to rethink the issue of color naming [102].

Even though the work [101] was questioned in [102], [103] due to restrictions in the initial study, the fundamental color concept in this analysis was utilized, including eleven basic colors provided in [101]. They have RGB values and the brown [104].

1. White (R 255, G 255, B 255)
2. Gray (R 128, G 128, B 128)
3. Black (R 0, G 0, B 0)
4. Red (R 255, G 0, B 0)
5. Orange (R 255, G 128, B)
6. Yellow (R 255, G 255, B 0)
7. Green (R 0, G 255, B 0)
8. Blue (R 0, G 0, B 255)
9. Purple (R 128, G 0, B 128)
10. Pink (R 255, G 192.0, B 203)
11. Brown (R 63.8, G 47.9, B 31.9)

These colors worked as attributes for classification and extraction of rules by using k-means in order to discover 10 colors that can be seen in the image. The Open Computer Vision library was used to position every pixel in the image in an RGB space and to find clusters [105]. The cluster centroids were checked against the reference colors [106]. The CIEDE2000 color-difference code [107] was utilized. Figure 7, Figure 8, Figure 9 show the results. Most of color gradation in the light part in Figure 8 was lost. Color complexity, color saturation and plants in Figure 7 and Figure 9 are removed and color gradation in the sky is disappeared. They can be compared them to the original images Figure 4, Figure 5, Figure 6.

Figure 4. The Initial Cityscape Composition.jpg

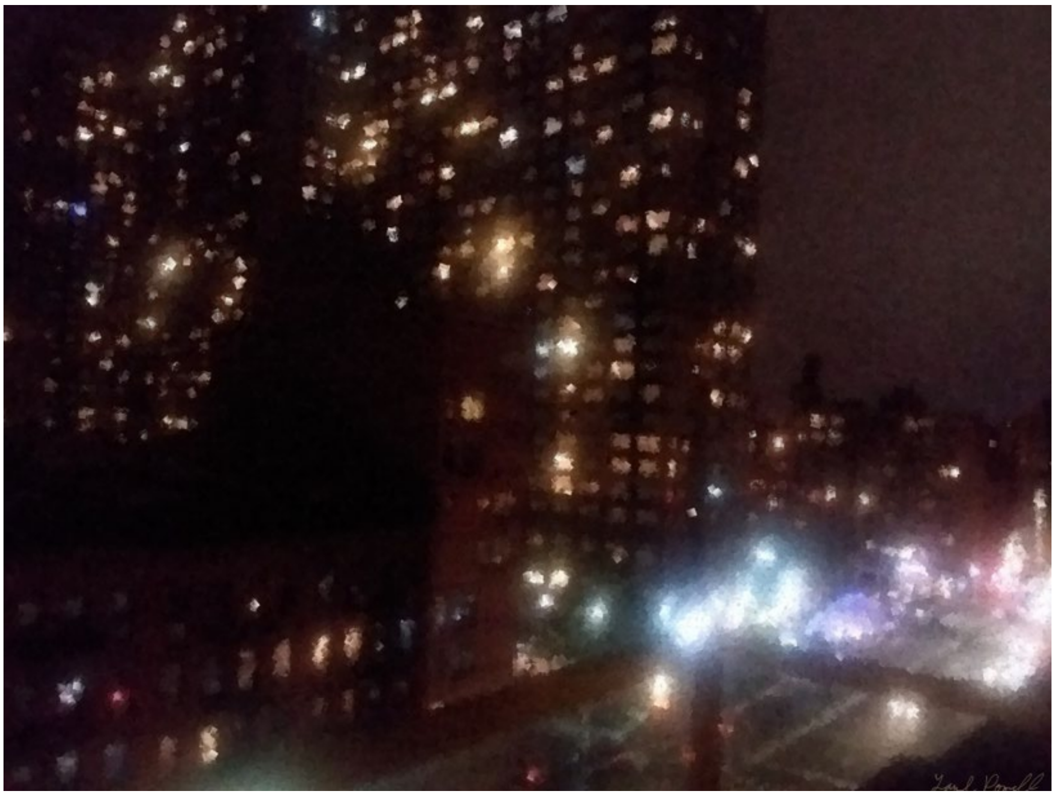


Figure 5. The Initial Tree Composition.jpg

Figure 6. The Initial Flower Composition.jpg

Figure 7. Reduction of Flower Composition to 10 colors.jpg

Many studies are devoted to exploring connections between colors and emotions. Two various scales are used in this research to quantify emotions induced by different colors. One of the methods uses the scale of *pleasure, arousal* and *dominance* known as the PAD [108], [109], [110]. All of these emotions can be used to classify the emotional conditions [108]. In [110], the author explores the relationships between the color brightness and saturation and its placement in the PAD scale. The PAD is a matrix which presents 3D space with the separate axes of pleasure, arousal and dominance [108] where pleasure levels from extreme pain to extreme pleasure, arousal -from the lethargy to super excitement, and dominance -from extreme powerlessness to total control. For example, 'joyful' or 'despairing' terms are connected to specific values on the PAD matrix [108], [109].

Authors in [110] used the PAD matrix to explore relationships between the dimensions of the scale and specific colors, where participants were asked to rate colors based on their emotional impact. Thus, the saturation and brightness of a color linked to the pleasure, arousal had linear connections with saturation and with brightness. Dominance was increasing with the growth of saturation and was decreasing with a color brightens decrease. In some cases, relationships were shifted after a brightness reached the certain level. It also relates to the conventional opinion about how 'warm' and 'cool' colors can influence an emotional level of a viewer [110]. Some color combinations, for example, blue-green, blue, red purple, could be more pleasant than others, for instance, green yellow [110]. Saturated colors evoked arousal, for example, highly saturated red evoked greater arousal in comparison to less saturated green. Brighter colors, for example, whites and lighter colors, were referred to as more pleasant. They produced less arousal and less dominance compared to less brighter color combinations like dark grays. Darker colors could elicit such emotions like aggression, hostility, or displeasure [110].

Figure 8. Reduction of Cityscape Composition to 10 colors. jpg

Figure 9. Reduction of Tree Composition to 10 colors. jpg

Color hue had a different- weaker emotional level impact in the research. It was mainly limited to the pleasure [110]. To quantify the relationships between color and emotions, authors presented equations [110]. This analysis took influence from the study of emotions in photographs in [111] that also had similarities with [112], which utilizes k-means clustering in order to discover the most dominant color in an image and combines it to PAD matrix. The PAD score of each color was discovered using its saturation and brightness. The hsv scale was utilized with the value which substitutes for brightness. The weight for the score was used to represent a percentage of the work that specific color represents. The scores were combined to discover the overall score of the emotional level of the viewer.

The other method of discovering links between color and emotions was presented in [113]. It examines various strategies for quantifying the influence of color on emotions. It comes with the following factors labeled as ‘color activity’, ‘color weight’ and ‘color heat’ [113]. After exploring different methods, the researchers created ten various scales for connecting colors with emotions. They utilized data from British and Chinese items to create three points to explore the user’s individual emotional reaction to color [113]. The first one labeled as ‘color activity’, presents levels of ‘active-passive’, ‘fresh-stale’, ‘clean-dirty’, ‘modern-classical’, ‘tense-relaxed’ which was discard due to cultural variations [113]. The ‘color weight’ incorporated the scales of ‘hard-soft’, ‘masculine-feminine’, heavy-light’ [113]. The ’color heat’ utilized just the ‘warm-cool’ range. ‘Like-dislike’ feature was dropped due to cultural variations [113]. The values were counted using the equations [113].

### 3.4.2 Edge Detection and Block Clustering

The amount of edges in one picture can be used to measure the image complexity and they can be calculated using Canny edge detection method [114]. This method uses the number of modifications in the colors surrounding a given pixel to identify if a pixel can be counted as a pixel edge [114]. In order to consider it as a feature, the amount of edge and non-edge pixels were calculated, and the percentage of pixels of edges in the entire composition was discovered. For this calculation the OpenCV [105] source was used. See here Figure 8. One technique of quantifying the image is to split it into nine equal blocks in order to quantify aspects of image. This study utilizes the method for two separate features. Part of the artwork has the highest average value of color using the gray scale and red, green and blue channels for that. It can represent the brightest portions of the work of art. After partitioning works of art into blocks, we examined it and combined the blocks. It provided with the possibility to determine the combined brightness and edge percentage for an image. The values then were clustered. That placed artists with the visual similarity into the same clusters. This technique would allow us to build personalized models which are relied on these artists' clusters. Figure 10, Figure 11, Figure 12.

Figure 10. Edge Detection of Cityscape Composition. Edges.jpg

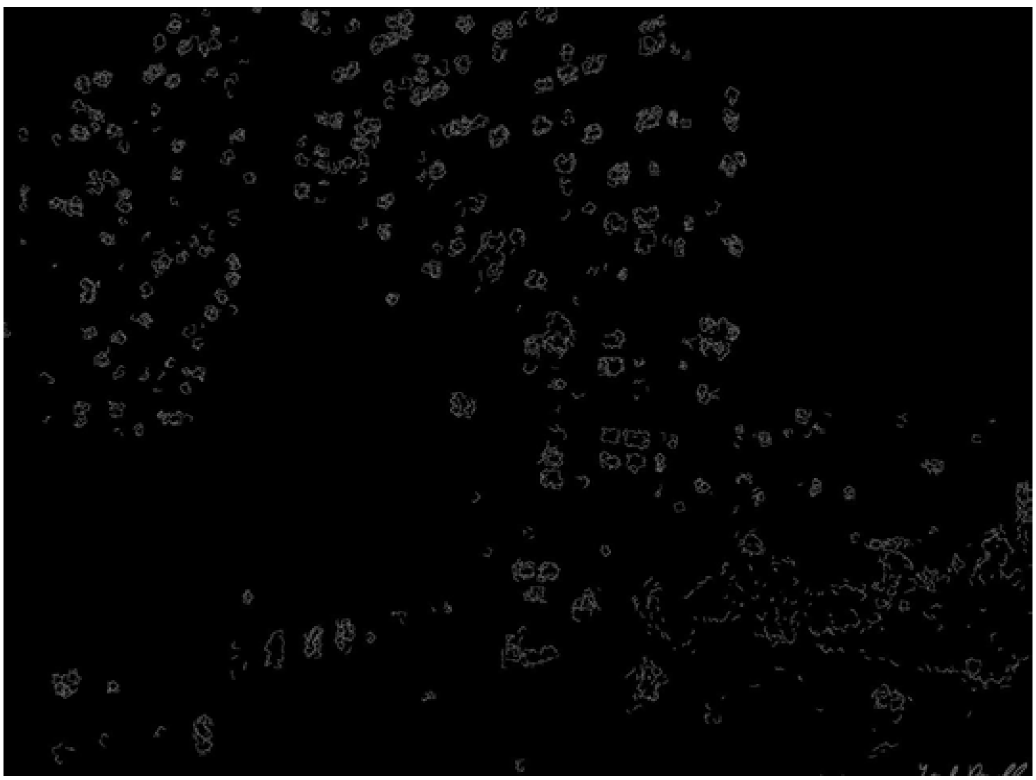


Figure 11. Edge Detection of Flower Composition. Edges.jpg

Figure 12. Edge Detection of Tree Composition. Edges.jpg

# Chapter 4: Developing Datasets and Constructing Features

## 4.1 Method

As I mentioned above, nowadays, artists often provide description of their works of art as well as biographical descriptions online. This information, with the image of picture and picture's tag are what consumers would search to acquire art online. However, this statistic is a configuration of the unstructured text. Sentiment analysis, text clustering and document vectors to transform the unstructured data into attributes are applied. Attributes which are based on the visual characteristics of work of art are constructed from the number edges in the image and the primary colors. Some features are developed to predict the leading emotions incited by the art piece. They are built from the picture's primary color characteristics. Attributes determined to be utilized in construction of auction rules. To build artist's personalization, artists based on similarity of their works of art in their price range are clustered. For clustering, artists images inside of each cluster are trained; when the artist is put in a relevant cluster - the work is assigned to the certain price interval.

## 4.2 Dataset

The original dataset was extracted from artworks retrieved from Artfinder.com website [120] with the use of web scraping tools. Python was the main language to develop the scraper, JavaScript with Apache Selenium and the Beautiful Soup [123] were the key text parser.

Artworks on Artfinder.com are presented and sold by the artists or by the art dealers that identify Artfinder as the primary art market. The secondary market should be discussed in later research. Artfinder represents many various art styles, nationalities, subjects and art mediums. Around 3300 artists from around 60 countries constitute this dataset.

The information about the medium, dimensions, and subject from the profile information provided by artists was retrieved. Biographical information with optional subsections for awards, education and events as well as segments for social media and comments are optional categories on the Artfinder platform. There is a review section (star rating on a 5-points scale), however, reviews for the artists' works provided are not reliable sources of information because it doesn't connect to specific sold item. There are restrictions on posting reviews to past buyers too. Artists who have not been on the website for enough time often lack reviews. About 45% of the artists in this dataset had visible reviews.

According to dataset, the artwork prices are ranged from 12.97 to 1,000,000 American dollars. About 85% of the artworks in the dataset cost less than 1000 American dollars. Majority of virtual sales contain art items less than 1,500 American dollars [124]. In this research, the price feature was discretized as set of intervals: 0 - 105, 105 - 205, 205 - 405, 405 - 605, 605 -

810, 810 - 1030, 1030 -1445, 1445 - 1825, 1825 - 2455, 2455 - 3855, 3855 - 5000, 5000 - 10,000, > 10000.

Discretization was built by analyzing the distribution of prices for intervals with a small number of items- Figure 13.

Splits were positioned in these ‘intervals’, but the amount of intervals discovered was large because the cost of the artworks clustered about multiples of 50, thus, smaller intervals were integrated in order to build the set of discrete prices shown above. Basic features were built for comparison reasons. The feature list was related to the list feature set in our previous work [105].

All of them are discrete, and they were discretized, other - extensions to the basic set of attributes.

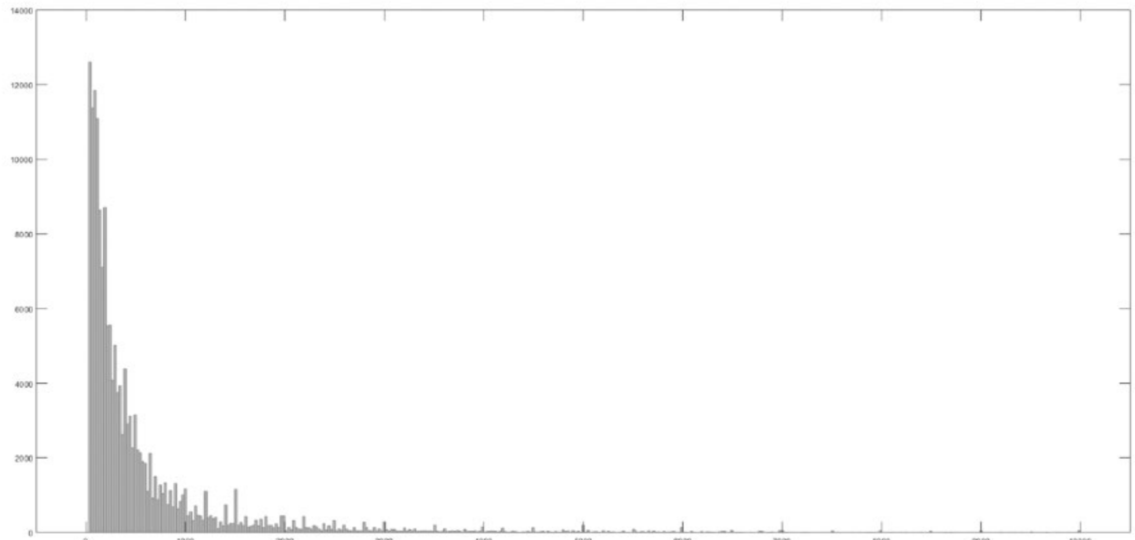
1. artistID: an artist identifier that can be a name or username.
2. artistCountry: the artist’s country.
3. artwork_height: the picture’s height (inches)
4. artwork_width: the picture’s width (inches).
5. Authentication: a method of authentication provided by the artist.
6. percent_five_stars: 5-star reviews (percentage).
7. percent_four_stars: 4-star reviews (percentage).
8. percent_three_stars: 3-star reviews (percentage).
9. percent_two_stars: 2-star reviews (percentage).
10. percent_one_star: 1-star reviews (percentage).

11. medium: medium of the picture.

12. style - style of the picture.

13. subject - subject of the picture.

Figure 13. Price Division



Text from the artist profile pages was retrieved and text description where each image had a title as well as short description were analyzed. Artists presented profiles with optional biographies as well as the information about their credentials (awards, education) and events. Artists have a choice to fill in all parts or just skip them. One of the useful applications became simply the word count of the biography- together with description of the work of art it proved to have some predictive value. There may be a connection between the length of the biography and the artist's credentials. See Figure 14, Figure 15 -the assortment of word count in the descriptions and word count in the biographies splitted by price intervals. The word length and text choice in the description tend to influence prices. Analyzing the prices of the eBay platform, the authors discovered that text descriptions between 40 and 55 words have a rather positive effect. The artist's presence on social media was another interesting feature to explore. Artists often include information in their profiles to the social media web platforms where they can be available. Here, the text was checked for the words such ‘facebook’, ‘twitter’ and ‘instagram’. This information was transformed into a Boolean variable. The relative frequency of the variables and price categories are shown in Figure 16, Figure 17, Figure 18.

Figure 14. Word Counts in Biography

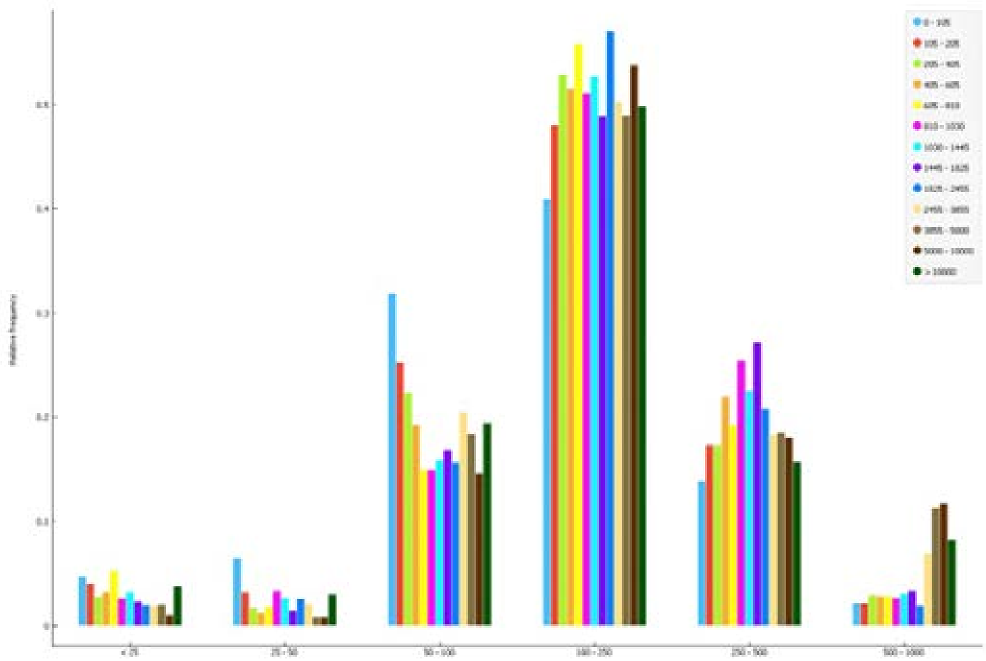


Figure 15. Word Counts in Description

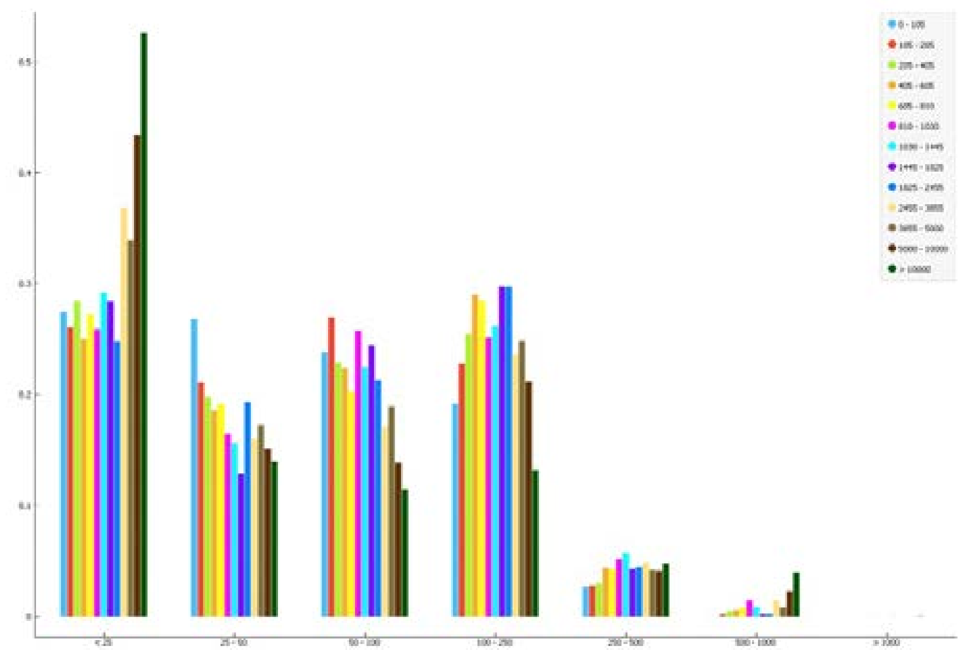


Figure 16. ‘Facebook’

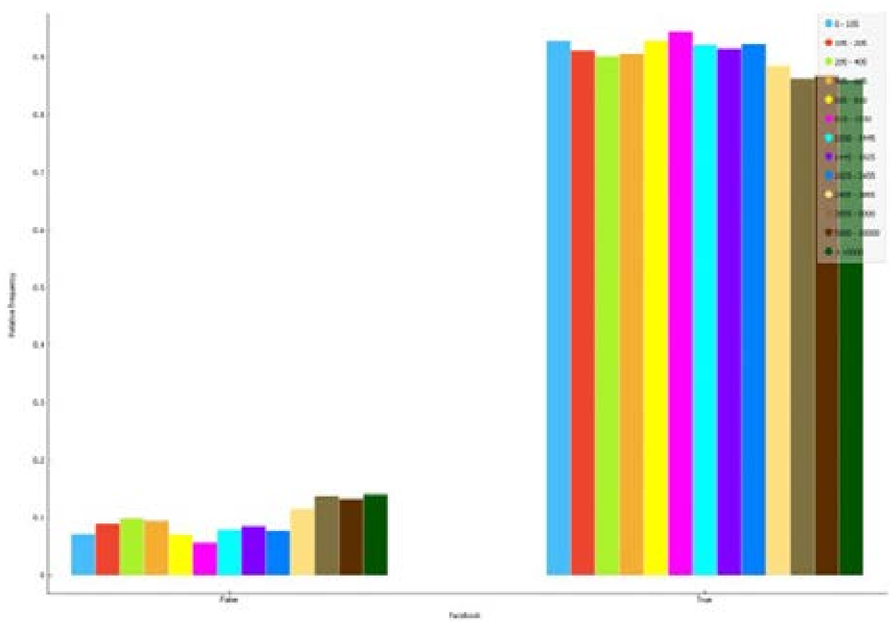


Figure 17. ‘Twitter’

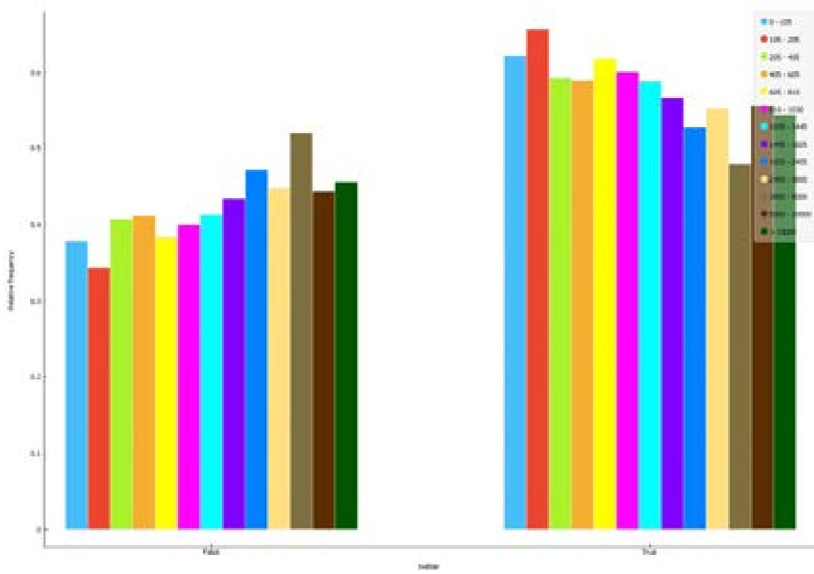
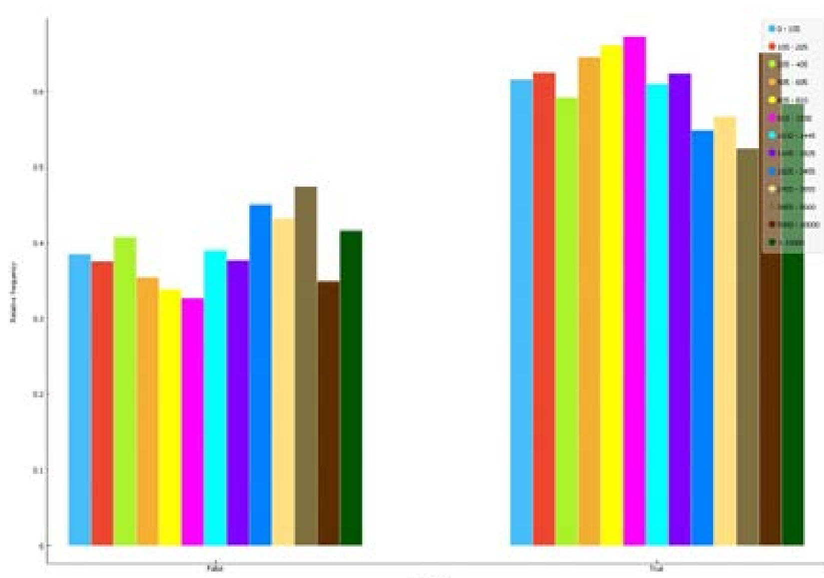


Figure 18. ‘Instagram’



Doc2Vec - implementation in Gensim [125] of Paragraph2Vec was utilized to generate document vector attributes [98]. A Gensim Paragraph2Vec was tested on the biographies of the artists as well as on their credentials such as educational training, events and awards, picture descriptions and titles. The text utilizing the Gensim (basic text preprocessing package) was used and the Paragraph2Vec was utilized to build vectors for every part of the training text. Vectors of 20 and 100 length were trained which we used again to attribute the text to clusters. For the clustering, we utilized The Sci-Kit Learn Library - implementation of K-Means. The polarity of the artist biographies, titles, works of art descriptions was determined. It was used as an extension added to the foundation set of characteristics. The 'Valence Aware Dictionary for Sentiment Reasoning' (VADER) which includes a combination of rules and an opinion text through the determination of human ratings was utilized. Figure 19, Figure 20, Figure 21show the levels of sentiment in 150,000 Descriptions. Figure 22, Figure, 23, Figure 24 show the sentiments of the Biographies. The titles figures show identical tendency. There is a small volume of positive and a very little number of negative sentiments.

Figure 19. (+) Sentiment in Description

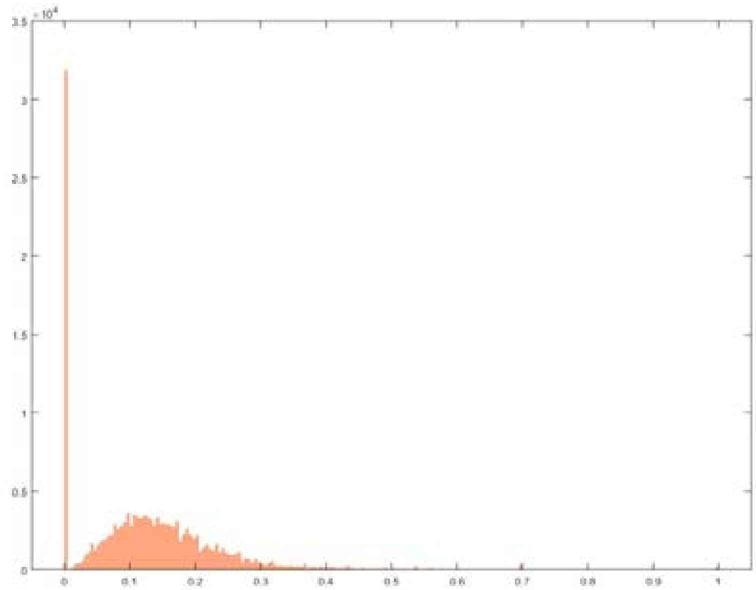


Figure 20. (–) Sentiment in Description

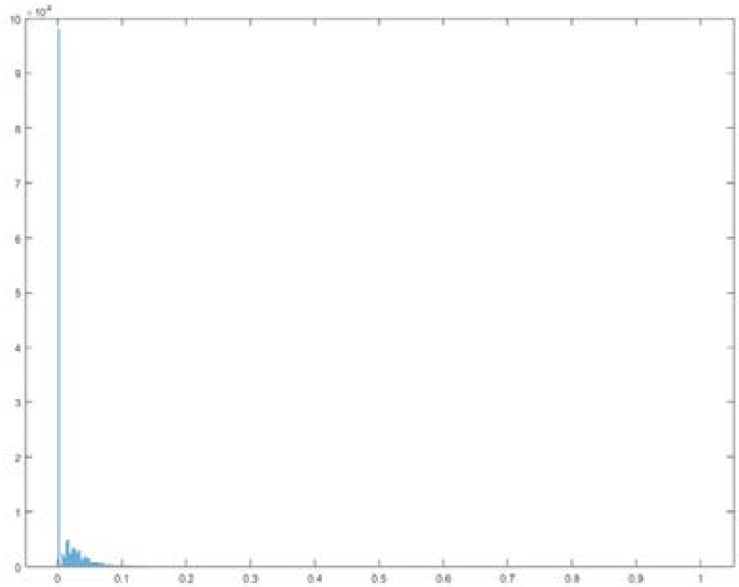



Figure 21. (+) Sentiment in Description

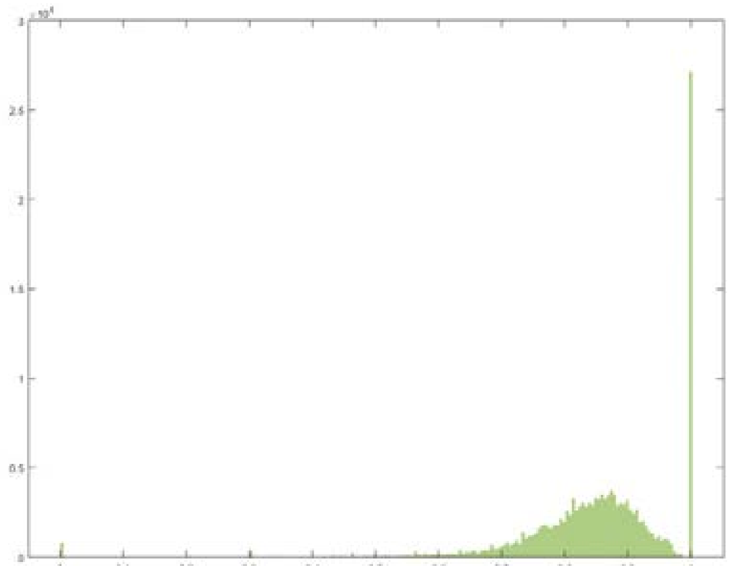


Figure 22. (+) Sentiment in Biography

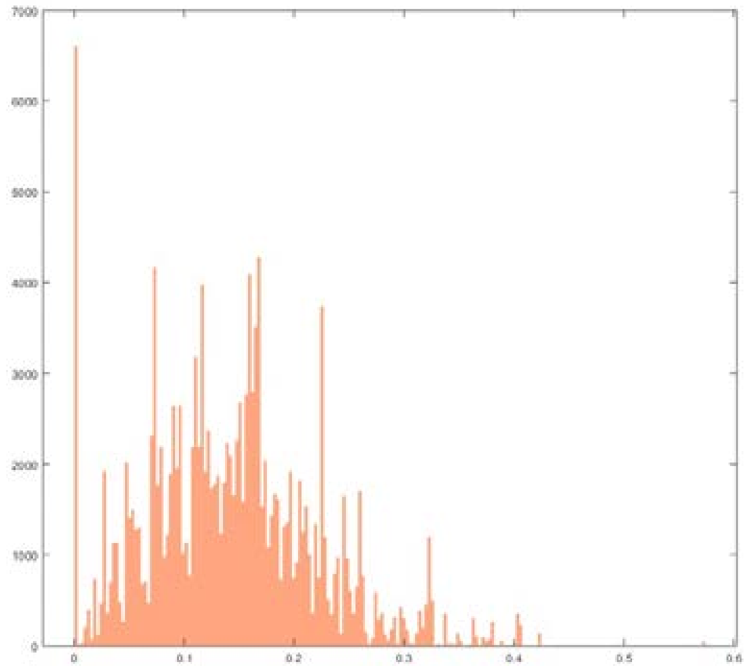



Figure 23. (–) Sentiment in Biography

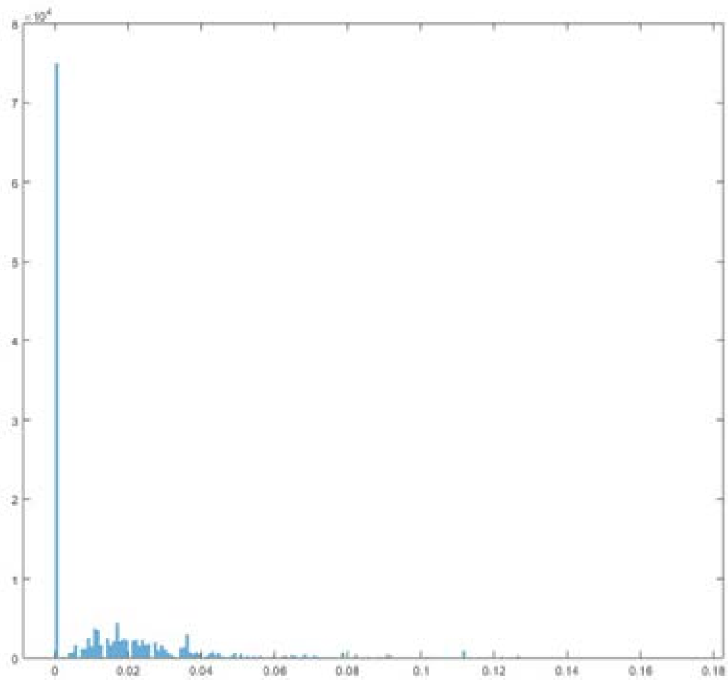
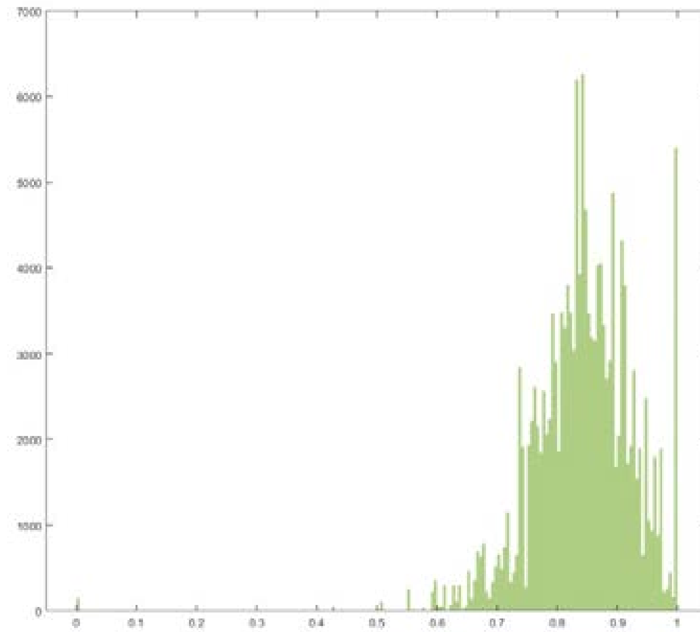


Figure 24. (+) Sentiment in Biography




## 4.3 Determine Features

The following tables display the original results of testing vector originated attributes, the social media, the word count and the sentiment features on an unspecified set of 150,000 points. Here, a random forest algorithm of 100 trees was utilized. It was tested using 10-fold cross validation. The word counts of the title, description and biographies which were utilized for the addition to the foundation of set of features shown in Figure 25. The biography and description word counts have significance in terms of price prediction compared to the features extracted from social media which have restricted significance in terms of predicting the price. That may be because of the extensive usage among all prices range as it is displayed in Figure 16, Figure 17, Figure 18.

Testing results are shown in Figure 27. As shown in Figure 27, Figure 28, Figure 29. the amount of clusters does not have a crucial impact on the classifier precision but there is a notable connection between the final model accuracy and which textual attribute clusters. Awards, education, biography and events clusters have a visible impact on the precision of the classifiers. Work description or title clusters do not have a significant impact. It can be because of the excessive number of titles and descriptions may create a vast amount diversity inside of the clusters. The text sentiment of the work of art description has an impact on the classifier precision as it shown in the full results of Figure 30. The compound score of positive sentiments for all three analyzed attributes has a relatively strong influence on classifier. Combination some of these features may have even stronger influence as it is shown in Figure 31. The description positive sentiment as well as the biography clusters overall make a classifier more efficient.

Figure 25. Word Counts

| | AUC | CA | F1 | Precision | Recall |
|---|---|---|---|---|---|
| Base Features | 0.938 | 0.667 | 0.664 | 0.663 | 0.667 |
| Base Features and Biography Word Count | 0.939 | 0.67 | 0.667 | 0.665 | 0.67 |
| Base Features and Description Word Count | 0.94 | 0.674 | 0.67 | 0.669 | 0.674 |
| Base Features and Title Word Count | 0.938 | 0.668 | 0.664 | 0.663 | 0.668 |
| Base Features, Biography Word Count and Description Word Count | 0.941 | 0.677 | 0.673 | 0.672 | 0.676 |
| Base Features, Biography Word Count and Title Word Count | 0.939 | 0.671 | 0.668 | 0.666 | 0.671 |
| Base Features, Description Word Count and Title Word Count | 0.94 | 0.674 | 0.67 | 0.669 | 0.674 |
| Base Features, Biography Word Count, Description Word Count and Title Word Count | 0.941 | 0.677 | 0.673 | 0.672 | 0.677 |

Figure 26 Social Media

| | AUC | CA | F1 | Precision | Recall |
|---|---|---|---|---|---|
| Base Features | 0.938 | 0.667 | 0.664 | 0.663 | 0.667 |
| Base Features and Facebook | 0.938 | 0.667 | 0.663 | 0.662 | 0.667 |
| Base Features and Twitter | 0.938 | 0.668 | 0.665 | 0.664 | 0.668 |
| Base Features and Instagram | 0.938 | 0.669 | 0.665 | 0.664 | 0.669 |
| Base Features, Facebook and Twitter | 0.939 | 0.669 | 0.666 | 0.665 | 0.669 |
| Base Features, Facebook and Instagram | 0.939 | 0.669 | 0.665 | 0.664 | 0.669 |
| Base Features, Twitter and Instagram | 0.939 | 0.669 | 0.666 | 0.665 | 0.669 |
| Base Features, Facebook, Twitter and Instagram | 0.9339 | 0.67 | 0.667 | 0.665 | 0.67 |

Figure 27. 10 Clusters

| | AUC | CA | F1 | Precision | Recall |
|---|---|---|---|---|---|
| Base Features (BF) | 0.938 | 0.667 | 0.664 | 0.663 | 0.667 |
| BF and Awards Cluster (Cl) | 0.938 | 0.669 | 0.665 | 0.664 | 0.669 |
| BF and Biography (Bio) Cl | 0.939 | 0.671 | 0.668 | 0.667 | 0.671 |
| BF and Description (Desc) Cl | 0.936 | 0.662 | 0.658 | 0.657 | 0.662 |
| BF and Education (Edu) Cl | 0.939 | 0.67 | 0.667 | 0.666 | 0.67 |
| BF and Events Cl | 0.939 | 0.669 | 0.666 | 0.665 | 0.669 |
| BF and Title Cl | 0.934 | 0.656 | 0.652 | 0.651 | 0.656 |
| BF, Awards Cl, Bio Cl, Desc Cl, Edu Cl, Events Cl, and Title Cl | 0.939 | 0.667 | 0.663 | 0.662 | 0.667 |

Figure 28. 25 Clusters

| | AUC | CA | F1 | Precision | Recall |
|---|---|---|---|---|---|
| Base Features (BF) | 0.938 | 0.667 | 0.664 | 0.663 | 0.667 |
| BF and Awards Cluster (Cl) | 0.939 | 0.669 | 0.666 | 0.665 | 0.669 |
| BF and Biography (Bio) Cl | 0.939 | 0.671 | 0.668 | 0.667 | 0.671 |
| BF and Description (Desc) Cl | 0.936 | 0.664 | 0.66 | 0.659 | 0.664 |
| BF and Education (Edu) Cl | 0.939 | 0.6 | 0.667 | 0.665 | 0.67 |
| BF and Events Cl | 0.939 | 0.67 | 0.667 | 0.665 | 0.67 |
| BF and Title Cl | 0.935 | 0.659 | 0.655 | 0.654 | 0.659 |
| Base Features, Awards, Bio, Desc, Edu, Events, Title Clusters | 0.941 | 0.672 | 0.668 | 0.667 | 0.672 |

Figure 29. 50 Clusters

| | AUC | CA | F1 | Precision | Recall |
|---|---|---|---|---|---|
| Base Features (BF) | 0.938 | 0.67 | 0.666 | 0.665 | 0.67 |
| BF and Awards Cluster (Cl) | 0.939 | 0.672 | 0.669 | 0.667 | 0.672 |
| BF and Biography (Bio) Cl | 0.94 | 0.674 | 0.671 | 0.669 | 0.674 |
| BF and Description (Desc) Cl | 0.937 | 0.667 | 0.663 | 0.662 | 0.667 |
| BF and Education (Edu) Cl | 0.939 | 0.672 | 0.669 | 0.668 | 0.672 |
| BF and Events Cl | 0.939 | 0.672 | 0.669 | 0.667 | 0.672 |
| BF and Title Cl | 0.936 | 0.66 | 0.656 | 0.655 | 0.66 |
| Base Features, Awards, Bio, Desc, Edu, Events, Title Clusters | 0.942 | 0.676 | 0.672 | 0.671 | 0.676 |

Figure 30. Sentiment Features

| | AUC | CA | F1 | Precision | Recall |
|---|---|---|---|---|---|
| Base Features (BF) | 0.938 | 0.668 | 0.665 | 0.663 | 0.668 |
| BF and Biography Positive Sentiment (BioPos) | 0.939 | 0.671 | 0.667 | 0.666 | 0.671 |
| BF and Biography Negative Sentiment (BioNeg) | 0.939 | 0.67 | 0.667 | 0.665 | 0.67 |
| BF and Biography Neutral Sentiment (BioNeu) | 0.939 | 0.671 | 0.668 | 0.667 | 0.671 |
| BF and Description Positive Sentiment (DescPos) | 0.94 | 0.679 | 0.676 | 0.675 | 0.679 |
| BF and Description Negative Sentiment (DescNeg) | 0.939 | 0.676 | 0.673 | 0.672 | 0.676 |
| BF and Description Neutral Sentiment (DescNeu) | 0.94 | 0.678 | 0.675 | 0.674 | 0.678 |
| BF and Title Positive Sentiment (TitlePos) | 0.938 | 0.668 | 0.664 | 0.663 | 0.668 |
| BF and Title Negative Sentiment (TitleNeg) | 0.938 | 0.668 | 0.665 | 0.663 | 0.668 |
| BF and Title Neutral Sentiment (TitleNeu) | 0.937 | 0.668 | 0.664 | 0.663 | 0.668 |
| BF, BioPos, DescPos, TitlePos | 0.941 | 0.682 | 0.679 | 0.678 | 0.682 |
| BF, BioNeg, DescNeg, TitleNeg | 0.94 | 0.679 | 0.675 | 0.674 | 0.679 |
| BF, BioNeu, DescNeu, TitleNeu | 0.941 | 0.682 | 0.679 | 0.678 | 0.682 |
| BF, BioPos, BioNeg, BioNeu | 0.94 | 0.673 | 0.669 | 0.668 | 0.673 |
| BF, DescPos, DescNeg, DescNeu | 0.942 | 0.682 | 0.678 | 0.677 | 0.682 |
| BF, TitlePos, TitleNeg, TitleNeu | 0.938 | 0.668 | 0.664 | 0.663 | 0.668 |
| BF, BioPos, BioNeg, BioNeu, DescPos, DescNeg, DescNeu, TitlePos, TitleNeg, TitleNeu | 0.944 | 0.687 | 0.683 | 0.683 | 0.687 |

Figure 31. Compound Features

| | AUC | CA | F1 | Precision | Recall |
|---|---|---|---|---|---|
| Base Features (BF) | 0.938 | 0.667 | 0.664 | 0.663 | 0.667 |
| BF, Facebook (FB), Twitter (TWT), Instagram (INST), Biography Word Count (BWC), Description Word Count (DWC), Title Word Count (TWC) | 0.942 | 0.681 | 0.677 | 0.676 | 0.681 |
| BF, FB, TWT, INST, BWC, DWC, TWC, Awards Cluster (10 Clusters) | 0.943 | 0.682 | 0.678 | 0.677 | 0.682 |
| BF, FB, TWT, INST, BWC, DWC, TWC, Biography Cluster (10 Clusters) | 0.943 | 0.683 | 0.679 | 0.678 | 0.683 |
| BF, FB, TWT, INST, BWC, DWC, TWC, Description Cluster (10 Clusters) | 0.941 | 0.677 | 0.673 | 0.672 | 0.677 |
| BF, FB, TWT, INST, BWC, DWC, TWC, Education Cluster (10 Clusters) | 0.943 | 0.682 | 0.679 | 0.678 | 0.682 |
| BF, FB, TWT, INST, BWC, DWC, TWC, Events Cluster (10 Clusters) | 0.943 | 0.682 | 0.678 | 0.677 | 0.682 |
| BF, FB, TWT, INST, BWC, DWC, TWC, Title Cluster (10 Clusters) | 0.941 | 0.674 | 0.67 | 0.669 | 0.674 |
| BF, FB, TWT, INST, BWC, DWC, TWC, Awards, Biography, Description, Education, Events, Title Clusters (10 Clusters) | 0.943 | 0.678 | 0.674 | 0.674 | 0.678 |
| BF, FB, TWT, INST, Awards Cluster (25 Clusters) | 0.939 | 0.672 | 0.669 | 0.667 | 0.672 |
| BF, FB, TWT, INST, Biography Cluster (25 Clusters) | 0.94 | 0.674 | 0.671 | 0.669 | 0.674 |
| BF, FB, TWT, INST, Description Cluster (25 Clusters) | 0.938 | 0.668 | 0.664 | 0.663 | 0.668 |

Figure 32. Compound Features

| | AUC | CA | F1 | Precision | Recall |
|---|---|---|---|---|---|
| BF, FB, TWT, INST, Education Cluster (25 Clusters) | 0.94 | 0.673 | 0.67 | 0.668 | 0.673 |
| BF, FB, TWT, INST, Events Cluster (25 Clusters) | 0.94 | 0.673 | 0.67 | 0.668 | 0.673 |
| BF, FB, TWT, INST, Title Cluster (25 Clusters) | 0.937 | 0.662 | 0.658 | 0.657 | 0.662 |
| BF, FB, TWT, INST, BWC, DWC, TWC, Awards Cluster (25 Clusters) | 0.943 | 0.683 | 0.679 | 0.678 | 0.683 |
| BF, FB, TWT, INST, BWC, DWC, TWC, Biography Cluster (25 Clusters) | 0.943 | 0.683 | 0.6679 | 0.679 | 0.683 |
| BF, FB, TWT, INST, BWC, DWC, TWC, Description Cluster (25 Clusters) | 0.941 | 0.677 | 0.672 | 0.672 | 0.677 |
| BF, FB, TWT, INST, BWC, DWC, TWC, Education Cluster (25 Clusters) | 0.942 | 0.683 | 0.68 | 0.679 | 0.683 |
| BF, FB, TWT, INST, BWC, DWC, TWC, Events Cluster (25 Clusters) | 0.942 | 0.683 | 0.679 | 0.678 | 0.683 |
| BF, FB, TWT, INST, BWC, DWC, TWC, Title Cluster (25 Clusters) | 0.941 | 0.674 | 0.67 | 0.669 | 0.674 |
| BF, FB, TWT, INST, BWC, DWC, TWC, Awards, Biography, Description, Education, Events, Title Clusters (25 Clusters) | 0.944 | 0.68 | 0.676 | 0.675 | 0.68 |
| BF, FB, TWT, INST, BWC, DWC, TWC, Awards Cluster (50 Clusters) | 0.943 | 0.683 | 0.679 | 0.678 | 0.683 |
| BF, FB, TWT, INST, BWC, DWC, TWC, Bio Cluster (50 Clusters) | 0.943 | 0.684 | 0.681 | 0.679 | 0.684 |
| BF, FB, TWT, INST, BWC, DWC, TWC, Desc Cluster (50 Clusters) | 0.941 | 0.677 | 0.673 | 0.672 | 0.677 |
| BF, FB, TWT, INST, BWC, DWC, TWC, Edu Cluster (50 Clusters) | 0.943 | 0.683 | 0.68 | 0.679 | 0.683 |

Figure 33. Compound Features

| | AUC | CA | F1 | Precision | Recall |
|---|---|---|---|---|---|
| BF, FB, TWT, INST, BWC, DWC, TWC, Events Cluster (50 Clusters) | 0.943 | 0.684 | 0.68 | 0.679 | 0.684 |
| BF, FB, TWT, INST, BWC, DWC, TWC, Title Cluster (50 Clusters) | 0.941 | 0.677 | 0.672 | 0.672 | 0.677 |
| BF, FB, TWT, INST, BWC, DWC, TWC, Awards, Biography,<br><br>Description, Education, Events, Title Clusters (50 Clusters) | 0.945 | 0.683 | 0.679 | 0.678 | 0.683 |
| BF, FB, TWT, INST, BioPos, DescPos, TitlePos | 0.943 | 0.687 | 0.684 | 0.683 | 0.687 |
| BF, FB, TWT, INST, BioNeg, DescNeg, TitleNeg | 0.941 | 0.681 | 0.678 | 0.677 | 0.681 |
| BF, FB, TWT, INST, BioNeu, DescNeu, TitleNeu | 0.942 | 0.685 | 0.681 | 0.68 | 0.685 |
| BF, FB, TWT, INST, BioPos, BioNeg, BioNeu | 0.941 | 0.675 | 0.672 | 0.671 | 0.675 |
| BF, FB, TWT, INST, DescPos, DescNeg, DescNeu | 0.943 | 0.686 | 0.682 | 0.681 | 0.686 |
| BF, FB, TWT, INST, TitlePos, TitleNeg, TitleNeu | 0.939 | 0.672 | 0.668 | 0.667 | 0.672 |
| BF, FB, TWT, INST, BioPos, BioNeg, BioNeu, DescPos,<br><br>DescNeg, DescNeu, TitlePos, TitleNeg, TitleNeu | 0.945 | 0.689 | 0.685 | 0.684 | 0.689 |
| BF, BWC, DWC, TWC, BioPos, DescPos, TitlePos | 0.944 | 0.686 | 0.682 | 0.682 | 0.686 |
| BF, BWC, DWC, TWC, BioNeg, DescNeg, TitleNeg | 0.942 | 0.683 | 0.68 | 0.679 | 0.683 |
| BF, BWC, DWC, TWC, BioNeu, DescNeu, TitleNeu | 0.944 | 0.686 | 0.682 | 0.682 | 0.686 |

Figure 34. Compound Features

| | AUC | CA | F1 | Precision | Recall |
|---|---|---|---|---|---|
| BF, BWC, DWC, TWC, BioPos, BioNeg, BioNeu | 0.943 | 0.683 | 0.68 | 0.679 | 0.683 |
| BF, BWC, DWC, TWC, descPos, descNeg, descNeu | 0.944 | 0.686 | 0.681 | 0.681 | 0.686 |
| BF, BWC, DWC, TWC, TitlePos, TitleNeg, TitleNeu | 0.941 | 0.678 | 0.674 | 0.674 | 0.678 |
| BF, BWC, DWC, TWC, BioPos, BioNeg, BioNeu, DescPos, DescNeg, DescNeu, TitlePos, TitleNeg, TitleNeu | 0.946 | 0.69 | 0.685 | 0.685 | 0.69 |
| BF, BioPos, BioNeg, BioNeu, DescPos, DescNeg, DescNeu, TitlePos, TitleNeg, TitleNeu, Awards Cl (50) | 0.945 | 0.688 | 0.684 | 0.684 | 0.688 |
| BF, BioPos, BioNeg, BioNeu, DescPos, DescNeg, DescNeu, TitlePos, TitleNeg, TitleNeu, Bio Cl (50) | 0.945 | 0.69 | 0.686 | 0.685 | 0.69 |
| BF, BioPos, BioNeg, BioNeu, DescPos, DescNeg, DescNeu, TitlePos, TitleNeg, TitleNeu, Desc Cl (50) | 0.946 | 0.688 | 0.684 | 0.684 | 0.688 |
| BF, BioPos, BioNeg, BioNeu, DescPos, DescNeg, DescNeu, TitlePos, TitleNeg, TitleNeu, Edu Cl (50) | 0.945 | 0.689 | 0.686 | 0.685 | 0.689 |
| BF, BioPos, BioNeg, BioNeu, DescPos, DescNeg, DescNeu, TitlePos, TitleNeg, TitleNeu, Events Cl (50) | 0.946 | 0.693 | 0.689 | 0.689 | 0.689 |

Figure 35. Compound Features

| | AUC | CA | F1 | Precision | Recall |
|---|---|---|---|---|---|
| BF, BioPos, BioNeg, BioNeu, DescPos, DescNeg, DescNeu, TitlePos, TitleNeg, TitleNeu, Title Cl (50) | 0.944 | 0.682 | 0.677 | 0.677 | 0.682 |
| BF, BioPos, BioNeg, BioNeu, DescPos, DescNeg, DescNeu, TitlePos, TitleNeg, TitleNeu, Awards Cl (50), Bio Cl (50), Desc Cl (50), Edu Cl (50), Events Cl (50), Title Cl (50) | 0.946 | 0.688 | 0.683 | 0.683 | 0.688 |
| BF, FB, TWT, INST, BWC, DWC, TWC, BioPos, BioNeg, BioNeu, DescPos, DescNeg, DescNeu, TitlePos, TitleNeg, TitleNeu, Awards Cl (50), Bio Cl (50), Desc Cl (50), Edu Cl (50), Events Cl (50), Title Cl (50) | 0.947 | 0.69 | 0.685 | 0.685 | 0.69 |

## 4.4 Results

Works on predicting prices for art with the focus on evaluating features and their usefulness in predicting art price were retrieved. The text shared by artists, including the tone of the words, functioned as a feature for price prediction.

These features, including the features generated from the word counts of biography, work's description, and work's title, have potential in price prediction, especially through combination with other attributes. The text duration influence on the interest of the potential consumers that can be justified that more established artists have longer biographies, however, that should be further studied as a feature.

Features of presence or absence of social media links have more limited value for price prediction. Linking social medias do not justify that the artists have active followers.

Compared to that, the text clustering has predictive potential, even though the most positive results were extracted from the biographies, education parts, credentials and events.

Finally, the text sentiment has a great impact on the classifier precision. A positive text sentiment features increases precision significantly. The features retrieved from titles tend to have no influence alone, may be because it does not include sentiment part.

# Chapter 5: Generating Action Rules for Pricing Art and Final Conclusions

Action rules, initially invented for improving outcomes in business, have been used to reclassify items from less desirable to more desirable class by changing values of some of their features as 'flexible' [115]. Flexible features are those which values can be changed whereas 'stable' features are those that either cannot be changed at all, or their changes cannot happen easily. Auction rules are utilized in many different application areas, for example, in education and healthcare [116].

This study focused not only on discovering action rules but also on their cost. Since many action rules may cover the same domain object, the choice of rules containing flexible features of the lowest cost is certainly our priority. The concept of the cost of action rules was introduced in [117] and discussed in [118]. Action rules were investigated with flexible features having a low cost.

Although there are many techniques of discovering auction rules, in this work GUHA method [119] was implemented in Lisp-Miner and discussed in [120]. It builds action rules by constructing contingency tables from items similar to association rules [119]. It uses a pair of these items and matches them with stable features. Some of the items have flexible and stable features. They match the original condition of the relevant tuple. The stable and flexible features match the chosen state. Resulting rules are labeled 'antecedent' and 'succedent' [119] and are used to generate G-Action rules [119].

LISp-Miner was implemented to develop action rules. The asked price of an art piece was considered as a decision feature. Flexible features listed in action rules focus on rather low-cost changes on the process of presenting work of art to the customers. Using Lisp-Miner discretization module the price feature were partitioned into 10 parts. Each part contained roughly an equal record, recalling to them as 1 to 10.

The number of flexible features is connected to the idea of the buyer perception and can be easily changed by the artist in order to improve sales. It was proved that the word counts of the biographies and descriptions as well as the presence of social media links had impact on price prediction. The sentiment of the descriptions and biographies appeared to be mainly neutral. Flexible features were utilized for constructing the antecedent are listed below. Lisp-Miner was used for discretization of features [126].

1. ( ) +Biography Sentiment (Bio. Ps.)
2. ( ) -Biography Sentiment (Bio. Ng.)
3. ( ) +Description Sentiment (Desc. Ps.)
4. ( ) -Description Sentiment (Desc. Ng.)
5. Word Count Biography (Bio. WC)
6. Word Count Description (Desc. WC)
7. Social Media (SM)

This set of stable features characterized the artwork. They were utilized in building the antecedent part of the G-Action rules. Following the previous research [77], attributes related to the work dimension as well as tagged by the artist are considered as stable. Using Lisp-Miner [126], the dimension of the artwork was discretized into five categories which have almost equal amounts of tuples. The artwork subject, style and medium were considered as stable features. The quantity of mediums was decreased to seven broad categories and one category which was identified as NA due to the diverse types of mediums. The presence or not visible to public reviews was determined as a binary stable feature. Canny edge detection [114] was implementated [105] to compute the edge percentage in the original image. Only the primary picture from those that artist posted was taken for the analysis, even though artists could upload multiple images of their art pieces. Some images had errors during the extraction and were not used. Open-CV [105] was implemented to cluster pixels in the image to discover the most noticeable color which was considered as a stable feature. The complete sets of features contains artistic style, subject, medium, height, width, artist has visible reviews, percentage of work edges.

A set of rules was generated to combine prices and flexible attributes using the Lisp-Miner Ac4ft-Miner tools. Listed previously stable attributes were used for comparison. Rules moved from one pricing level to the next higher level. Following partitions were done:

- (<12.97 - 58.28)
- (58,28 - 95.90)
- (95.90 - 130.04)
- (130.04 - 188.13)

- (188.13 - 250)
- (250 - 350)
- (350 - 490)
- (490 - 742)
- (742 - 1351.24)
- (1351.24 - >1,000,000)

It was required to have minimum threshold for the confidence and support of every two component rules. To consider the rule, it must have the support of at least two previous rule which represents the original state as well as after rule, which represents the final state. Confidence had to be at least 60%. Rules were limited to one stable and one flexible attributes.

In Figure 36, the level of rules coverage is very different. For example, social media, had a lower influence on the coverage. On the contrary, attributes impacting a biography had a higher influence of the resulting rules coverage. This is especially visible when comparing the coverage of the biography's negativity or positivity with the similar attribute in the description. The coverage appears to be lesser in the middle of the price levels, may be because of the large changes in pricing needed to shift works of art from category to category. The principal color attribute was added as a stable feature. With the rules generated,100,000 records were tested considering the rules which had a support of at least two 'before' and 'after' rules and 60% of confidence. More rules were created at every one price point where the confidence and the coverage appeared to be increased. The sample of flexible features which had the greatest impact was redone. As previously, the better coverage had the lowest pricing points. Figure 37 shows the full coverage.

Figure 36. With Stable Features

| | SM | Bio.WC | Desc.WC | Bio.Ps | Desc.Ps | Bio.Ng | Desc.Ng |
|---|---|---|---|---|---|---|---|
| **1->2** | 19.24 | 38.89 | 30.26 | 37.05 | 26.56 | 35.86 | 19.45 |
| **2->3** | 4.31 | 16.35 | 13.03 | 17.04 | 11.97 | 9.70 | 5.04 |
| **3->4** | 3.60 | 11.91 | 9.52 | 11.42 | 9.40 | 7.78 | 3.52 |
| **4->5** | 2.51 | 7.87 | 5.80 | 8.02 | 5.67 | 4.41 | 2.35 |
| **5->6** | 2.21 | 7.31 | 5.91 | 7.82 | 5.54 | 5.18 | 1.64 |
| **6->7** | 1.30 | 8.20 | 6.91 | 7.96 | 5.77 | 3.41 | 3.54 |
| **7->8** | 1.34 | 7.28 | 4.80 | 6.34 | 4.41 | 3.47 | 1.54 |
| **8->9** | 1.94 | 7.79 | 6.59 | 8.91 | 6.03 | 5.14 | 2.05 |
| **9->10** | 4.77 | 14.25 | 12.18 | 13.17 | 10.87 | 11.35 | 5.21 |

To examine it further, more rules, using the Lisp-Miner discretization tool, were created. In order to improve the result, some changes in the rule generation process were made and additional variants of stable features were explored. Rules were created using different visual attributes of the works of art as stable features. PAD scale as well as the activity, heat, weight levels as stable features were considered. The average picture brightness and its deviation became also stable attributes. The average red, green and blue values (RGB) were analyzed. Referring to the improvement in Figure 37 the second color was considered. Finally, the artwork was partitioned into 9 equal sized blocks where the brightest and darkest parts were considered as stable features. That was an attempt to identify the nearest location of the image focal point.The requirements for confidence and support were stable and the stable feature medium was enlarged from seven broad categories and NA; with NA category restricting the number of tuples to 50,000. Longer rules which contained up to two stable features and two flexible features were added. The complete coverage is displayed in Figure 38. The AWH (activity, weight, heat) scores and PAD (pleasure, arousal, dominance), the prominent color out of ten, and two prominent colors out of ten were considered as stable attributes. The average brightness as well as standard pixel deviation limited to monochrome colors, the average intensity red, green and

Figure 37. Stable Features + Principal Color

| | SM | Bio.WC | Desc.WC | Bio.Ps | Desc.Ps | Bio.Ng | Desc.Ng |
|---|---|---|---|---|---|---|---|
| **1->2** | 25.45 | 55.11 | 47.57 | 54.12 | 44.77 | 48.22 | 26.05 |
| **2->3** | 8.93 | 26.44 | 22.25 | 25.33 | 21.92 | 17.04 | 8.05 |
| **3->4** | 5.62 | 20.50 | 17.12 | 18.83 | 15.88 | 12.03 | 7.27 |
| **4->5** | 5.09 | 13.57 | 12.66 | 14.68 | 11.66 | 7.89 | 5.64 |
| **5->6** | 3.81 | 14.71 | 11.52 | 13.42 | 11.15 | 7.75 | 3.77 |
| **6->7** | 4.21 | 14.38 | 12.30 | 15.09 | 10.65 | 8.16 | 5.20 |
| **7->8** | 4.08 | 13.76 | 11.53 | 13.66 | 11.03 | 7.04 | 4.22 |
| **8->9** | 4.94 | 16.46 | 13.41 | 17.09 | 14.57 | 10.16 | 5.01 |
| **9->10** | 12.51 | 27.51 | 26.67 | 27.37 | 23.80 | 21.58 | 11.51 |

Figure 38. New Attributes

| | BF | AWH | PAD | 1 Color | 2 Colors | Gray Mn Sd | Min9Max9 | RGBMn | RGB Sd |
|---|---|---|---|---|---|---|---|---|---|
| **1->2** | 64.05033 | 64.94907 | 65.36848 | 66.30717 | 67.98482 | 64.60955 | 65.96765 | 64.80927 | 65.08888 |
| **2->3** | 22.94918 | 24.02961 | 24.12965 | 25.29012 | 28.31132 | 24.02961 | 26.23049 | 24.2497 | 24.26971 |
| **3->4** | 19.35936 | 20.58058 | 20.34034 | 21.6016 | 23.4034 | 19.93994 | 22.16216 | 20.48048 | 20.84084 |
| **4->5** | 11.37271 | 11.99122 | 11.95132 | 13.50758 | 15.04389 | 11.67199 | 13.7071 | 11.85156 | 12.27055 |
| **5->6** | 9.482759 | 9.963913 | 10.14435 | 11.64796 | 13.47233 | 9.703288 | 10.70569 | 10.06415 | 9.983962 |
| **6->7** | 8.96 | 9.78 | 9.52 | 11.06 | 13.18 | 9.48 | 9.98 | 9.66 | 9.68 |
| **7->8** | 10.03799 | 10.5179 | 10.9978 | 11.87762 | 13.81724 | 10.17796 | 11.09778 | 10.55789 | 10.45791 |
| **8->9** | 10.94438 | 11.40456 | 11.48459 | 13.46539 | 15.42617 | 11.26451 | 11.94478 | 11.72469 | 11.28451 |
| **9->10** | 23.2 | 23.96 | 24.44 | 26.42 | 28.92 | 23.84 | 25.24 | 24.12 | 24.02 |

blue channels, the standard pixel deviation in the red, green, blue channels (RGB Mn) were determined as stable attributes. The pixel deviation in (RGB Sd) -red, green and blue channels -as well as their location in case when image partitioned into three-by-three grid were determined as stable attributes. The brightest and darkest image part decreased to grayscale (Min9 Max9) were determined as additional stable features. A similar repetition of middle partitions with specifically low coverage took place. Two color stable features addition or addition of the blocks of the brightest and darkest parts of the artwork, can improve the coverage slightly. However, there is no stable feature which has a dramatically higher coverage. Over 3,000 rules were generated with the use of only the base attributes which goes from price 1 to price 2. To improve the model's accuracy and to receive higher coverage, artists with visual similarities were grouped. For clustering artists, their artworks into single style were combined, and these groups were clustered using two sets of features to cluster the artwork edges and to combine its pixel brightness. Ten clusters which were very diverse in dimension were formed.

The smallest cluster had one artist with multiple works. The biggest cluster contained 1759 artists. The highest number of images determined was 50,000. However, fewer could be utilized if a smaller amount of works exists in the cluster. This level of personalization noticeably improved the rules coverage. Some clusters, when located on edges, had a low coverage because of the small number of only four artists. That tends to prevent generation of some rules. Some of the clusters, for example, one that contains 415 artists have superb coverage. The patterns of less coverage inside of the middle price levels and the absence of very big changes when including new stable features is constant. These clusters also were utilized to build predictive models as was shown above. These models showed the same accuracy in patterns and refer to previous ones. APPENDIX B.

# Chapter 6: Art Experiment

## 6.1 Introduction

One of the options for exploring new art forms, mediums, techniques, computational tools, web interaction and interconnections with digital reality is to be emerged into the creative process which involves all of these activities. For me, this experiment also started with my art market exploration and with the implementation of the computational techniques in order to resolve the problem of the art pricing. In this art experiment I tested computational tools and techniques which I became familiar with during my study at the Software and Information Systems Department. Art market research provided me with the valuable insights and experience which shaped my interdisciplinary approach to the art problems and art form development. Authors of [116] state that “The need for art as an autonomous force in society does not fade or change, but rather our perspective changes about its role and its form. The latter are subject to wildly fluctuating external influences in the form of political and social forces, which grow inevitably out of changing technological conditions. These transform awareness and provide new tools from which new art forms develop." My previous studies have had more an artistic approach, however, my study at the School of Architecture helped me to form interdisciplinary approach. My recent art research is shaped by this multidisciplinary approach and implementation of computational tools to explore new mediums and hybrid spatial environments which I translate into visual language. The outcome of this research- "VIRTUAL CONTINUUM - ZOOM IT IN" art exhibition Figure 39. explores the hybrid space 'real-virtual' continuum of the environmental transformation stimulated by social shift towards online activities over the pandemic lockdown that developed my artistic creation. Multiple zoom classes during the lockdown triggered the range of different emotions and assumptions that zoom participants produce a sequence of physical and emotional activities which tend to alter the spatial environment around them. I connect these activities with the various colors to generate continuous visual effects which reflect the state of the emotional and physical conditions. Adding the dynamic of motion into the static condition, producing visual digital effects and contextualizing techniques, I intend to overreach the conventional vision of space as a physical element and to expand the boundaries of individual imagination stimulated by the social isolation. I argue that despite the fact that contextualizing techniques and modified physical spatial environment had received rapid development at the end of 20th century, the full articulation of the emerging hybrid (real+virtual) environment came during the pandemic lockdown. Recently, hybrid meetings, hybrid classes, hybrid education, hybrid work conditions, hybrid exhibitions became widely accepted increasing the sense of personal freedom and transforming the world, including the art world. Online art exhibitions, virtual viewing rooms became common ways of communications between stakeholders in the art market. My experiment aims to make a contribution into the exploration of these spacial conditions to develop the awareness of the dramatic space transformation that our society recently experienced, to boost viewers' imagination for better adaptation to these conditions as well as to articulate a problem of new art mediums and techniques. The exhibition encompasses possible variations and compositions of mixed reality (real and virtual objects) providing viewers with the open-ended conclusion and individual imaginative process. It consists of media recordings, installations, video fragments, posters articulated my creative processes. To make exhibition interactive, I apply the set of tools -TouchDesigner, Kantan Mapper, Arduino, Fabrication, Multple Screens and Projector. Thus, I achieve various visual effects to create the "mixed reality". Below, I go through my art process explaining the triggers, insights, inspirational figures, new tools and techniques. I provide the conceptual visualizations of this process, video recordings, images and plans.

## 6.2 Inspiration

In March 1914, Kazimir Malevich and his artist friend went for a walk. They had “shocking look” - wearing a black coats, a black top hats but the red spoons were attached to their buttonholes. The next day, they made newspaper headlines. Art histories pointed out that it was not just a promotion campaign. They also made desperate attempts to sell their art works and this event found a response even in the literature. One of the writers in his story described two artists with red spoons in their buttonholes who tried to sell to a collector for a large amount of money paintings of the wooden boards nailed to the canvas, a pig with five legs, and dead rat nailed to a tray [129, 130]. Many years ago, my interest in avant-garde movement and apparently in the mechanism of the art market started with this fascinating art market story. Whether Kazimir Malevich and his friend sold a dead rat on a tray or not, their appearance in public with red spoons in their buttonholes, claiming the large amount of money for the unknown provocative art made them a perfect case study to start my art market research. Later, I learned that it is a category of novelty that made Malevich's art so popular and high priced in the art market. Nowadays, every person who is interested in art can probably repeat "Black Square" or "Black Circle" because of the shape simplicity but a century ago it was a context that made " Black Square" to be seen as a revolutionary step of the creativity that offered a new vision to the public.

In my research, some major insights came from avant-garde and Malevich's revolutionary statements and manifestations. It also encouraged my speculative project of building the recommender system for art pricing and exploration the potential of new art mediums and computational tools which can be used in the art process. Malevich's statement that "without revolutionary spirit it is impossible to move forward" [127] encouraged me to find funds and support a team which participated in the part of this research.

A category which comes ahead of the novelty is a courage. The Last Exhibition of Futurist Painting 0.10 held in Petrograd (Russia) in 1915 which featured fourteen artists – "seven men and seven women", the exhibition where at the first time Malevich showed his Black Square [131] changed the direction of the art world forever and was an act of courage. Often, on my way to the Art Academy, I was crossing this exhibition spot thinking about artists who during winter 1915-1916 changed the art history. Responsibility of keeping the tradition of breaking the conventional art rules came later when I had gotten the opportunity to see the first version of Malevich's "Black Square" which due to the fragility of the black color never left Moscow State Tretyakov gallery [127]. The cracks of the black color in the first version of Black Square were the distinctive features that gave me the thoughts about Multidimensional Space. They reminded me of the stars networked inside of the Black universe with the multiple unknowns and profound depth of dimensionality. The square outline determined roughly the space. There was not too much logic when I was looking at the Black Square and my emotional part referred to the Malevich's statement that his Black Square was the end of the beginning - understanding and seeing space differently was one of his priorities. At the same time, the white space Malevich associated with the ultimate infinity [127]. Another artist who shed light towards the space logic was Futurist artist Gino Severini. Finally, personal meetings with the artists Julio Le Parc (b.1928) and John Baldessari (1931 – 2020) triggered my interest in the kinetic art and conceptional art thinking. Julio Le Parc's color and kinetic research forced me to move beyond my black and white "architectural palette" to start exploring Color Wheel, color combinations, color movements and color contortions. Julio Le Parc's light and reflection experiments which he started conducting in 1959 developed my interest to projections and materials [140].

## 6.3 Spatiality and Dimensionality

In the beginning of 20th century, Malevich was drawn to the idea of spatiality from the various perspectives. He saw space revolutionary, compressing it between the planes of his abstract objects. Malevich was interested in philosophical works of Pyotr Ouspenskiy who stated that the true artist realizes and depicts the structure of the world. He insisted that there was 6-Dimensional space which Malevich mentioned as well: 1. Length 2. Width 3. Height 4. Time 5. The point from where it is possible to observe the present, past and future. 6. The one that connects everything in the world between each other [129]. Some of the Malevich's artworks contained the word "dimensions", for example, "Picturesque realism of a peasant woman in two dimensions." My study on the spatial environment had the similar attitude towards the space articulated by Ouspenskiy and Malevich. I studied environment since I became a student at the School of Architecture, where the articulation of space was based on the conventional 3-Dimentional modeling. During the pandemic lockdown the perception of the space was radically changed and architectural projects started strongly referring to the expanded space dimensions. My daily university activities were merged into the virtual world of zoom meetings and novel spatial reality. Real-time virtual interactions became a foundation to form the concept of my spatial attitude based on the multiple dimensions. It boosted the chain of my digital tests and art experiments with kinetic mechanisms and emerging “mixed reality”. I based my experiments on the Ouspenskiy's, Malevich's, Severini's perceptions of multiple dimensional spatial environment. The term of my "mixed reality" was based on the last sixth definition of Ouspenskiy's space - one that is connected everything in the world between each other [129]. Exploration of this topic deeper got me familiar with Plastic Analogies of futurist painter Gino Severini and manifestos of Futurism. The term Plastic Analogies between desired correlated subjects, for instance, bodies and landscapes, appeared in 1914 and described the method of presenting "perceptual experience" or "rendering sensation" through the "visual kinetic approach" [132]." His idea was to "expand the perception of human experience in a modern world [132]." Artist's "kinetic approach" boosted my curiosity to explore the concept of Spatiality from the perspective of kinetic phenomena to expand the limits of viewer perception and visual abstraction. Severini places the body experience at the center until the logic of his system transforms outside the body [132]. This transformation formed the one of the concepts of my art experiment where I intended to decentralize the subject of the compositions with the help of visual effects in order to express sensation rather than form. The concept of speed which been implemented in Futurists' works gave me an insight on the conceptualization of motion. According to Severini speed "altered perception of all types of phenomena -biological, experiential, physical, social, and historical [132]" and experiments with kinetic apparatuses concentrated on "sensorial qualities" rather than on "discrete objects [132]." "Futurists tracings of physical or kinetic motion were meant to trigger feelings of momentous historical and societal change [132]." They believed "every sensation may be rendered in plastic manner [132]."

Severini referred to the change towards modernity. In my art experiment, I also refer to the special time conditions boosted by the pandemic lockdown which influenced the state of society worldwide. I embraced the Futurist attempts to show the modernity in order to express the moment of recent societal change during the times of social isolation. Pandemic lockdown was a period that all of us could refer as to the times when "we need to find means of understanding world differently [127]." As I mentioned, during the pandemic lockdown my daily university activities were merged into the illusory world of virtual zoom meetings. Real-time virtual interactions became a foundation for my spatial experiments with kinetic mechanisms and emerging “mixed reality” that, as I argue, became fully articulated during the pandemic lockdowns. The human body placed into the center of my video fragments tends to merge with the virtual world and visually disappear inside of the mixed reality Figure 40. The viewer perception is decentralized embracing rather sensorial qualities of the video compositions which is achieved with the help of mechanical (Rotating Color Wheel) and digital visual effects. "In the development from moving figures to sensory perceptions and then to generalized energies, Severini aimed to increase the field of perception, while avoiding concreteness and specificity" articulating "a visual logic that gestured toward a parallel world of conditions beyond the senses [132]." My art experiment is inspired by this strategy and by the idea to bring "nonvisual inputs into visual medium" [132]. One of the points I explore is a generation of the novel art mediums and their implementation into spatial environment. I state that over the pandemic lockdown "Space no longer appears to be a vacuum in which solid bodies live, but rather a medium through which information is diffused [134]." Julio Le Parc's tests and experiments without "paint and brushes" became my references. His work "Salle de Jeux" is described as the "movement-surprise" for the viewers who are able to participate in the installation "games" in order to present "active and multiple behavior". His other work "Image en vibration autoportrait" that included the motion moved my concept towards self-portrait and self-representation through increasing the surface depth and replacing the real object representation with the virtual portrait and visual effects Figure 41.

## 6.4 Color Energy

The concept of color energy implemented into my work shed light on how to approach to the range of the sensational gradation. The supremacy of color was one of the narratives in Kazimir Malevich's manifestation of suprematism art, he used pure colors as a strong variable and explained his painting as "a collusion of colors" bringing the pure color emotionalism. According to Malevich the viewer should "feel" the tension in the painting, not simply "look" at the artwork [129]. His last period was "the white period". In his later works Malevich tried to show the infinity of spatiality through the white color. However, 'white' for Malevich was an ultimate mixture of all colors [129]. Severini also explained color and forms implementation to express "non-visual sensations". Like Malevich, he connected these sensations with fourth and fifth dimensions [132] and used color range to fill in the space.

I realized the scale of color impact in terms of color theories, studies, scientific and artistic developments when I visited the exhibition *Saturated: The Allure and Science of Color* [135] which explored the history of the development the color theories and complexity of color perception studied by multiple artists, scientists and designers. The exhibition's argument that "color is an illusion, but not an unfounded illusion" [135] brought me closely to the color discourse and understanding that color perception was not fully explained. Indeed, it is a very subjective experience which is different for every person and based on individual memory and experience. Thus, in my exhibition, I investigate the color range and dimensions through my personal sensations and perception. Designers and artists deploy color using "wide array of media" [135]. I also generate different media to express my color perception of space. Example of these experiments shown in Figure 39-40 and video fragments (link). Spatiality in my work is saturated with color and, as I mentioned,based on the individual color assumption. Using the range of color saturation in my art experiment, I attempt to express my sensation during the pandemic lockdown which was boosted by the restricted physical space. Like Julio Le Parc fills in his 'Game Room" with the various objects which transform the physical space, I fill in surrounded me environment with the colorful atmosphere of my daily virtual activities and I express it through the gradation of variously intense color waves. During the lockdown my weekly daily routine is similar day after day, filled with saturation of my personal daily sensations. To discover my sensational individual spatial rhythms, I add a time scale, speed and motion into my experiment. Lockdown boosted a range of scientific digital studies and references to the works that explored the phenomenon of hybrid spaces and kinetic digital devices. I dissolve my physical appearance in the saturated spatiality of my physical room and boost the virtual world of my computer screen. I become a hybrid element and everything inside of my room does not look the same anymore. Being in "hybrid" mood, I have more freedom to choose what to see and what to explore following the statement of Paul Virilio: "You only what you look at and you only look at what you want to see [133]". He explores "innovation of artificial vision" and he delegates " the analysis of objective reality to a machine [133]". I delegate the reality to my zoom meetings. To conduct my experiment, I explore the exercises for color theory classes done by Bauhaus artists where color basic courses were taught by Johannes Itten, Paul Klee and Vasily Kandinsky who focused on primary, secondary colors, laws of simultaneous contrasts, combinations, scales and formats, including the complimentary colors effects. Some of them stated that colors "possessed not only different temperatures" but "also different personalities" described them as "active, passive, or neutral [136]." Kandinsky asked students to fill in with colors different shapes - circle, triangle, square [136]. I used his red color statement on how red color dominate the composition as well as Eugen Batz's theory of intersecting shapes and distinguished various color zones [136]. It was Ludwig Hirschfeld-Mack whose Color-Light-Plays experiments brought me the insights about the transitions and movements of colorful surfaces which radiate light creating new spatial dimension through light and movement. "Light in motion, arranged in rhythm based on time sequences [136]" became my formula for implementation of intersecting colors into the kinetic moving machine (rotating Color Wheel) Figure 41 - 42. to automate the vision. Color interactions generate the sensational waves - a metaphor of the people's motion in the attempt to "survive" once they are in the infinite water of unknown (later, at the university, we called each other "zoom survivors"). Images (Figure 39.) are the snapshots of the video recordings of the part of my art experiment where I explore “the solid cluster the primaries overlap to create the secondaries” colors [136] to build the spatial color rhythms. For Color Wheel fabrication, I used transparent color film lighting plastic sheets of primary colors (red, blue and yellow) and Bristol Board. The Wheel diameter is 20 cm. The supremacy of color energy was one of the narratives in Kazimir Malevich’s manifestations. It was important for me to use this narrative in my exhibition.

### 6.5 Light, Screens, Projection

In "The Practice of Light", Sean Cubitt argues that avant-garde movement, left us with the insightful legacy in terms of space construction and the space definition: "of all the alternative modes of constructing space, perhaps the most invigorating can be traced through the legacy of a short-lived early twentieth- century avant-garde movement" " and it "reflected a fundamental disjuncture in the construction of space [134]".

Author continues: "Even so, there are many options for volume rendering that draw on the fundamental insight of the cubists: that space is neither a premeasured geometric grid nor a geometric projection from a vanishing point, but a construction of the projection of each entity and the relations between them, and that these projections of entities and their relations are space. Space, in other words, is not a void vacuum waiting to be filled in but the product of relationships [134]". The idea of the relationships built between the all entities of space to make so-called invisible void visible and to create "the effect of spatial presence" and "two-dimensional window onto a virtual three-dimensionality" [137] drove my following experiment. To create "hyperspace" and to articulate new dimensions I explore the appropriate texture and material for my final 'mediatic conflation' [137] of the surfaces. Giuliana Bruno in the "Depth of Surface Screen Fabrics" argues that for this purpose the architects can "turn the facades of their buildings into screens, making them into translucent surfaces [137]" and artists can "reinvent the art of projection [137]." "The projective mode and visual plasticity, the sartorial texture and opaque transparency that is, the luminous material transference—that is our medium [137]." The main insight of this part of my study is that I can use a screen as an entity of the environment and it becomes my "mediatic passage of environments" [137], my medium towards the "movement of rematerialization [137]" and an attempt to make the environment active. My installation is the experiment of turning mixed environment into surfaces and allowing the viewers to be absorbed by this condition and interact. I attempt to transform a part of the interior space into a type of hybrid environment with the help not only a digital medium but using physical properties of things -screens, light, textures, projections. This integration helps to activate the superficial, hyperspace layers and to allow viewers to sense all means of the conflated surfaces and "real nature of the "virtual" imagery [133]." In many cases, I choose the red color as a main color of representation referring to Kandinsky's statement that the red can hold composition plane more effectively [136] and following the interior specifications.

As it was mentioned above, Malevich, Severini and many artists of the avant-garde movement relied on the perception not 3-Dimensional world but five and six dimensional world in order to show that the space is not a voidness but complex tensile matter. Nowadays, when we attempt to visualize multiple data sets - fill in the void with the information- we often assume more than 3-Dimentional space. Forms consist of the 3-Dimensional shapes -regular and irregular. When I talk about the hybridity of the space or about the surface depth I also assume that hyperspace cannot be a voidness and I use here the avant-garde artists' assumptions of six dimensional space -their "radical reorientation" [132] of spatial perception. I argue that the human perception can be expanded with the help of computational tools and in my installations I strive to create such multi-dimensional environment in order to increase viewers spatial sensitivity. I use multiple screens and textures to activate viewers ability to perceive the space differently as shown in Figure 43. As it was noticed by Giuliana Bruno, screens and projections have ability to activate space "compelling configurations of the screen's ability to activate multiple, material passages of temporality and spatiality, and to touch upon and communicate across different fields [137]." This transformation was articulated by another avant-garde artist Moholy-Nagy in his work "Light Architecture" where he introduces the transformation of the "bidimensional surface into a plastic, luminous plane [137]" using light. Screens have multiple planes and viewpoints providing viewers with the opportunities to expand their space perception and to enhance the viewer's spatial experience as it shown in Figure 43-46. Space transformation increases the environmental spatial complexity allowing multiple movements, vistas and viewers. "The act of screening has incorporated polyphonic potentials and different kinds of mobility [137]." As we can see in Figure 46. the viewers journey may involve "tracing commonalities between the screen as a surface activated by light and the types of material support of the image that can be found in art [137]" as Giuliana Bruno states in "Depth of Surface, Screen Fabrics".

It provides surface with the mediation, and generates conditions for the materiality of media" Figure 46-47. Figure 39-40, 47-48. show my actual tests of generating a spatial hybrid environment using video transmissions. It is considered that in the viewing experience "the luminosity of the screen of projection is an important factor [137]". The luminous and transparent screens of boxes extend the sensation of light transformation. I use planes as screens and projector lighting to intensify the viewers spatial experience and to express the manifestation of multiple dimensions and surface layers. Arduino set, Webcam, Color Wheel and Computational Techniques can turn ordinary space, objects and gestural movements into artistic abstract elements appearing in motions of visual effects. Continuous virtual iterations allowed me to study emerged hybrid spatial environment, explore art mediums, involve audience into this research. One of my arguments in these tests is to assume a connection of physical cardiac movements with the spatial exploration which also refers to the concept of Einfühlung or Empathy [138]. It does not only refer to the empathy by itself but to the physiological concept of feeling where "the body structure becomes the material absolute of the beautiful artistic form. The result of the spatial relationship with an object [138]". It is a respond of viewer to the external restricted material world such as space, image, object where lights of projection screens can generate the "atmospheric “feeling into” [137] and spatial shifts from one condition to another. Figures 47,48 present the test conducted in smaller scale. Now, I intend to present my research in the bigger scale to allow the viewers be fully engaged into the illusionary world of the hybrid reality and to communicate with each other through the virtual spatiality, as it happened during zoom meetings. It was discovered that the emphatic feeling is one of the tools of social and cultural transmissions. It activated through the neurons of empathy "when you perform an action and when that same action is performed by others [138]". Speaking in other words "The sympathy for things evokes the concept of Einfühlung that discovers, analyzes and expresses the symbolical relationship which is established between the observer and the natural object [138]".

My intension to use the screens, projections, light, colors and other elements is connected to the goal of engaging the layers of environmental surface to make the spatiality palpable and to mobilize all viewer modes to generate "alchemy of transformation, enabling the mind to gravitate to the surface of matter [137]", to create "the movement of the imagination [137]" and to underline the importance of social communications. “I communicate, therefore I am” [138]- the statement that revealed its new importance during the pandemic restrictions. The installation surface deformation creates various dimensions where viewer can interact with other viewers through the barrier of translucent screens as it visualized conceptually in Figure 49. Added colors and projections as shown in Figures 39, 46-48. append emotional unity into this interaction. My installation encourages viewers' circulation to intensify the rhythms of breathing. It also tends to embrace the concept presented by artist Won Ju Lim who explores the relationship among "perception, space and subjectivity" in her multimedia works. She "questions" the material reality with the help of projection, lighting and video installation exploring the mix of the personal and social spaces. It reveals the "media imagery" that influences our individual experience and imagination [122]. The circulation of the simulation is reflected in Figure 56-57. (video fragments). Transparency of the surfaces and lightning intensifies "zoomed", mixed reality and unite people inside of spatial internal and external conditions. Sometimes it is used in the architectural design of the housing to unite habitants and neighbors and to make the place more habitable as in Anri Sala's experiment [139]. It made also my room space more filled-in over the pandemic lockdown (Figure 39). I follow the idea of making the public space more private, and private space- more vivid and diversified. As a pandemic metaphor I use transparent barriers which were in common use. I use mixed media to reflect the relationships between art and technology. I utilize my earlier work "Scatters" as an idea of the space construction splitting the surfaces to create multiple layers of additional dimensions.

The transparent material are used for screens for the light projections and to express the range of the dimensionality from the realistic image to the abstract reproduction of the real world picture. The Figures 54-57. show simulations (plans, elevations, perspectives and video simulations) inside of two level public space. The schematic concept is presented in the Figures 51-53. Figure 51. presents the range of the different dimensions and conditions of 'mixed reality' generated with the help of various mediums and techniques. 1. Realistic Image of Real-Time Realistic Video 2. Outline abstract Image Generated with TouchDesigner script 3. Virtual Reality Set (Generated with TouchDesigner tests of Speed changing) 4. Outline and Color Wheel Combination (Integration of Color Wheel and TouchDesinger visual effects) 5. Interaction with Colors (Real-Time Interaction with the Viewer who is in front of the Camera Set) 6. Interaction with the Author's Video Set (Combination of Pre-recorded videos and real -time audience). Figure 52. shows a concept of how viewers can interact with the installation being in front of Color Wheel and Arduino Camera Set to detect themselves on the projection boxes in the different "mixed reality" conditions. Series of objects are installed to cover a sequence of projections which have different outcome of the camera set which reflected into six dimensions as soon as viewer is detected. Figure 53. presents how viewers can interact with the installation standing in front of Color Wheel and Arduino Camera Set to detect themselves on the projection objects in the different "mixed reality" conditions. The projector as a light source can be placed in any location -the location is not specified in design. The concept expresses the condition of non-materiality inside of the material world to evoke a viewer's sensation allowing the viewers to expand their space perception employing the dynamic of motion, lightning, visual digital effects and contextualizing techniques. I intend to overreach the conventional vision of spatial environment to expand the boundaries of the individual imagination, perception and space subjectivity which were stimulated by the pandemic conditions of social isolation.

## 6.6 Conclusion

This chapter is the demonstration of my personal artistic journey which was encouraged by the multiple art studies, events, technologies, inspirational figures and movements such a Malevich and suprematism. Studies on the meaning of the spatiality and dimensionality related to the spatial environment were based on Ouspenskiy's, Malevich's, Severini's perceptions of space. I followed a kinetic approach in my exploration of viewer perception and movement transformation and I formed the idea of spatiality from the point of hyperspace phenomena. Hybrid Mixed environment became fully articulated over the pandemic lockdowns that generated the conditions for the various spatial explorations based on the concept of bringing the nonvisual inputs into the visual language and implementing new computational tools and art mediums -sensations rendered in a plastic manner.

Another aspect of my study was adding the energy of color into my experiment that also was inspired by the manifestations of the color in terms of the suprematism, futurism and Bauhaus movements. In this experiment I touched on the development of color theories and complexity of color perception. Using different media, I investigated the range of dimensions and spatiality through my individual color perception. To determine my personal color rhythms, I added a time scale, speed and motion into my exploration. I referred to the series of color studies done by Kandinsky, Hirschfeld-Mack and others. I tended to implement intersecting colors into the kinetic motion using the Rotating Color Wheel.

In the part Light, Screens, Projection I explored the space as not a void vacuum but the product of relationship of all entities. One of the aspects of my exhibition follows the concept of converting invisible void into visible space -hyperspace and active environment. For that, I implemented lighting, textures and materials (screens) into the project. I used projections and computational techniques to activate these entities and create the relationship between them and viewers- to allow viewers to merge into the virtual imagery.

To explore the ‘depth’ of the space and to create a hybrid environment I used a multidimensional space definition which was articulated by the avant-garde artists as well as modern tools and computational techniques. I followed the concept of the space construction based on real-time interaction with the viewers where they can stand in front of the color wheel and detect themselves on the projection screens in the various “mixed reality” conditions and vistas. Sequences of projections have different outcomes and reflect the idea of multidimensional space expressing the condition of non-material space and expanding a viewer's space perception. It tends to overcome the conventional spatial vision and expand the frontiers of personal imagination in order to articulate a new reality we live in now.

Here, I presented the concept and digital prototype of the exhibition. I will also present partial results of my artistic experiment and one part of my exhibition in the gallery space of the Polish-Japanese Academy of Information Technology. The exhibition will include not only my main artistic idea but specially prepared models and mock-ups of the final, two-level multimedia installation concept.

## Final Conclusions

Observation of the changes taking place in art is often a barometer of civilization worldwide changes. That happens because the art flow usually goes beyond the present. Innovative art movements, including suprematism and changes in communication between the viewer and the artwork, proved to be a parallel premonition by artists about the upcoming tremendous changes in communication that came with the development of technology after the World War II, the development of technologies and computers, and the consequent global development of digital art. The artistic revolution in the early 20th century stimulated the emergence of multiple novel styles and activated new media in terms of artistic expression. This had its influence on the artistic ecosystem - social and cultural movements, and experiments related to art innovations. Artists' enthusiasm, utilization of new mediums and educational efforts made computer-generated art a strong part of the visual art environment. Digital space and the Internet became a new medium for many artists. At the same time, various art movements enlarged the thresholds for entering the art world and the art market. After the revolutionary act of “readymade art” everything could be called “art” and to be sold. That significantly complicated the art pricing process. The Internet totally transformed the role of contemporary art and the ways of its distribution. The development of the Internet made the art distribution go beyond local geographies and made the artists global participants involved in the global online art trade. Virtual trade became an essential part of the art market during the pandemic and continues to grow. Internet infrastructure development boosted the development of the various datasets, mediums and AI techniques including neural networks. AI is one of new technologies that can influence the art market in the future. The method of evaluating and pricing AI art pieces is still uncertain. Data became an essential element in the computing age. Not only artists can use data as a creative medium, but stakeholders in the art market can also use databases to create a system for the art pricing. One of the ways of artistic creativity became data visualization practice that enhances the viewer's opportunity of seeing and understanding the world because datasets by themselves often do not contain elements of visual representation. New art pricing methods have to address these historical, technological, cultural and economic changes to have a reliable price validation system.

The factors that shape art pricing seem complex in the 21st century. In the art market there is a paradox between commercial and artistic values. Artists often do not know how to price their works of art and other stakeholders in the art market often use ‘the word of mouse’. Thus, some of the artists do not have commercial success and cannot sustain themselves via their art sales. Currently, auctions play a crucial role in price shaping, but they mainly refer to the “old master” artworks which have some number of auction records.  There are not enough sales records for the art in the primary art market.

Thus, it is not easy to answer a question ‘what is my artwork worth in the 21st century’ and what finally determines the artwork price. After the number of research iterations and art experiment, I can argue that the computer science and computational techniques can be applied not only to the contemporary fine art evaluation in order to build a recommender system for solving the problem of art pricing but to the artistic creative process of generation of new art mediums and new types of spatial environments as well as visual effects. Consumer perception of artists and their works of art influence the artwork price. This is one of the reasons that the role of artist biographies as well as descriptions of their works is crucial to improve sales.

I argue that even the general text sentiment plays an important contribution in an artist's effort to find potential buyers and assure them that the artwork is a special piece of art and that it should be acquired. Factors such as number of words in the artist’s biography or even the words of an art item’s title influence the customer’s perception and understanding of the work of art and form their willingness to purchase the art. New art mediums can boost consumers' interest. However, it is still difficult to say with certainty what precisely impacts a consumer decision to purchase a work of fine art and how an artist should adjust the artwork description as well as biographic information to make the work more commercially profitable.

The development of action rules to generate personalized sets of rules have a much higher coverage than arbitrarily choosing tuples for the rule’s creation. The personalization approach and personalized models may even allow predicting the artist’s creative direction not only style or trend of the individual work of art. It indicates that creating highly personalized models to predict art price is a required step to build the recommender systems for art pricing. This study presents a possible example for generating such personalization methods. The study explores the generation of new art mediums and art interaction techniques in order to boost consumer interest.

Future development requires the further study of possible methods to group artists to develop methods of personalization and rules. The computer science techniques which can be applied to build the art pricing tool in this research were only focused on the usage of visual attributes to cluster artists. However, adding the information on artist’s sales may also contribute to the construction of the recommender art pricing system. The method which includes levels for categorization would be valuable for building recommendations. Research on visual features may be combined, for example, with the research on current art trends or seasonal trends. The role of attributes in artwork pricing is compound. Some features, for example the texts and wording of biographies are more relevant than other features. The price intervals we explored here may be a contributor into the future study and price range.One of the study observations is that the price of the work of art relates to the artist as well.It often indicates the guarantee of the artist's future career path and connected to the artist’s social activity.

Development of the recommender systems for art pricing requires clustering artists relying on their similarity. Artists with similar traits and prices can be put together. As it was mentioned, here the similarity was based on visual attributes, but the study can be extended, and more methods can be tested. For example, the datasets we explored may be also divided for the purpose of training models of personalization for every cluster. This may improve the rule coverage and model precision. The model may be trained on the new similar works of art. Selection of the relevant clusters and pricing cluster for artists refers to the system personalization. Such a system of pricing can be adjusted according to the artist’s career steps.

Currently the prototype of the Recommender System for Art Pricing built during the NSF I-Corps program is rather primitive. However, it is a promising novelty in this area of research.

It can be significantly improved by applying the computer science techniques (similar that we discussed in our study) and interdisciplinary methods of research which can include experiments with art mediums, computational tools and data visualization. This study is an example of only a small contribution to the problem of pricing the contemporary works of fine art in order to help artists to make their artworks more commercially viable in the 21st century. My artistic experiment involves novel art mediums, computational and visualization tools and interactive art exploring the new type of mixed reality we started to live in. My art exhibition “VIRTUAL CONTINUUM - ZOOM IT IN” based on my art research. It contributes to understanding the mechanisms of artistic process, generation of novel art mediums, and their implementation into new type of spatial environment based on a new types of social virtual communications. The novelty of my artwork can be assigned both to my artistic (visual) experiment in a public space with the participation of viewers and, in parallel, to my research and commercial value assessment. One of my arguments is that the element of novelty has the highest value in the contemporary art market.

My interactive art exhibition expresses individual perception of the recently emerged spatial hybrid environment based on the color and communication theories articulated in a new way during the pandemic lockdown. It attempts to activate the superficial hyperspace layers of spatial environment to develop artistic and social spatial awareness based on the interdisciplinary connections. It replaces the concept of space as a void vacuum with the idea of space based on the assumption of spatial environment as relationships and visionary interactions between viewers -the hybrid space- as an outcome of the recent pandemic lockdown and social changes. The exhibition also contains a provocative element on the tools that can be applied in order to produce mixed reality and articulate it.

Figure 39. Snapshots of the video recordings. https://youtu.be/JcWj5n_YaSA

Figure 40. Snapshot of the video recordings (Detail).

Figure 41. Rotating Color Wheel

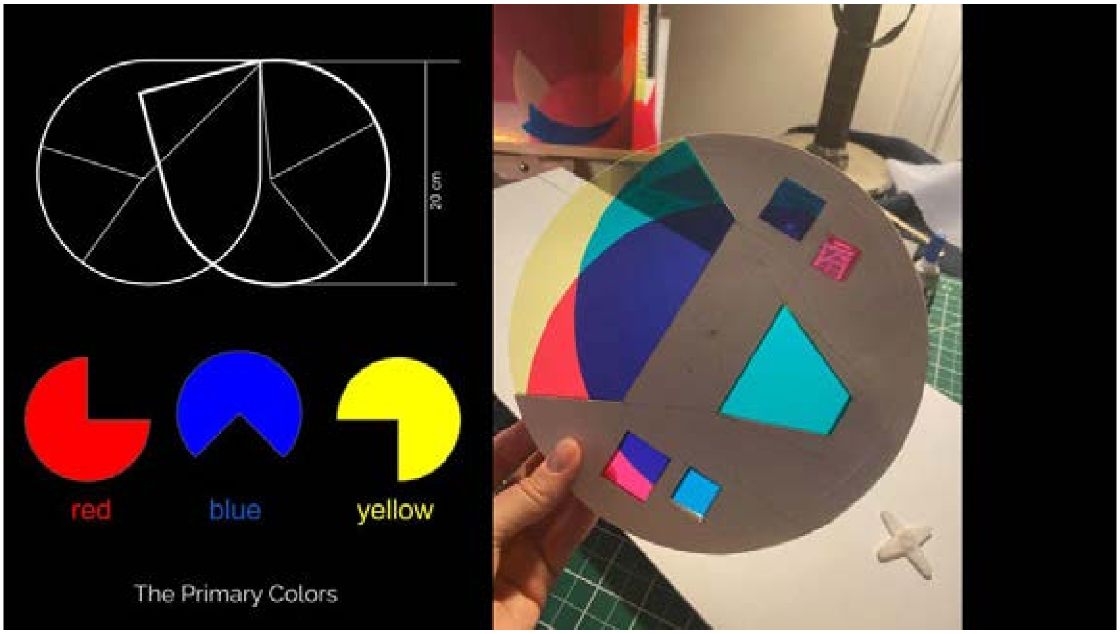



Figure 42. Rotating Color Wheel+Arduino Set. https://youtu.be/joreMRzT5es

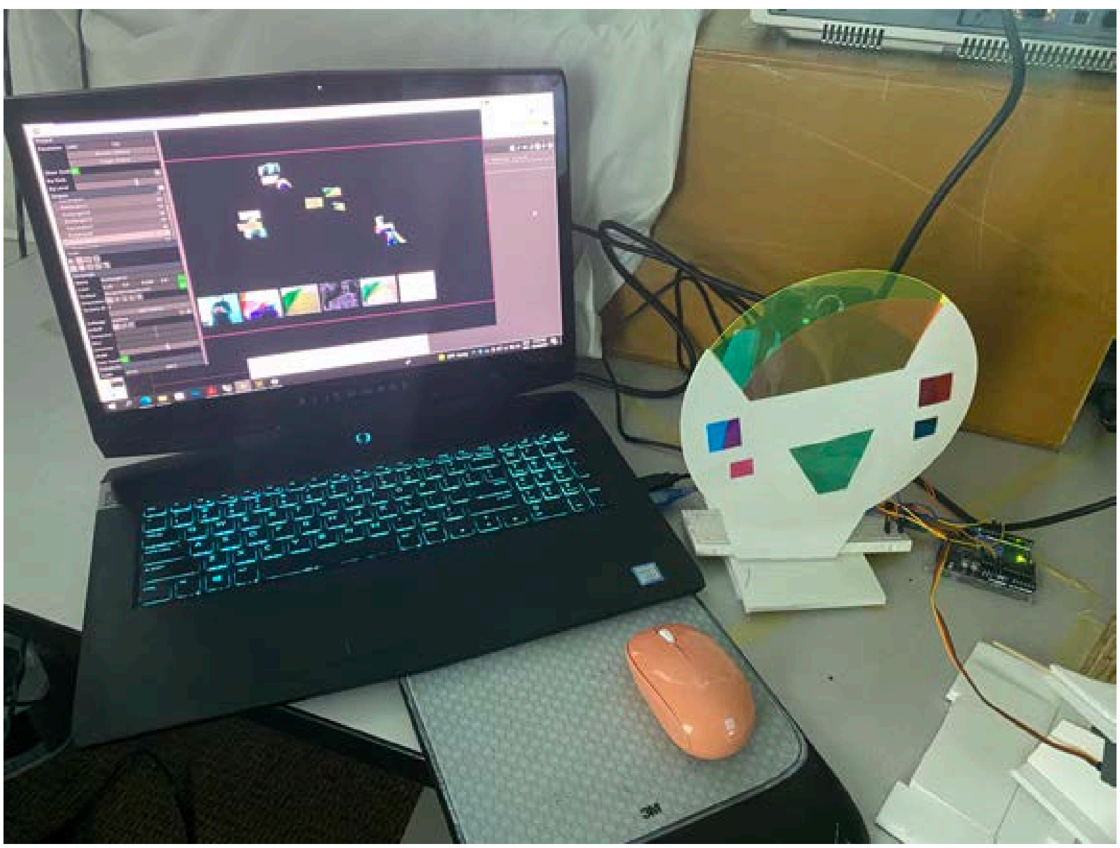


Figure 43. Translucent screens and textures.

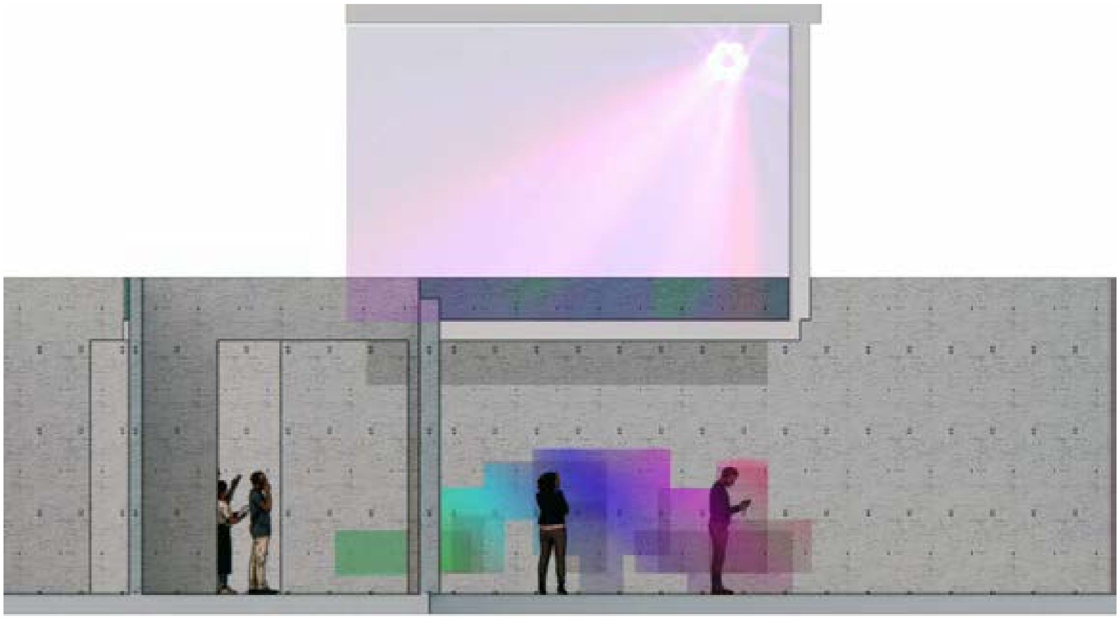


Figure 44. Translucent screens and video transmission.

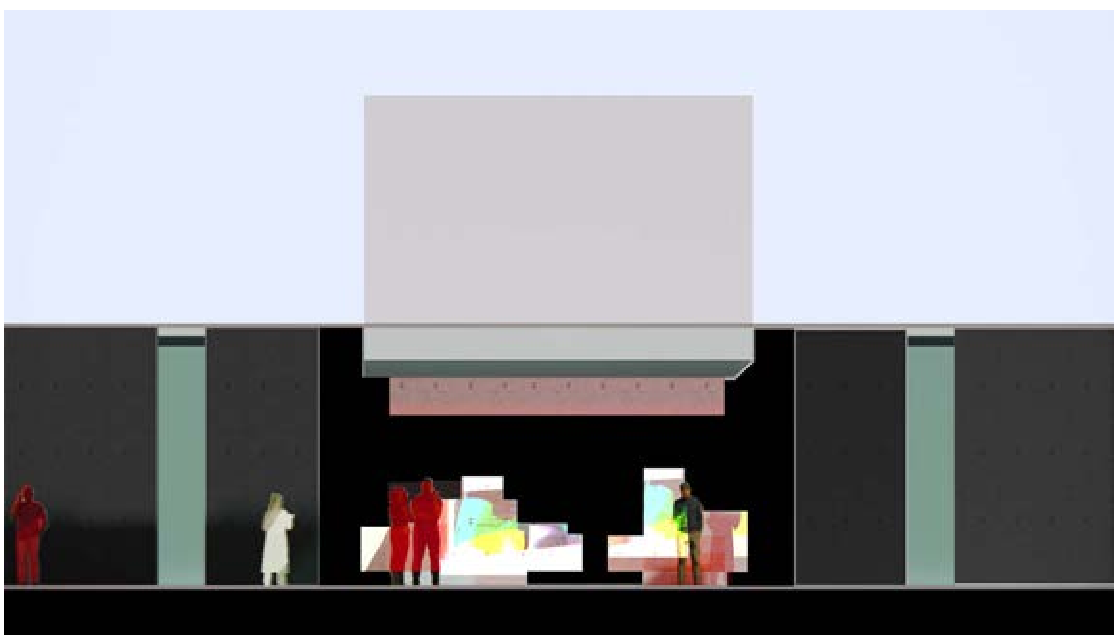


Figure 45. Translucent screens and video transmission.

Figure 46. Translucent screens, projector and video transmission.

Figure 47. Snapshots of tests conducted during small scale experiments.
https://youtu.be/mJQFqeR5laI

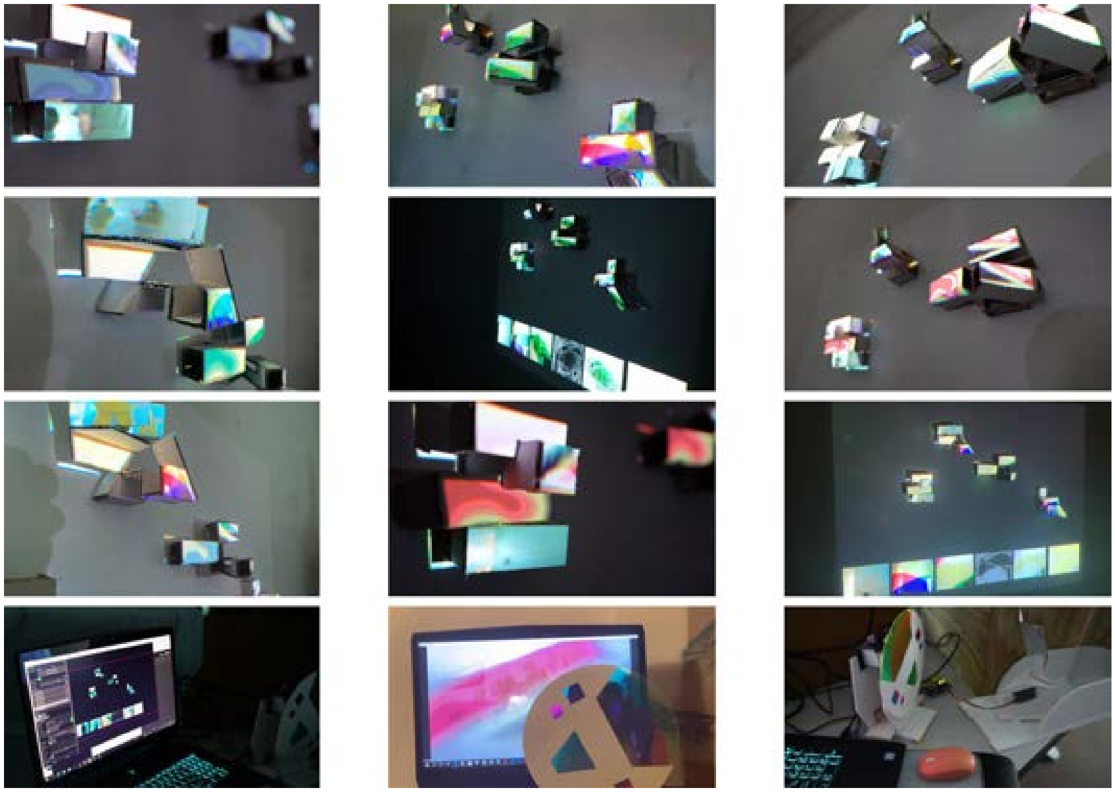


Figure 48. Tests conducted during small scale experiments.

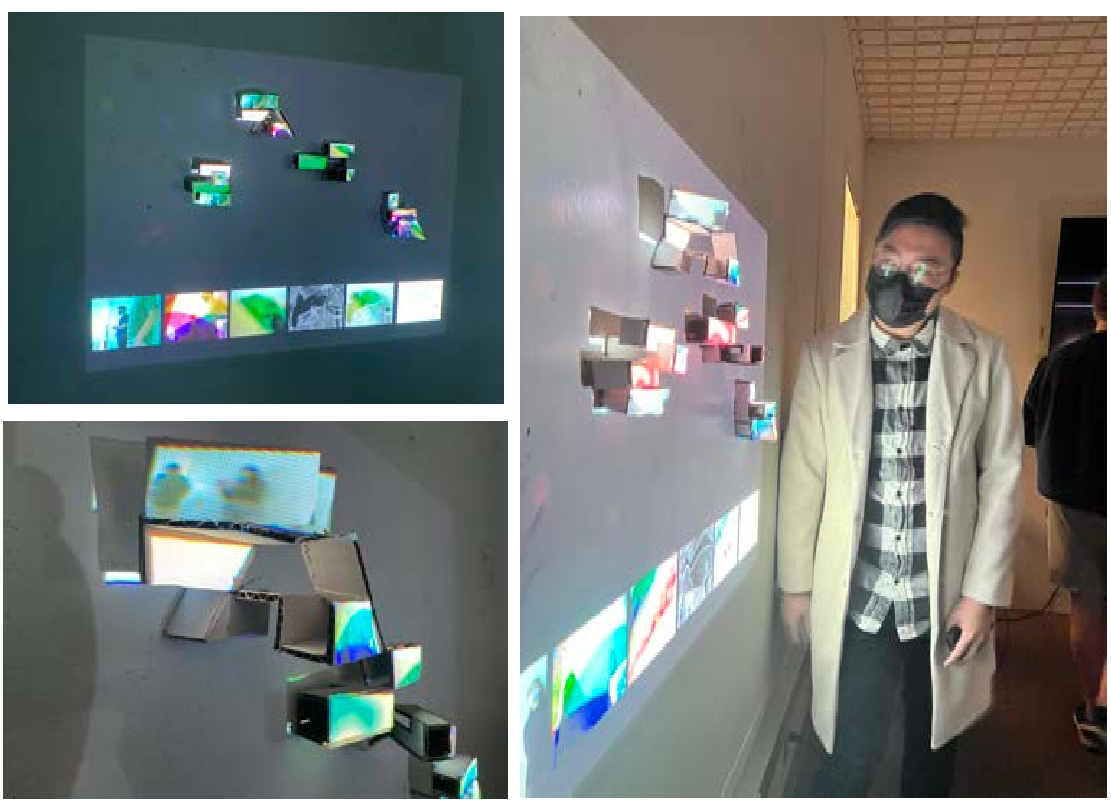


Figure 49. Model and simulation of large scale exhibition.

Figure 50. Models and simulations of large scale exhibition.

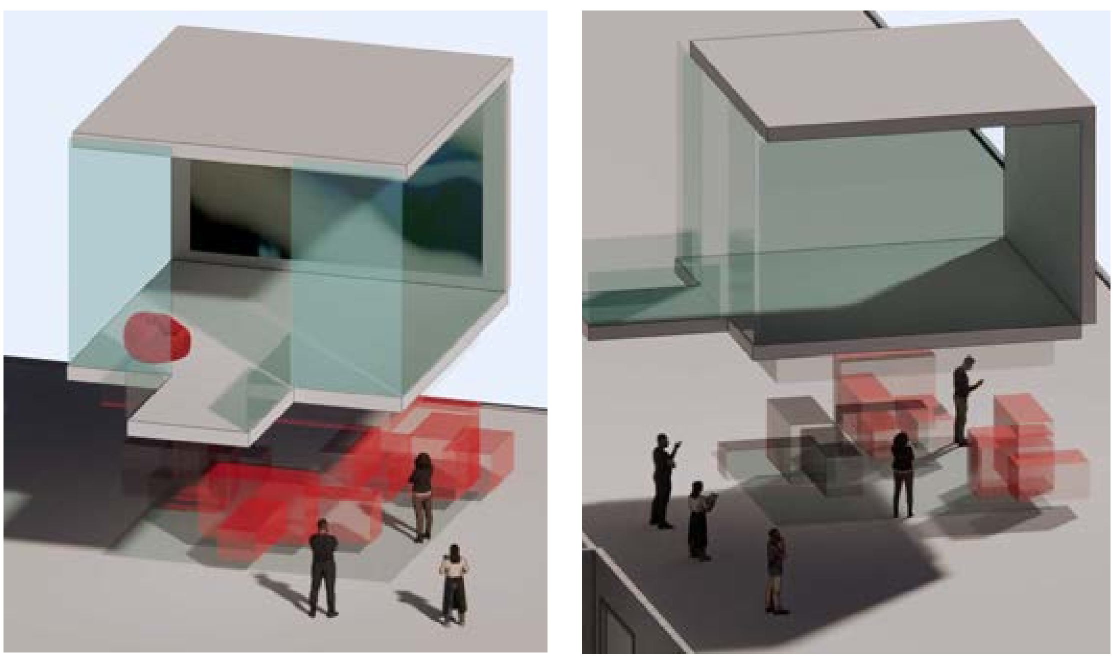


Figure 51. Project Concept (step 1)

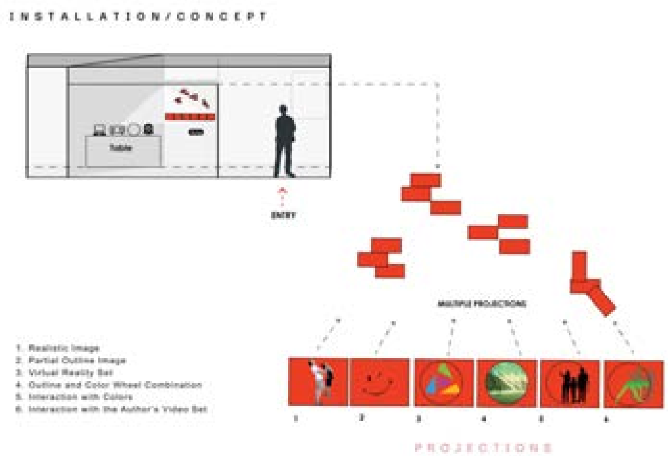



Figure 52. Project Concept (step 2)

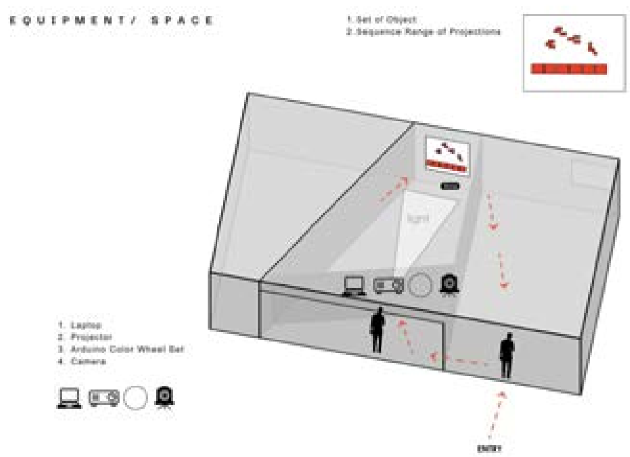



Figure 53. Project Concept (step 3)

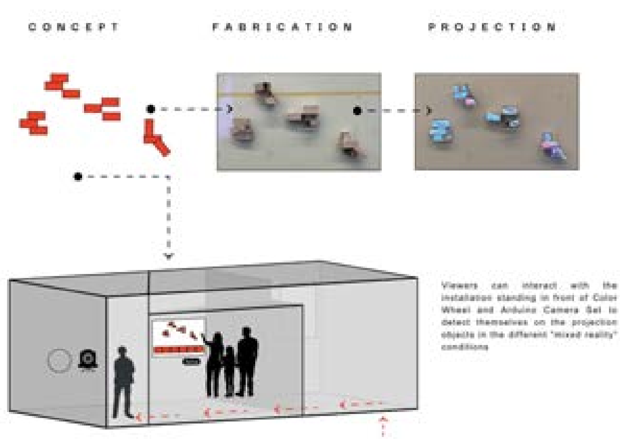


Figure 54. Simulations at certain location. Plans, Elevations, section

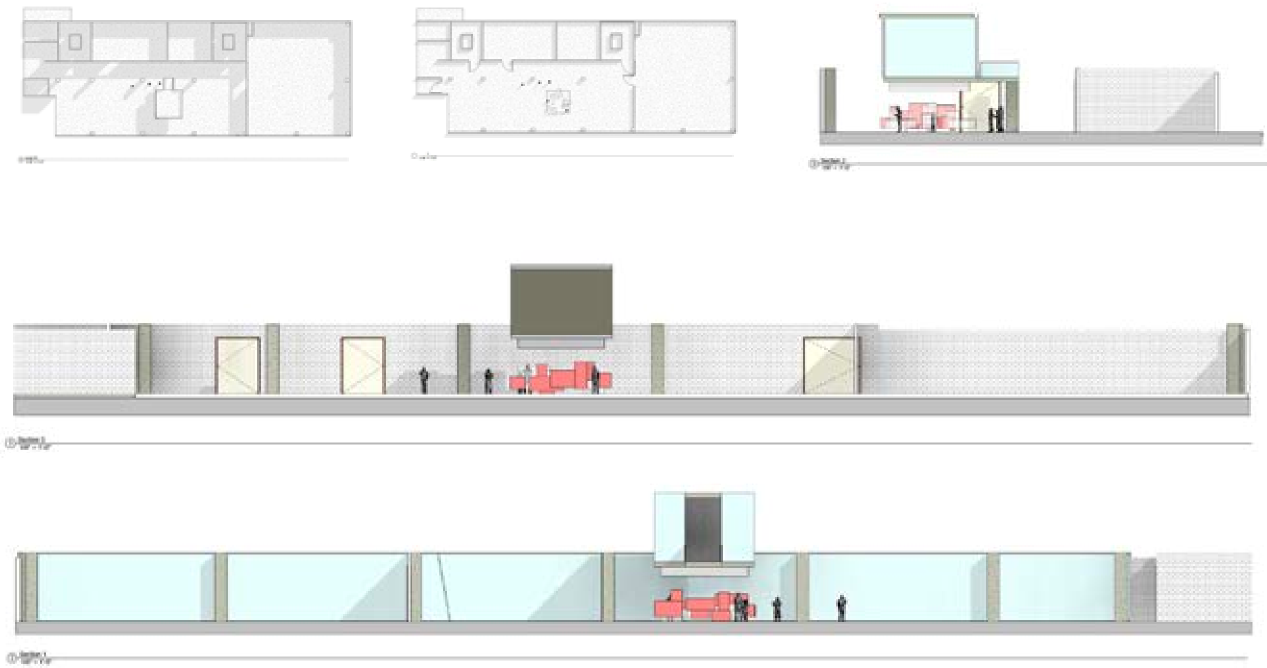


Figure 55. Simulations at certain location. Perspectives

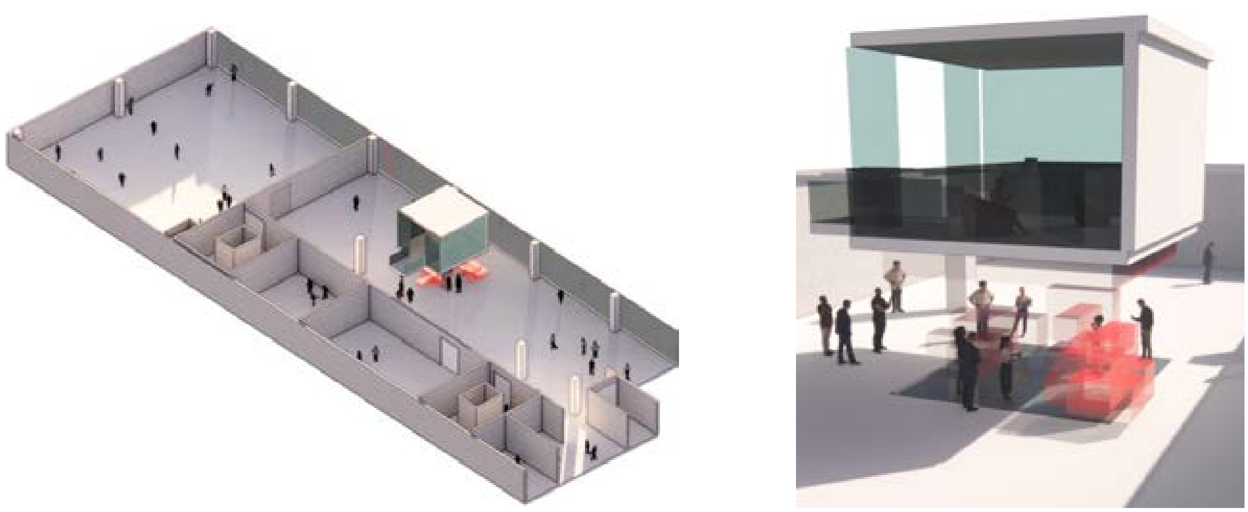


Figure 56. Video Simulation https://youtu.be/4Ud7UgcKO50?si=WodeMA25TWZCzEVv

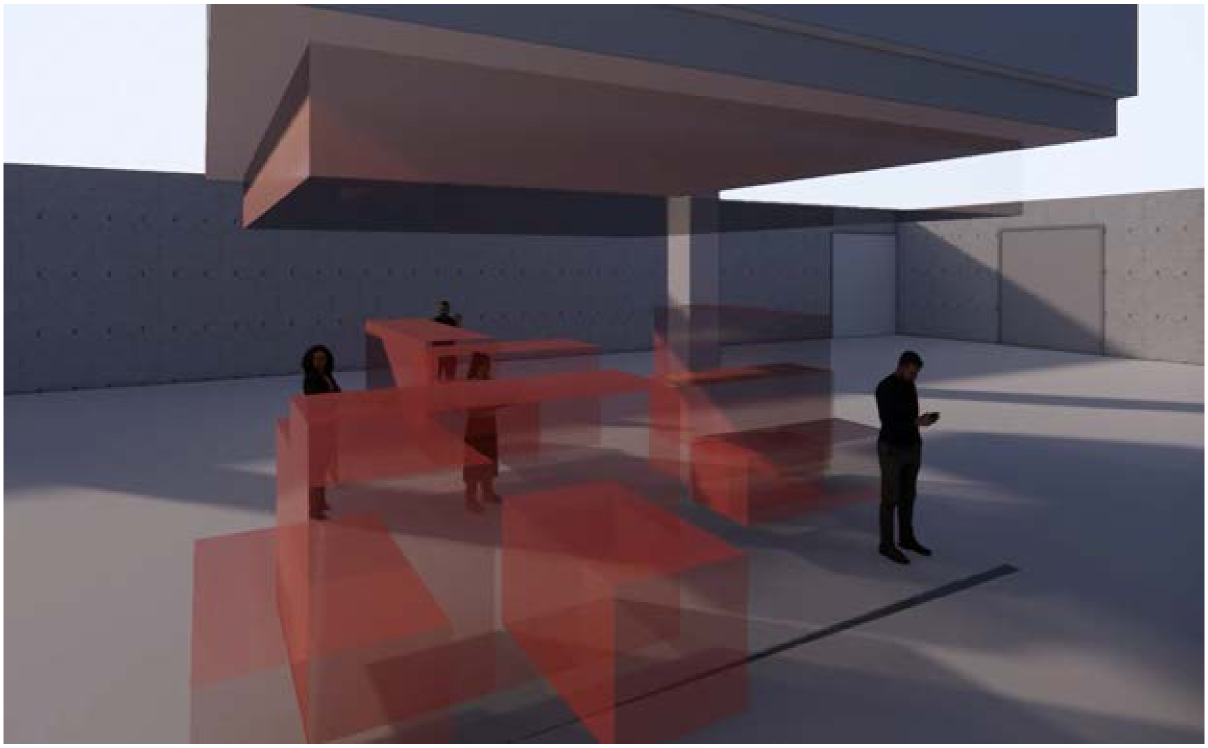
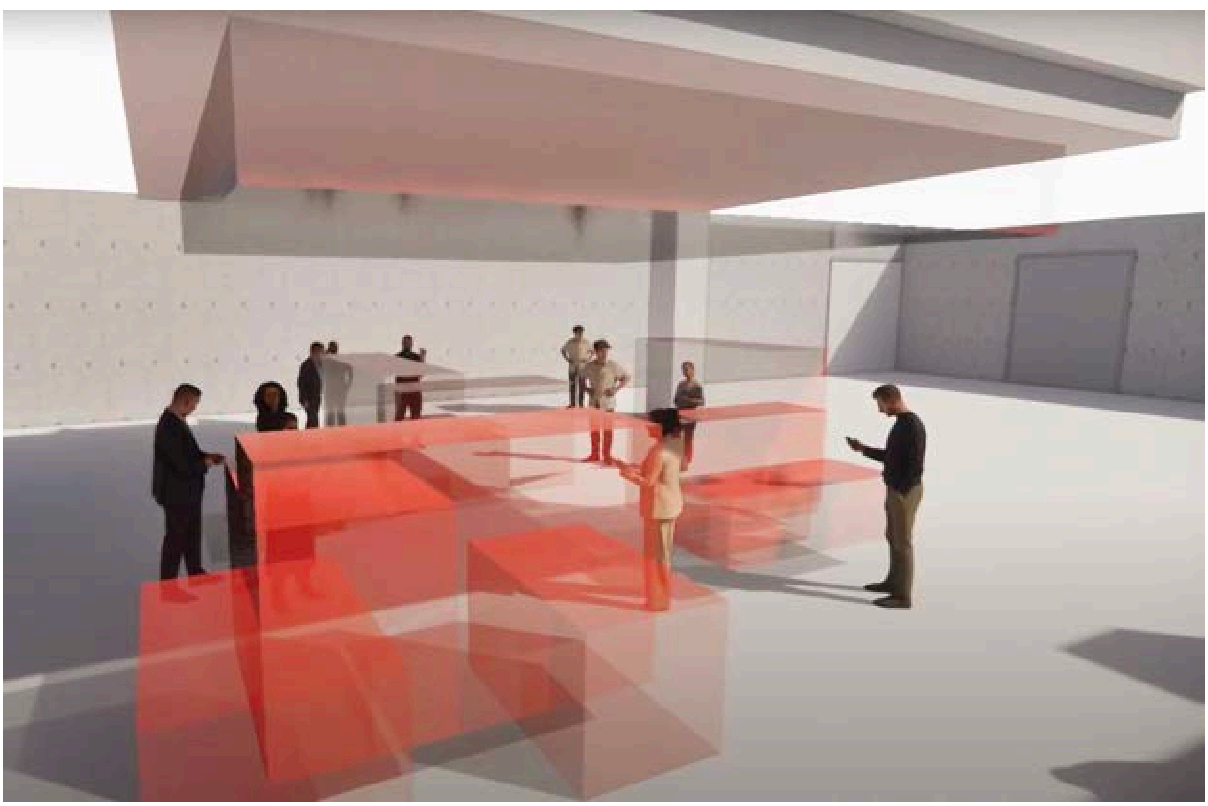


Figure 57. Video Simulation https://youtu.be/N6N3Fx0nyW0



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# APPENDIX A: QUESTIONAIRE

1. How do you evaluate your art works? Please, tell about this process.
2. What do you consider as the most crucial factor in this evaluation?
3. Does anybody help you to evaluate your art works?
4. Was it difficult for you to evaluate your art works as a student?
5. Is it difficult for you to evaluate your art works now?
6. Can you quantify the time it takes to evaluate your art work?
7. Do you sell your art works?
8. What is the category of price you sell your art works for?
9. Do you work with art collectors?
10. Can you sustain yourself selling your art works?
11. Do you have an additional job?
12. Can you quantify the time you spend for the additional job?
13. Would this time be valuable to work on your art?
14. Does additional job help in your creative process?
15. Do you work with the art dealer, art gallery, art museum, art foundation etc.? If yes, can you tell, please, about your experience?
16. Do you promote art works via social media- FB, Instagram, personal website etc.?
17. Can you quantify the time you spend on social media to promote your art work?
18. Do you use social media resources to sell your art?

19. Have you ever had any problems with the customers because of pricing?
20. Have you ever felt that your art work is underpriced, or overpriced?
21. Are you an established artist? Could you tell about the turning point in your career? What was the crucial factor?
22. Can you quantify the amount of art works you produce in a month, in year?
23. Do you have difficulties to manage your art works' information, taxes?
24. Do you use any tool (software) to manage your art works? (sales, prices, taxes).
25. If you teach, do you think that students might have problems starting to evaluate their art works?
26. Do you think students (young artists) might have low self-esteem?
27. Do you think talented students should have a tool which can help them to boost their confidence in the art market?
28. Do you think an artist's success is connected to the art market?
29. From your point of view, is the art market dependent on politics?
30. Have you ever experienced the situation when your gender was a reason to be refused from a promotion in the art gallery etc.?
31. Have you ever felt uncomfortable to be in the art market because of your gender?
32. During your career what was the most challenging?
33. Do you agree with the statement that "women of reproductive age have difficulties being promoted by art galleries?"
34. Do you agree with the statement that "the numbers of opportunities afforded to artists may differ significantly based on discipline, race/ethnicity, class, gender, physical ability and geography among other factors?"

35. Do you agree with the statement that “there is a domination of the white men in the art market?”
36. What do you think generally about the art market?
37. Do you see any problems inside of the art market which should be fixed?
38. Is there anything in the art market what you consider as “unfair”?
39. Is there anything in the art market which you personally stand for?
40. Is there anything in the art market what you are fighting against?
41. From your point of view, what is the most significant problem in the art market?
42. Do you work with the auction houses? If yes, please, tell about your experience.
43. Do you think technologies are helpful for the art market?
44. Do technologies help you personally in your career?
45. Do you think artists communicate between each other? Does communication help them in their careers?
46. Do artists use specific platform to communicate? If no, do you think that a single platform for artists’ communication can be useful?
47. How do artists generally communicate?
48. What else should I ask you?
49. Can you recommend someone who might be a good person for me to interview?

# APPENDIX B: DATA CLASSIFICATION MODEL

Control: arbitrarily chosen 50,000 works of art

Gray 0: arbitrarily chosen 36,410 works of art. 568 artists

Gray 1: arbitrarily chosen 3,769 works of art. 39 artists

Gray 2: arbitrarily chosen 50,000 works of art. 913 artists

Gray 3: arbitrarily chosen 905 works of art. 20 artists

Gray 4: arbitrarily chosen 3,024 works of art. 29 artists

Gray 5: arbitrarily chosen 1,341 works of art. 30 artists

Gray 6: arbitrarily chosen 12,489 works of art. 159 artists

Gray 7: arbitrarily chosen 240 works of art. 1 artist

Gray 8: arbitrarily chosen 50,000 works of art. 1,399 artists

Gray 9: arbitrarily chosen 11,481 works of art. 187 artists

Edge 0: arbitrarily chosen 50,000 works of art. 1,759 artists

Edge 1: arbitrarily chosen 8,043 works of art. 73 artists

Edge 2: arbitrarily chosen 450 works of art. 12 artists

Edge 3: arbitrarily chosen 12,077 works of art. 212 artists

Edge 4: arbitrarily chosen 27,509 works of art. 425 artists

Edge 5: arbitrarily chosen 3,906 works of art. 57 artists

Edge 6: arbitrarily chosen 530 works of art. 4 artists

Edge 7: arbitrarily chosen 365 works of art. 12 artists

Edge 8: arbitrarily chosen 2,103 works of art.13 artists

Edge 9: arbitrarily chosen 50,000 artworks. 778 artists

Table A: 1. Based Data Classification Models. Control Group

| | F1 | Precision | Recall |
|---|---|---|---|
| **Bio Ng, Bio Ps Bio WC, Desc WC** | 0.542 | 0.54 | 0.545 |
| **Bio Ng, Bio Ps Facebook, Twitter, Instagram** | 0.525 | 0.524 | 0.528 |
| **Bio Ng, Bio Neu, Bio Ps** | 0.519 | 0.517 | 0.522 |
| **Bio WC, Desc WC Facebook, Twitter, Instagram** | 0.513 | 0.512 | 0.517 |
| **Bio Ng, Bio Ps** | 0.507 | 0.506 | 0.511 |
| **Bio Ng, Bio Ps, Dominance** | 0.502 | 0.5 | 0.505 |
| **Bio Ng, Bio Ps, Gray Mn** | 0.501 | 0.499 | 0.504 |
| **Bio Ng, Bio Ps, Weight** | 0.501 | 0.499 | 0.505 |
| **Bio Ng, Bio Ps, Gray Sd** | 0.5 | 0.498 | 0.503 |
| **Bio Ng, Bio Ps, Color1** | 0.5 | 0.498 | 0.504 |
| **Bio Ng, Bio Ps, Arousal** | 0.5 | 0.498 | 0.504 |
| **Bio Ng, Bio Ps, Activity** | 0.5 | 0.498 | 0.504 |
| **Bio Ng, Bio Ps, Gray Mn, Gray Sd** | 0.499 | 0.498 | 0.503 |
| **Bio Ng, Bio Ps, Pleasure** | 0.499 | 0.497 | 0.503 |
| **Bio Ng, Bio Ps, Heat** | 0.498 | 0.496 | 0.502 |
| **Bio Ng, Bio Ps, Color1-2** | 0.496 | 0.494 | 0.5 |

Table A: 2. Based Data Classification Models. Control Group

| | F1 | Precision | Recall |
|---|---|---|---|
| **Bio Ng, Bio Ps, Min 9 Max 9** | 0.496 | 0.494 | 0.5 |
| **Bio Ng, Bio Ps, Min 16 Max 16** | 0.495 | 0.493 | 0.499 |
| **Bio Word Count, Desc Word Count** | 0.491 | 0.489 | 0.494 |
| **Bio Ng, Bio Ps, PAD** | 0.491 | 0.489 | 0.495 |
| **Bio Ng, Bio Ps, RGB Sd** | 0.491 | 0.489 | 0.495 |
| **Bio Ng, Bio Ps, Color1-3** | 0.491 | 0.489 | 0.495 |
| **Bio Neg, Bio Ps, RGB Mn** | 0.49 | 0.488 | 0.495 |
| **Bio Ng, Bio Ps, AWH** | 0.488 | 0.486 | 0.492 |
| **Bio Ng, Bio Ps, Color1-4** | 0.487 | 0.485 | 0.491 |
| **Bio WC, Desc WC, Activity** | 0.486 | 0.484 | 0.49 |
| **Bio Ng, Bio Ps, Gray Mn, RGB Mn** | 0.485 | 0.483 | 0.489 |
| **Bio Ng, Bio Ps, Color1-5** | 0.485 | 0.483 | 0.49 |
| **Bio WC, Desc WC, Gray Mn** | 0.485 | 0.483 | 0.49 |
| **Bio WC, Desc WC, Dominance** | 0.485 | 0.484 | 0.49 |
| **Bio WC, Desc WC, Weight** | 0.484 | 0.482 | 0.488 |
| **Bio WC, Desc WC, Heat** | 0.484 | 0.483 | 0.489 |

Table A: 3. Based Data Classification Models. Control Group

| | F1 | Precision | Recall |
|---|---|---|---|
| **Bio Ng, Bio Ps, Gray Sd, RGB Sd** | 0.483 | 0.481 | 0.488 |
| **Bio WC, Desc WC, Gray Sd** | 0.483 | 0.481 | 0.487 |
| **Bio WC, Desc WC, Color1** | 0.483 | 0.481 | 0.487 |
| **Bio WC, Desc WC, Pleasure** | 0.483 | 0.481 | 0.487 |
| **Bio WC, Desc WC, Arousal** | 0.483 | 0.481 | 0.487 |
| **Bio WC, Desc WC, Color Gray Mn, Color Gray Sd** | 0.481 | 0.48 | 0.486 |
| **Bio WC, Desc WC, Min 9 Max 9** | 0.48 | 0.478 | 0.484 |
| **Bio Ng, Bio Ps, Color1-6** | 0.479 | 0.477 | 0.484 |
| **Bio WC, Desc WC, Min 16 Max 16** | 0.479 | 0.477 | 0.483 |
| **Bio WC, Desc WC, Color1-2** | 0.478 | 0.476 | 0.483 |
| **Bio Ng, Bio Ps, RGB Mn, RGB Sd** | 0.477 | 0.475 | 0.482 |
| **Bio WC, Desc WC, Color1-3** | 0.476 | 0.474 | 0.481 |
| **Bio WC, Desc WC, PAD** | 0.475 | 0.473 | 0.48 |
| **Bio Ng, Bio Ps, Color1-7** | 0.474 | 0.472 | 0.479 |
| **Bio WC, Desc WC, AWH** | 0.473 | 0.471 | 0.478 |
| **Bio WC, Desc WC, RGB Mn** | 0.471 | 0.469 | 0.476 |

Table A: 4. Based Data Classification Models. Control Group

| | F1 | Precision | Recall |
|---|---|---|---|
| **Bio Ng, Bio Ps, Color1-8** | 0.47 | 0.468 | 0.476 |
| **Bio WC, Desc WC, RGB Sd** | 0.47 | 0.468 | 0.475 |
| **Bio Ng, Bio Ps, Gray Mn, RGB Mn, Gray Sd, RGB Sd** | 0.468 | 0.466 | 0.473 |
| **Bio WC, Desc WC, Gray Mn, RGB Mn** | 0.467 | 0.465 | 0.472 |
| **Bio WC, Desc WC, Color1-4** | 0.467 | 0.465 | 0.472 |
| **Bio Ng, Bio Ps, Color1-9** | 0.466 | 0.464 | 0.472 |
| **Bio WC, Desc WC, Color1-5** | 0.466 | 0.464 | 0.471 |
| **Bio Ng, Bio Ps, Color1-10** | 0.465 | 0.463 | 0.471 |
| **Bio WC, Desc WC, Gray Sd, RGB Sd** | 0.465 | 0.463 | 0.471 |
| **Bio WC, Desc WC, Color RGB Mn, Color RGB Sd** | 0.458 | 0.457 | 0.464 |
| **Bio WC, Desc WC, Color1-6** | 0.458 | 0.456 | 0.464 |
| **Bio WC, Desc WC, Color1-7** | 0.452 | 0.45 | 0.458 |
| **Bio WC, Desc WC, Color1-8** | 0.452 | 0.45 | 0.458 |
| **Bio WC, Desc WC, Gray Mn, RGB Mn, Gray Sd, RGB Sd** | 0.449 | 0.447 | 0.455 |
| **Facebook, Twitter, Instagram, Gray Mn, Gray Sd** | 0.448 | 0.446 | 0.453 |
| **Facebook, Twitter, Instagram** | 0.447 | 0.445 | 0.45 |

Table A: 5. Based Data Classification Models. Control Group

| | F1 | Precision | Recall |
|---|---|---|---|
| **Facebook, Twitter, Instagram, Gray Mn** | 0.447 | 0.445 | 0.451 |
| **Facebook, Twitter, Instagram, Gray Sd** | 0.447 | 0.444 | 0.451 |
| **Facebook, Twitter, Instagram, Dominance** | 0.447 | 0.445 | 0.451 |
| **Bio WC, Desc WC, Color1-9** | 0.445 | 0.443 | 0.451 |
| **Facebook, Twitter, Instagram, Color1** | 0.445 | 0.443 | 0.449 |
| **Facebook, Twitter, Instagram, Color1-2** | 0.445 | 0.442 | 0.449 |
| **Facebook, Twitter, Instagram, Activity** | 0.445 | 0.443 | 0.45 |
| **Bio WC, Desc WC, Color1-10** | 0.444 | 0.442 | 0.45 |
| **Facebook, Twitter, Instagram, Min 16 Max 16** | 0.444 | 0.442 | 0.449 |
| **Facebook, Twitter, Instagram, Pleasure** | 0.444 | 0.442 | 0.449 |
| **Facebook, Twitter, Instagram, Arousal** | 0.444 | 0.442 | 0.448 |
| **Facebook, Twitter, Instagram, PAD** | 0.442 | 0.44 | 0.447 |
| **Facebook, Twitter, Instagram, Weight** | 0.442 | 0.44 | 0.446 |
| **Desc Ng, Desc Neu, Desc Ps** | 0.442 | 0.439 | 0.446 |
| **Facebook, Twitter, Instagram, Color1-3** | 0.441 | 0.439 | 0.446 |
| **Facebook, Twitter, Instagram, Heat** | 0.44 | 0.438 | 0.444 |

Table A: 6. Based Data Classification Models. Control Group

| | F1 | Precision | Recall |
|---|---|---|---|
| **Desc Ng, Desc Ps** | 0.439 | 0.437 | 0.444 |
| **Facebook, Twitter, Instagram, Min 9 Max 9** | 0.439 | 0.437 | 0.444 |
| **Facebook, Twitter, Instagram, AWH** | 0.438 | 0.436 | 0.443 |
| **Facebook, Twitter, Instagram, RGB Mn** | 0.438 | 0.436 | 0.444 |
| **Facebook, Twitter, Instagram, Color1-4** | 0.437 | 0.435 | 0.443 |
| **Facebook, Twitter, Instagram, RGB Sd** | 0.435 | 0.433 | 0.44 |
| **Facebook, Twitter, Instagram, Gray Mn, RGB Mn** | 0.434 | 0.432 | 0.439 |
| **Facebook, Twitter, Instagram, Color1-5** | 0.433 | 0.431 | 0.439 |
| **Facebook, Twitter, Instagram, Gray Sd, RGB Sd** | 0.431 | 0.428 | 0.436 |
| **Facebook, Twitter, Instagram, RGB Mn, RGB Sd** | 0.43 | 0.428 | 0.436 |
| **Facebook, Twitter, Instagram, Color1-6** | 0.429 | 0.427 | 0.435 |
| **Facebook, Twitter, Instagram, Color1-7** | 0.425 | 0.423 | 0.432 |
| **Facebook, Twitter, Instagram, Gray Mn, RGB Mn, Sd** | 0.423 | 0.421 | 0.43 |
| **Facebook, Twitter, Instagram, Color1-8** | 0.421 | 0.419 | 0.428 |
| **Facebook, Twitter, Instagram, Color1-9** | 0.42 | 0.418 | 0.427 |
| **Facebook, Twitter, Instagram, Color1-10** | 0.414 | 0.412 | 0.422 |

Table A: 7. Based Data Classification Models. Control Group

| | F1 | Precision | Recall |
|---|---|---|---|
| **Title WC** | 0.409 | 0.406 | 0.414 |
| **Gray Mn, Gray Sd** | 0.4 | 0.397 | 0.406 |
| **Gray Mn** | 0.399 | 0.397 | 0.404 |
| **Gray Sd** | 0.397 | 0.394 | 0.402 |
| **Color1-2** | 0.397 | 0.395 | 0.403 |
| **Color1-3** | 0.397 | 0.394 | 0.402 |
| **Arousal** | 0.397 | 0.395 | 0.402 |
| **Dominance** | 0.397 | 0.394 | 0.402 |
| **Activity** | 0.397 | 0.395 | 0.402 |
| **Pleasure, Arousal, Dominance** | 0.396 | 0.393 | 0.402 |
| **Activity, Weight, Heat** | 0.396 | 0.393 | 0.402 |
| **RGB Mn** | 0.396 | 0.393 | 0.403 |
| **Color1** | 0.396 | 0.393 | 0.4 |
| **Color1-4** | 0.396 | 0.394 | 0.403 |
| **Max 16** | 0.396 | 0.394 | 0.401 |
| **Min 9 Max 9** | 0.396 | 0.393 | 0.402 |

Table A: 8. Based Data Classification Models. Control Group

| | F1 | Precision | Recall |
|---|---|---|---|
| **Min 16 Max 16** | 0.396 | 0.393 | 0.401 |
| **Weight** | 0.396 | 0.393 | 0.401 |
| **Max 9** | 0.395 | 0.392 | 0.4 |
| **Min 16** | 0.395 | 0.393 | 0.401 |
| **Base Features** | 0.394 | 0.391 | 0.398 |
| **Pleasure** | 0.394 | 0.391 | 0.399 |
| **Heat** | 0.394 | 0.391 | 0.399 |
| **RGB Mn, RGB Sd** | 0.393 | 0.39 | 0.4 |
| **Color1-5** | 0.393 | 0.39 | 0.399 |
| **Min 9** | 0.393 | 0.39 | 0.398 |
| **Gray Mn, RGB Mn** | 0.391 | 0.388 | 0.397 |
| **RGB Sd** | 0.391 | 0.388 | 0.397 |
| **Gray Sd, RGB Sd** | 0.389 | 0.386 | 0.395 |
| **Color1-6** | 0.388 | 0.385 | 0.396 |
| **Gray Mn, RGB Mn, Gray Sd, RGB Sd** | 0.387 | 0.384 | 0.394 |
| **Color1-7** | 0.386 | 0.383 | 0.394 |

Table A: 9. Based Data Classification Models. Control Group

| | F1 | Precision | Recall |
|---|---|---|---|
| **Color1-8** | 0.384 | 0.381 | 0.392 |
| **Color1-9** | 0.38 | 0.378 | 0.389 |
| **Color1-10** | 0.379 | 0.376 | 0.388 |

Table A: 10. Based Data Classification Models. Gray 0

| | F1 | Precision | Recall |
|---|---|---|---|
| **BioNg, BioPs BioWC, DescWC** | 0.63 | 0.63 | 0.631 |
| **BioWC, DescWC Facebook, Twitter, Instagram** | 0.62 | 0.619 | 0.62 |
| **BioNg, BioPs Facebook, Twitter, Instagram** | 0.612 | 0.611 | 0.613 |
| **BioNg, BioNeu, BioPs** | 0.609 | 0.609 | 0.611 |
| **Bio Word Count, Desc Word Count** | 0.604 | 0.604 | 0.605 |
| **BioWC, DescWC, Color1** | 0.602 | 0.601 | 0.603 |
| **BioWC, DescWC, Pleasure** | 0.602 | 0.602 | 0.604 |
| **BioNg, BioPs, Color1** | 0.601 | 0.6 | 0.602 |
| **BioWC, DescWC, Dominance** | 0.601 | 0.6 | 0.602 |
| **BioWC, DescWC, Gray Sd** | 0.6 | 0.599 | 0.601 |
| **BioWC, DescWC, Color1-2** | 0.6 | 0.599 | 0.601 |
| **BioNg, BioPs, Arousal** | 0.6 | 0.599 | 0.601 |
| **BioWC, DescWC, Arousal** | 0.6 | 0.6 | 0.602 |
| **BioWC, DescWC, Activity** | 0.6 | 0.6 | 0.602 |
| **BioNg, BioPs** | 0.599 | 0.599 | 0.601 |
| **BioNg, BioPs, Gray Mn** | 0.599 | 0.599 | 0.601 |

Table A: 11. Based Data Classification Models. Gray 0

| | F1 | Precision | Recall |
|---|---|---|---|
| **BioNg, BioPs, Color1-2** | 0.599 | 0.598 | 0.6 |
| **BioWC, DescWC, Gray Mn** | 0.599 | 0.599 | 0.6 |
| **BioWC, DescWC, Min 16 Max 16** | 0.599 | 0.598 | 0.6 |
| **BioNg, BioPs, Pleasure** | 0.599 | 0.598 | 0.6 |
| **BioWC, DescWC, Weight** | 0.599 | 0.599 | 0.6 |
| **BioWC, DescWC, Heat** | 0.599 | 0.598 | 0.6 |
| **BioNg, BioPs, Dominance** | 0.598 | 0.597 | 0.599 |
| **BioNg, BioPs, Activity** | 0.598 | 0.597 | 0.599 |
| **BioNg, BioPs, Gray Mn, Gray Sd** | 0.597 | 0.597 | 0.599 |
| **BioNg, BioPs, Min 16 Max 16** | 0.597 | 0.596 | 0.598 |
| **BioWC, DescWC, Min 9 Max 9** | 0.597 | 0.596 | 0.598 |
| **BioNg, BioPs, Weight** | 0.597 | 0.597 | 0.599 |
| **BioNg, BioPs, PAD** | 0.596 | 0.595 | 0.597 |
| **BioNg, BioPs, AWH** | 0.596 | 0.595 | 0.597 |
| **BioNg, BioPs, Gray Sd** | 0.596 | 0.596 | 0.598 |
| **BioWC, DescWC, RGB Mn** | 0.596 | 0.595 | 0.597 |

Table A: 12. Based Data Classification Models. Gray 0

| | F1 | Precision | Recall |
|---|---|---|---|
| **BioWC, DescWC, Color Gray Mn, Color Gray Sd** | 0.596 | 0.596 | 0.598 |
| **BioWC, DescWC, Color1-3** | 0.596 | 0.596 | 0.598 |
| **BioNg, BioPs, Min 9 Max 9** | 0.596 | 0.595 | 0.597 |
| **BioNeg, BioPs, RGB Mn** | 0.595 | 0.594 | 0.596 |
| **BioNg, BioPs, Color1-3** | 0.595 | 0.595 | 0.597 |
| **BioNg, BioPs, Color1-4** | 0.595 | 0.594 | 0.596 |
| **BioWC, DescWC, AWH** | 0.595 | 0.594 | 0.597 |
| **BioNg, BioPs, Heat** | 0.595 | 0.594 | 0.596 |
| **BioNg, BioPs, RGB Sd** | 0.594 | 0.593 | 0.596 |
| **BioWC, DescWC, PAD** | 0.594 | 0.594 | 0.596 |
| **BioWC, DescWC, RGB Sd** | 0.594 | 0.593 | 0.595 |
| **BioWC, DescWC, Color1-4** | 0.594 | 0.593 | 0.596 |
| **BioNg, BioPs, RGB Mn, RGB Sd** | 0.592 | 0.592 | 0.594 |
| **BioNg, BioPs, Color1-5** | 0.592 | 0.591 | 0.594 |
| **BioNg, BioPs, Gray Mn, RGB Mn** | 0.591 | 0.59 | 0.592 |
| **BioWC, DescWC, Gray Sd, RGB Sd** | 0.591 | 0.59 | 0.593 |

Table A: 13. Based Data Classification Models. Gray 0

| | F1 | Precision | Recall |
|---|---|---|---|
| **BioNg, BioPs, Gray Sd, RGB Sd** | 0.59 | 0.59 | 0.592 |
| **BioWC, DescWC, Gray Mn, RGB Mn** | 0.59 | 0.59 | 0.592 |
| **BioWC, DescWC, Color1-5** | 0.59 | 0.589 | 0.592 |
| **BioNg, BioPs, Color1-6** | 0.589 | 0.589 | 0.591 |
| **BioWC, DescWC, Color RGB Mn, Color RGB Sd** | 0.588 | 0.588 | 0.59 |
| **BioWC, DescWC, Color1-6** | 0.587 | 0.587 | 0.589 |
| **BioNg, BioPs, Color1-7** | 0.586 | 0.585 | 0.588 |
| **BioWC, DescWC, Color1-7** | 0.586 | 0.586 | 0.588 |
| **BioNg, BioPs, Gray Mn, RGB Mn, Gray Sd, RGB Sd** | 0.585 | 0.584 | 0.587 |
| **BioNg, BioPs, Color1-8** | 0.584 | 0.583 | 0.586 |
| **BioNg, BioPs, Color1-9** | 0.583 | 0.583 | 0.586 |
| **BioWC, DescWC, Color1-8** | 0.583 | 0.582 | 0.585 |
| **BioNg, BioPs, Color1-10** | 0.582 | 0.581 | 0.584 |
| **BioWC, DescWC, Gray Mn, RGB Mn, Gray Sd, RGB Sd** | 0.58 | 0.579 | 0.582 |
| **BioWC, DescWC, Color1-9** | 0.58 | 0.579 | 0.582 |
| **Facebook, Twitter, Instagram, Heat** | 0.577 | 0.556 | 0.558 |

Table A: 14. Based Data Classification Models. Gray 0

| | F1 | Precision | Recall |
|---|---|---|---|
| **BioWC, DescWC, Color1-10** | 0.576 | 0.576 | 0.579 |
| **DescNg, DescNeu, DescPs** | 0.569 | 0.569 | 0.571 |
| **DescNg, DescPs** | 0.565 | 0.564 | 0.567 |
| **Facebook, Twitter, Instagram, Color1** | 0.564 | 0.563 | 0.565 |
| **Facebook, Twitter, Instagram, Color1-2** | 0.563 | 0.563 | 0.565 |
| **Facebook, Twitter, Instagram, Gray Mn** | 0.562 | 0.561 | 0.563 |
| **Facebook, Twitter, Instagram, Gray Mn, Gray Sd** | 0.561 | 0.56 | 0.562 |
| **Facebook, Twitter, Instagram, Color1-3** | 0.561 | 0.56 | 0.562 |
| **Facebook, Twitter, Instagram, Weight** | 0.561 | 0.56 | 0.562 |
| **Facebook, Twitter, Instagram** | 0.56 | 0.559 | 0.562 |
| **Facebook, Twitter, Instagram, PAD** | 0.56 | 0.559 | 0.561 |
| **Facebook, Twitter, Instagram, AWH** | 0.56 | 0.559 | 0.562 |
| **Facebook, Twitter, Instagram, Color1-4** | 0.56 | 0.559 | 0.562 |
| **Facebook, Twitter, Instagram, Pleasure** | 0.56 | 0.559 | 0.562 |
| **Facebook, Twitter, Instagram, Arousal** | 0.56 | 0.559 | 0.561 |
| **Facebook, Twitter, Instagram, RGB Mn** | 0.559 | 0.558 | 0.561 |

Table A: 15. Based Data Classification Models. Gray 0

| | F1 | Precision | Recall |
|---|---|---|---|
| **Facebook, Twitter, Instagram, Dominance** | 0.559 | 0.558 | 0.561 |
| **Facebook, Twitter, Instagram, Activity** | 0.559 | 0.558 | 0.56 |
| **Facebook, Twitter, Instagram, Gray Sd** | 0.558 | 0.557 | 0.559 |
| **Facebook, Twitter, Instagram, Min 9 Max 9** | 0.558 | 0.557 | 0.56 |
| **Facebook, Twitter, Instagram, Min 16 Max 16** | 0.558 | 0.557 | 0.56 |
| **Facebook, Twitter, Instagram, RGB Mn, RGB Sd** | 0.557 | 0.556 | 0.559 |
| **Facebook, Twitter, Instagram, Color1-5** | 0.556 | 0.555 | 0.559 |
| **Facebook, Twitter, Instagram, Gray Mn, RGB Mn** | 0.554 | 0.553 | 0.556 |
| **Facebook, Twitter, Instagram, RGB Sd** | 0.554 | 0.553 | 0.555 |
| **Facebook, Twitter, Instagram, Color1-6** | 0.554 | 0.553 | 0.556 |
| **Facebook, Twitter, Instagram, Color1-7** | 0.552 | 0.551 | 0.554 |
| **Facebook, Twitter, Instagram, Gray Sd, RGB Sd** | 0.55 | 0.55 | 0.552 |
| **Facebook, Twitter, Instagram, Color1-8** | 0.549 | 0.548 | 0.552 |
| **Facebook, Twitter, Instagram, Gray Mn, RGB Mn, Sd** | 0.548 | 0.548 | 0.551 |
| **Facebook, Twitter, Instagram, Color1-9** | 0.547 | 0.546 | 0.549 |
| **Facebook, Twitter, Instagram, Color1-10** | 0.545 | 0.544 | 0.548 |

Table A: 16. Based Data Classification Models. Gray 0

| | F1 | Precision | Recall |
|---|---|---|---|
| **Title WC** | 0.543 | 0.542 | 0.545 |
| **Color1-3** | 0.527 | 0.526 | 0.529 |
| **Color1** | 0.526 | 0.525 | 0.528 |
| **Color1-2** | 0.526 | 0.525 | 0.528 |
| **Gray Mn** | 0.525 | 0.524 | 0.526 |
| **Gray Mn, Gray Sd** | 0.525 | 0.524 | 0.527 |
| **Color1-4** | 0.524 | 0.523 | 0.526 |
| **Pleasure, Arousal, Dominance** | 0.523 | 0.522 | 0.525 |
| **Activity, Weight, Heat** | 0.523 | 0.522 | 0.526 |
| **Min 16 Max 16** | 0.523 | 0.522 | 0.525 |
| **Arousal** | 0.523 | 0.522 | 0.524 |
| **RGB Mn** | 0.522 | 0.521 | 0.525 |
| **Min 9 Max 9** | 0.522 | 0.521 | 0.524 |
| **Color1-5** | 0.521 | 0.52 | 0.524 |
| **Min 9** | 0.521 | 0.52 | 0.523 |
| **Pleasure** | 0.521 | 0.52 | 0.523 |

Table A: 17. Based Data Classification Models. Gray 0

| | F1 | Precision | Recall |
|---|---|---|---|
| **Weight** | 0.521 | 0.52 | 0.522 |
| **RGB Mn, RGB Sd** | 0.52 | 0.519 | 0.523 |
| **Dominance** | 0.52 | 0.519 | 0.522 |
| **Gray Mn, RGB Mn** | 0.519 | 0.518 | 0.521 |
| **Gray Sd** | 0.519 | 0.518 | 0.521 |
| **RGB Sd** | 0.519 | 0.518 | 0.522 |
| **Min 16** | 0.519 | 0.518 | 0.521 |
| **Activity** | 0.519 | 0.518 | 0.521 |
| **Max 16** | 0.518 | 0.517 | 0.52 |
| **Base Features** | 0.517 | 0.516 | 0.519 |
| **Color1-6** | 0.517 | 0.516 | 0.52 |
| **Max 9** | 0.517 | 0.516 | 0.519 |
| **Gray Sd, RGB Sd** | 0.516 | 0.515 | 0.518 |
| **Color1-7** | 0.516 | 0.515 | 0.519 |
| **Gray Mn, RGB Mn, Gray Sd, RGB Sd** | 0.515 | 0.514 | 0.518 |
| **Color1-8** | 0.515 | 0.514 | 0.518 |

Table A: 18. Based Data Classification Models. Gray 0

| | F1 | Precision | Recall |
|---|---|---|---|
| **Heat** | 0.515 | 0.514 | 0.517 |
| **Color1-9** | 0.513 | 0.512 | 0.516 |
| **Color1-10** | 0.509 | 0.508 | 0.512 |

Table A: 19. Based Data Classification Models. Gray 1

| | F1 | Precision | Recall |
|---|---|---|---|
| **BioWC, DescWC Facebook, Twitter, Instagram** | 0.65 | 0.651 | 0.651 |
| **BioNg, BioPs BioWC, DescWC** | 0.644 | 0.646 | 0.645 |
| **BioWC, DescWC, Gray Mn** | 0.639 | 0.64 | 0.639 |
| **Bio Word Count, Desc Word Count** | 0.638 | 0.639 | 0.639 |
| **BioWC, DescWC, Color1** | 0.637 | 0.638 | 0.638 |
| **BioWC, DescWC, Min 16 Max 16** | 0.636 | 0.638 | 0.637 |
| **BioWC, DescWC, Arousal** | 0.635 | 0.636 | 0.636 |
| **BioWC, DescWC, Activity** | 0.635 | 0.636 | 0.636 |
| **BioWC, DescWC, RGB Mn** | 0.634 | 0.636 | 0.635 |
| **BioWC, DescWC, Gray Sd** | 0.634 | 0.635 | 0.635 |
| **BioWC, DescWC, Color1-2** | 0.634 | 0.636 | 0.635 |
| **BioWC, DescWC, Color Gray Mn, Color Gray Sd** | 0.633 | 0.635 | 0.634 |
| **BioWC, DescWC, Pleasure** | 0.633 | 0.634 | 0.634 |
| **BioWC, DescWC, Min 9 Max 9** | 0.632 | 0.634 | 0.633 |
| **BioWC, DescWC, Heat** | 0.629 | 0.63 | 0.63 |
| **BioNg, BioPs Facebook, Twitter, Instagram** | 0.629 | 0.629 | 0.63 |

Table A: 20. Based Data Classification Models. Gray 1

| | F1 | Precision | Recall |
|---|---|---|---|
| **BioWC, DescWC, Color1-4** | 0.628 | 0.63 | 0.629 |
| **BioWC, DescWC, Weight** | 0.628 | 0.629 | 0.629 |
| **BioWC, DescWC, Dominance** | 0.627 | 0.628 | 0.627 |
| **BioWC, DescWC, RGB Sd** | 0.626 | 0.627 | 0.628 |
| **BioWC, DescWC, AWH** | 0.625 | 0.627 | 0.627 |
| **BioNg, BioPs, Arousal** | 0.625 | 0.626 | 0.626 |
| **BioNg, BioPs, Activity** | 0.625 | 0.626 | 0.627 |
| **DescNg, DescNeu, DescPs** | 0.625 | 0.627 | 0.626 |
| **BioWC, DescWC, PAD** | 0.624 | 0.626 | 0.626 |
| **BioWC, DescWC, Color1-3** | 0.624 | 0.626 | 0.625 |
| **BioWC, DescWC, Color1-5** | 0.624 | 0.625 | 0.625 |
| **BioNg, BioPs, Gray Mn** | 0.623 | 0.624 | 0.625 |
| **BioWC, DescWC, Gray Mn, RGB Mn** | 0.623 | 0.625 | 0.624 |
| **BioWC, DescWC, Color RGB Mn, Color RGB Sd** | 0.623 | 0.625 | 0.625 |
| **Facebook, Twitter, Instagram, Min 16 Max 16** | 0.623 | 0.624 | 0.625 |
| **BioWC, DescWC, Gray Sd, RGB Sd** | 0.622 | 0.623 | 0.624 |

Table A: 21. Based Data Classification Models. Gray 1

| | F1 | Precision | Recall |
|---|---|---|---|
| **Facebook, Twitter, Instagram, Heat** | 0.622 | 0.622 | 0.632 |
| **BioNg, BioPs, Gray Sd** | 0.621 | 0.622 | 0.623 |
| **BioNg, BioPs, Gray Mn, Gray Sd** | 0.621 | 0.621 | 0.622 |
| **BioWC, DescWC, Color1-8** | 0.621 | 0.624 | 0.623 |
| **Facebook, Twitter, Instagram, Gray Mn** | 0.621 | 0.621 | 0.622 |
| **Facebook, Twitter, Instagram, Gray Sd** | 0.621 | 0.622 | 0.623 |
| **Facebook, Twitter, Instagram, RGB Sd** | 0.621 | 0.622 | 0.623 |
| **BioNg, BioPs, Min 16 Max 16** | 0.621 | 0.621 | 0.622 |
| **BioNg, BioNeu, BioPs** | 0.621 | 0.621 | 0.623 |
| **BioNg, BioPs** | 0.62 | 0.62 | 0.621 |
| **BioNg, BioPs, Color1-6** | 0.62 | 0.623 | 0.621 |
| **BioWC, DescWC, Color1-6** | 0.62 | 0.621 | 0.621 |
| **DescNg, DescPs** | 0.619 | 0.621 | 0.62 |
| **BioWC, DescWC, Gray Mn, RGB Mn, Gray Sd, RGB Sd** | 0.619 | 0.621 | 0.621 |
| **Facebook, Twitter, Instagram, Gray Sd, RGB Sd** | 0.619 | 0.62 | 0.62 |
| **BioNg, BioPs, Min 9 Max 9** | 0.619 | 0.62 | 0.621 |

Table A: 22. Based Data Classification Models. Gray 1

| | F1 | Precision | Recall |
|---|---|---|---|
| **Facebook, Twitter, Instagram, Arousal** | 0.619 | 0.62 | 0.62 |
| **BioNeg, BioPs, RGB Mn** | 0.618 | 0.619 | 0.619 |
| **BioNg, BioPs, RGB Sd** | 0.618 | 0.619 | 0.62 |
| **BioNg, BioPs, Color1-5** | 0.618 | 0.619 | 0.62 |
| **Facebook, Twitter, Instagram, Gray Mn, Gray Sd** | 0.618 | 0.619 | 0.62 |
| **Facebook, Twitter, Instagram, Min 9 Max 9** | 0.618 | 0.619 | 0.619 |
| **BioNg, BioPs, Heat** | 0.618 | 0.619 | 0.62 |
| **Facebook, Twitter, Instagram, Pleasure** | 0.618 | 0.619 | 0.62 |
| **Facebook, Twitter, Instagram** | 0.617 | 0.617 | 0.618 |
| **BioNg, BioPs, Weight** | 0.617 | 0.618 | 0.619 |
| **BioNg, BioPs, Color1-2** | 0.616 | 0.616 | 0.618 |
| **Facebook, Twitter, Instagram, AWH** | 0.616 | 0.617 | 0.617 |
| **BioNg, BioPs, PAD** | 0.615 | 0.616 | 0.617 |
| **BioNg, BioPs, Gray Mn, RGB Mn** | 0.615 | 0.616 | 0.617 |
| **BioNg, BioPs, Gray Mn, RGB Mn, Gray Sd, RGB Sd** | 0.615 | 0.617 | 0.617 |
| **BioNg, BioPs, RGB Mn, RGB Sd** | 0.615 | 0.616 | 0.617 |

Table A: 23. Based Data Classification Models. Gray 1

| | F1 | Precision | Recall |
|---|---|---|---|
| **BioNg, BioPs, Color1-3** | 0.615 | 0.616 | 0.616 |
| **Facebook, Twitter, Instagram, Color1-4** | 0.615 | 0.617 | 0.616 |
| **BioNg, BioPs, Pleasure** | 0.615 | 0.616 | 0.617 |
| **Facebook, Twitter, Instagram, Activity** | 0.615 | 0.615 | 0.616 |
| **BioNg, BioPs, AWH** | 0.614 | 0.616 | 0.616 |
| **BioNg, BioPs, Color1-4** | 0.614 | 0.616 | 0.616 |
| **BioWC, DescWC, Color1-9** | 0.614 | 0.617 | 0.616 |
| **Facebook, Twitter, Instagram, Color1-5** | 0.614 | 0.615 | 0.616 |
| **BioNg, BioPs, Gray Sd, RGB Sd** | 0.613 | 0.614 | 0.615 |
| **BioNg, BioPs, Color1** | 0.613 | 0.613 | 0.615 |
| **Facebook, Twitter, Instagram, Gray Mn, RGB Mn** | 0.612 | 0.613 | 0.614 |
| **BioWC, DescWC, Color1-7** | 0.611 | 0.614 | 0.613 |
| **BioWC, DescWC, Color1-10** | 0.611 | 0.614 | 0.613 |
| **BioNg, BioPs, Dominance** | 0.611 | 0.611 | 0.613 |
| **Facebook, Twitter, Instagram, Dominance** | 0.611 | 0.611 | 0.612 |
| **Facebook, Twitter, Instagram, PAD** | 0.61 | 0.611 | 0.612 |

Table A: 24. Based Data Classification Models. Gray 1

| | F1 | Precision | Recall |
|---|---|---|---|
| **Facebook, Twitter, Instagram, RGB Mn, RGB Sd** | 0.609 | 0.61 | 0.611 |
| **Facebook, Twitter, Instagram, Color1-7** | 0.609 | 0.61 | 0.611 |
| **BioNg, BioPs, Color1-10** | 0.608 | 0.611 | 0.61 |
| **Facebook, Twitter, Instagram, Gray Mn, RGB Mn, Sd** | 0.608 | 0.609 | 0.611 |
| **Facebook, Twitter, Instagram, Color1-2** | 0.608 | 0.609 | 0.609 |
| **Facebook, Twitter, Instagram, Color1-3** | 0.608 | 0.609 | 0.61 |
| **Facebook, Twitter, Instagram, Color1-8** | 0.608 | 0.61 | 0.609 |
| **BioNg, BioPs, Color1-8** | 0.607 | 0.61 | 0.61 |
| **BioNg, BioPs, Color1-7** | 0.606 | 0.608 | 0.608 |
| **Facebook, Twitter, Instagram, Color1-9** | 0.606 | 0.608 | 0.608 |
| **Facebook, Twitter, Instagram, Color1-10** | 0.606 | 0.608 | 0.609 |
| **Facebook, Twitter, Instagram, Weight** | 0.606 | 0.606 | 0.608 |
| **BioNg, BioPs, Color1-9** | 0.605 | 0.607 | 0.607 |
| **Facebook, Twitter, Instagram, RGB Mn** | 0.605 | 0.605 | 0.607 |
| **Facebook, Twitter, Instagram, Color1** | 0.605 | 0.605 | 0.606 |
| **Facebook, Twitter, Instagram, Color1-6** | 0.605 | 0.607 | 0.608 |

Table A: 25. Based Data Classification Models. Gray 1

| | F1 | Precision | Recall |
|---|---|---|---|
| **Title WC** | 0.605 | 0.605 | 0.606 |
| **Gray Mn, Gray Sd** | 0.604 | 0.604 | 0.606 |
| **Gray Mn** | 0.603 | 0.604 | 0.605 |
| **Max 16** | 0.601 | 0.601 | 0.602 |
| **Gray Sd** | 0.6 | 0.601 | 0.602 |
| **Arousal** | 0.599 | 0.599 | 0.601 |
| **Activity** | 0.599 | 0.599 | 0.6 |
| **Base Features** | 0.597 | 0.598 | 0.598 |
| **Activity, Weight, Heat** | 0.597 | 0.598 | 0.599 |
| **RGB Mn** | 0.595 | 0.595 | 0.597 |
| **Min 16 Max 16** | 0.595 | 0.596 | 0.597 |
| **Heat** | 0.595 | 0.595 | 0.597 |
| **Min 9** | 0.594 | 0.595 | 0.595 |
| **Max 9** | 0.594 | 0.595 | 0.596 |
| **Pleasure** | 0.594 | 0.594 | 0.596 |
| **Gray Sd, RGB Sd** | 0.593 | 0.593 | 0.595 |

Table A: 26. Based Data Classification Models. Gray 1

| | F1 | Precision | Recall |
|---|---|---|---|
| **Gray Mn, RGB Mn, Gray Sd, RGB Sd** | 0.592 | 0.593 | 0.595 |
| **Min 16** | 0.592 | 0.593 | 0.594 |
| **Color1-2** | 0.591 | 0.592 | 0.591 |
| **Color1-6** | 0.591 | 0.592 | 0.593 |
| **Color1-3** | 0.59 | 0.59 | 0.592 |
| **Min 9 Max 9** | 0.59 | 0.591 | 0.592 |
| **RGB Sd** | 0.589 | 0.589 | 0.591 |
| **Color1-7** | 0.589 | 0.59 | 0.592 |
| **Color1-5** | 0.588 | 0.589 | 0.59 |
| **Weight** | 0.588 | 0.587 | 0.589 |
| **Color1** | 0.587 | 0.588 | 0.588 |
| **Color1-4** | 0.587 | 0.588 | 0.588 |
| **Color1-8** | 0.587 | 0.588 | 0.59 |
| **Gray Mn, RGB Mn** | 0.585 | 0.585 | 0.588 |
| **Dominance** | 0.585 | 0.585 | 0.586 |
| **Pleasure, Arousal, Dominance** | 0.583 | 0.583 | 0.586 |

Table A: 27. Based Data Classification Models. Gray 1

| | F1 | Precision | Recall |
|---|---|---|---|
| **Color1-8** | 0.384 | 0.381 | 0.392 |
| **Color1-9** | 0.38 | 0.378 | 0.389 |
| **Color1-10** | 0.379 | 0.376 | 0.388 |

Table A: 28. Based Data Classification Models. Gray 2

| | F1 | Precision | Recall |
|---|---|---|---|
| **BioNg, BioPs BioWC, DescWC** | 0.644 | 0.644 | 0.646 |
| **BioWC, DescWC Facebook, Twitter, Instagram** | 0.63 | 0.629 | 0.631 |
| **BioNg, BioPs Facebook, Twitter, Instagram** | 0.627 | 0.626 | 0.628 |
| **BioNg, BioNeu, BioPs** | 0.62 | 0.62 | 0.621 |
| **BioNg, BioPs** | 0.612 | 0.611 | 0.613 |
| **BioNg, BioPs, Gray Sd** | 0.612 | 0.611 | 0.614 |
| **BioNg, BioPs, Gray Mn, Gray Sd** | 0.612 | 0.611 | 0.614 |
| **BioNg, BioPs, Arousal** | 0.612 | 0.611 | 0.613 |
| **BioNg, BioPs, Color1-2** | 0.611 | 0.61 | 0.613 |
| **BioNg, BioPs, Pleasure** | 0.611 | 0.61 | 0.612 |
| **BioNg, BioPs, Gray Mn** | 0.61 | 0.61 | 0.612 |
| **BioNg, BioPs, Color1** | 0.61 | 0.609 | 0.611 |
| **BioNg, BioPs, Dominance** | 0.61 | 0.609 | 0.612 |
| **BioWC, DescWC, Gray Mn** | 0.609 | 0.608 | 0.611 |
| **BioNg, BioPs, Activity** | 0.609 | 0.608 | 0.611 |
| **BioNg, BioPs, Color1-3** | 0.608 | 0.607 | 0.61 |

Table A: 29. Based Data Classification Models. Gray 2

| | F1 | Precision | Recall |
|---|---|---|---|
| **BioNg, BioPs, Min 9 Max 9** | 0.608 | 0.607 | 0.61 |
| **BioNg, BioPs, Weight** | 0.608 | 0.608 | 0.61 |
| **Bio Word Count, Desc Word Count** | 0.607 | 0.605 | 0.608 |
| **BioNg, BioPs, PAD** | 0.607 | 0.606 | 0.609 |
| **BioNg, BioPs, Heat** | 0.607 | 0.606 | 0.608 |
| **BioWC, DescWC, Arousal** | 0.607 | 0.606 | 0.609 |
| **BioNg, BioPs, RGB Sd** | 0.606 | 0.605 | 0.608 |
| **BioNg, BioPs, Color1-4** | 0.606 | 0.606 | 0.608 |
| **BioWC, DescWC, Color1** | 0.606 | 0.605 | 0.609 |
| **BioNg, BioPs, Min 16 Max 16** | 0.606 | 0.605 | 0.608 |
| **BioWC, DescWC, Dominance** | 0.606 | 0.605 | 0.608 |
| **BioWC, DescWC, Activity** | 0.606 | 0.605 | 0.608 |
| **BioWC, DescWC, Weight** | 0.606 | 0.605 | 0.608 |
| **BioNg, BioPs, AWH** | 0.605 | 0.604 | 0.607 |
| **BioNeg, BioPs, RGB Mn** | 0.605 | 0.604 | 0.607 |
| **BioWC, DescWC, Color Gray Mn, Color Gray Sd** | 0.605 | 0.604 | 0.607 |

Table A: 30. Based Data Classification Models. Gray 2

| | F1 | Precision | Recall |
|---|---|---|---|
| **BioWC, DescWC, Heat** | 0.605 | 0.604 | 0.607 |
| **BioWC, DescWC, Gray Sd** | 0.604 | 0.603 | 0.606 |
| **BioWC, DescWC, Color1-2** | 0.604 | 0.603 | 0.606 |
| **BioNg, BioPs, RGB Mn, RGB Sd** | 0.603 | 0.602 | 0.605 |
| **BioWC, DescWC, Pleasure** | 0.603 | 0.602 | 0.605 |
| **BioNg, BioPs, Color1-5** | 0.602 | 0.601 | 0.604 |
| **BioNg, BioPs, Gray Mn, RGB Mn** | 0.601 | 0.6 | 0.603 |
| **BioNg, BioPs, Gray Sd, RGB Sd** | 0.601 | 0.6 | 0.603 |
| **BioNg, BioPs, Color1-6** | 0.6 | 0.599 | 0.603 |
| **BioWC, DescWC, Color1-3** | 0.6 | 0.599 | 0.603 |
| **BioWC, DescWC, Min 16 Max 16** | 0.6 | 0.599 | 0.602 |
| **BioWC, DescWC, PAD** | 0.599 | 0.598 | 0.601 |
| **BioWC, DescWC, RGB Mn** | 0.599 | 0.598 | 0.601 |
| **BioWC, DescWC, Min 9 Max 9** | 0.599 | 0.598 | 0.601 |
| **BioWC, DescWC, AWH** | 0.597 | 0.596 | 0.599 |
| **BioWC, DescWC, RGB Sd** | 0.597 | 0.596 | 0.599 |

Table A: 31. Based Data Classification Models. Gray 2

| | F1 | Precision | Recall |
|---|---|---|---|
| **BioNg, BioPs, Gray Mn, RGB Mn, Gray Sd, RGB Sd** | 0.596 | 0.595 | 0.599 |
| **BioNg, BioPs, Color1-7** | 0.596 | 0.596 | 0.599 |
| **BioNg, BioPs, Color1-8** | 0.596 | 0.595 | 0.599 |
| **BioWC, DescWC, Color1-4** | 0.596 | 0.594 | 0.598 |
| **BioWC, DescWC, Gray Mn, RGB Mn** | 0.594 | 0.592 | 0.596 |
| **BioWC, DescWC, Gray Sd, RGB Sd** | 0.593 | 0.592 | 0.595 |
| **BioNg, BioPs, Color1-9** | 0.592 | 0.591 | 0.595 |
| **BioWC, DescWC, Color1-5** | 0.592 | 0.591 | 0.594 |
| **BioWC, DescWC, Color1-6** | 0.592 | 0.591 | 0.594 |
| **BioNg, BioPs, Color1-10** | 0.591 | 0.59 | 0.594 |
| **BioWC, DescWC, Color RGB Mn, Color RGB Sd** | 0.591 | 0.59 | 0.594 |
| **BioWC, DescWC, Color1-8** | 0.587 | 0.586 | 0.59 |
| **BioWC, DescWC, Gray Mn, RGB Mn, Gray Sd, RGB Sd** | 0.586 | 0.585 | 0.589 |
| **BioWC, DescWC, Color1-7** | 0.585 | 0.584 | 0.588 |
| **BioWC, DescWC, Color1-9** | 0.579 | 0.578 | 0.583 |
| **BioWC, DescWC, Color1-10** | 0.579 | 0.578 | 0.582 |

Table A: 32. Based Data Classification Models. Gray 2

| | F1 | Precision | Recall |
|---|---|---|---|
| **Facebook, Twitter, Instagram, Color1-2** | 0.563 | 0.562 | 0.565 |
| **Facebook, Twitter, Instagram, Arousal** | 0.563 | 0.562 | 0.565 |
| **Facebook, Twitter, Instagram, Gray Mn, Gray Sd** | 0.562 | 0.561 | 0.564 |
| **Facebook, Twitter, Instagram, Gray Mn** | 0.561 | 0.56 | 0.563 |
| **Facebook, Twitter, Instagram, Color1** | 0.561 | 0.56 | 0.563 |
| **Facebook, Twitter, Instagram, Dominance** | 0.561 | 0.56 | 0.563 |
| **Facebook, Twitter, Instagram, Gray Sd** | 0.56 | 0.559 | 0.562 |
| **Facebook, Twitter, Instagram** | 0.559 | 0.559 | 0.561 |
| **Facebook, Twitter, Instagram, Color1-3** | 0.559 | 0.558 | 0.561 |
| **Facebook, Twitter, Instagram, RGB Mn** | 0.558 | 0.557 | 0.56 |
| **Facebook, Twitter, Instagram, Pleasure** | 0.558 | 0.557 | 0.56 |
| **Facebook, Twitter, Instagram, Activity** | 0.558 | 0.557 | 0.56 |
| **Facebook, Twitter, Instagram, Min 16 Max 16** | 0.557 | 0.556 | 0.559 |
| **DescNg, DescPs** | 0.556 | 0.555 | 0.558 |
| **Facebook, Twitter, Instagram, PAD** | 0.556 | 0.555 | 0.558 |
| **Facebook, Twitter, Instagram, RGB Sd** | 0.556 | 0.555 | 0.558 |

Table A: 33. Based Data Classification Models. Gray 2

| | F1 | Precision | Recall |
|---|---|---|---|
| **Facebook, Twitter, Instagram, Min 9 Max 9** | 0.556 | 0.555 | 0.559 |
| **Facebook, Twitter, Instagram, Weight** | 0.556 | 0.555 | 0.558 |
| **Facebook, Twitter, Instagram, AWH** | 0.555 | 0.554 | 0.558 |
| **Facebook, Twitter, Instagram, Color1-4** | 0.555 | 0.554 | 0.558 |
| **DescNg, DescNeu, DescPs** | 0.555 | 0.554 | 0.558 |
| **Facebook, Twitter, Instagram, Color1-5** | 0.554 | 0.553 | 0.556 |
| **Facebook, Twitter, Instagram, RGB Mn, RGB Sd** | 0.553 | 0.552 | 0.556 |
| **Facebook, Twitter, Instagram, Heat** | 0.553 | 0.552 | 0.555 |
| **Facebook, Twitter, Instagram, Gray Mn, RGB Mn** | 0.552 | 0.551 | 0.554 |
| **Facebook, Twitter, Instagram, Gray Sd, RGB Sd** | 0.55 | 0.549 | 0.552 |
| **Facebook, Twitter, Instagram, Color1-6** | 0.549 | 0.548 | 0.552 |
| **Facebook, Twitter, Instagram, Gray Mn, RGB Mn, Sd** | 0.548 | 0.547 | 0.551 |
| **Facebook, Twitter, Instagram, Color1-7** | 0.547 | 0.546 | 0.55 |
| **Facebook, Twitter, Instagram, Color1-8** | 0.545 | 0.544 | 0.548 |
| **Facebook, Twitter, Instagram, Color1-9** | 0.542 | 0.541 | 0.545 |
| **Facebook, Twitter, Instagram, Color1-10** | 0.538 | 0.536 | 0.541 |

Table A: 34. Based Data Classification Models. Gray 2

| | F1 | Precision | Recall |
|---|---|---|---|
| **Title WC** | 0.526 | 0.525 | 0.529 |
| **Gray Mn, Gray Sd** | 0.513 | 0.512 | 0.516 |
| **Color1-2** | 0.512 | 0.511 | 0.515 |
| **Color1** | 0.51 | 0.508 | 0.512 |
| **Pleasure, Arousal, Dominance** | 0.509 | 0.508 | 0.512 |
| **Gray Mn** | 0.509 | 0.508 | 0.512 |
| **Color1-3** | 0.509 | 0.507 | 0.512 |
| **Arousal** | 0.509 | 0.508 | 0.512 |
| **Min 9 Max 9** | 0.508 | 0.506 | 0.511 |
| **Dominance** | 0.508 | 0.507 | 0.511 |
| **RGB Mn** | 0.506 | 0.505 | 0.51 |
| **RGB Mn, RGB Sd** | 0.506 | 0.505 | 0.51 |
| **Base Features** | 0.505 | 0.503 | 0.507 |
| **Gray Sd** | 0.505 | 0.503 | 0.508 |
| **Color1-4** | 0.505 | 0.504 | 0.509 |
| **Max 9** | 0.505 | 0.504 | 0.508 |

Table A: 35. Based Data Classification Models. Gray 2

| | F1 | Precision | Recall |
|---|---|---|---|
| **Pleasure** | 0.505 | 0.504 | 0.508 |
| **Activity** | 0.505 | 0.504 | 0.508 |
| **Activity, Weight, Heat** | 0.504 | 0.503 | 0.507 |
| **Color1-5** | 0.504 | 0.502 | 0.507 |
| **Min 16** | 0.504 | 0.503 | 0.507 |
| **Max 16** | 0.504 | 0.502 | 0.507 |
| **Min 16 Max 16** | 0.504 | 0.502 | 0.507 |
| **Weight** | 0.504 | 0.503 | 0.507 |
| **Gray Mn, RGB Mn** | 0.503 | 0.502 | 0.506 |
| **Min 9** | 0.503 | 0.502 | 0.506 |
| **RGB Sd** | 0.502 | 0.501 | 0.506 |
| **Color1-6** | 0.502 | 0.5 | 0.506 |
| **Gray Mn, RGB Mn, Gray Sd, RGB Sd** | 0.501 | 0.5 | 0.505 |
| **Color1-7** | 0.5 | 0.499 | 0.504 |
| **Gray Sd, RGB Sd** | 0.499 | 0.497 | 0.502 |
| **Heat** | 0.498 | 0.497 | 0.501 |

Table A: 36. Based Data Classification Models. Gray 2

| | F1 | Precision | Recall |
|---|---|---|---|
| **Color1-8** | 0.496 | 0.494 | 0.5 |
| **Color1-9** | 0.493 | 0.492 | 0.498 |
| **Color1-10** | 0.492 | 0.491 | 0.496 |

Table A: 37. Based Data Classification Models. Gray 3

| | F1 | Precision | Recall |
|---|---|---|---|
| **BioWC, DescWC Facebook, Twitter, Instagram** | 0.744 | 0.749 | 0.744 |
| **BioWC, DescWC, Pleasure** | 0.74 | 0.747 | 0.739 |
| **BioNg, BioPs BioWC, DescWC** | 0.738 | 0.743 | 0.738 |
| **BioWC, DescWC, Color1** | 0.735 | 0.739 | 0.735 |
| **Bio Word Count, Desc Word Count** | 0.733 | 0.738 | 0.734 |
| **BioWC, DescWC, Gray Sd** | 0.733 | 0.738 | 0.734 |
| **BioWC, DescWC, Arousal** | 0.732 | 0.739 | 0.731 |
| **BioWC, DescWC, Heat** | 0.73 | 0.735 | 0.73 |
| **BioWC, DescWC, Color1-3** | 0.728 | 0.736 | 0.728 |
| **BioWC, DescWC, Weight** | 0.728 | 0.735 | 0.728 |
| **BioWC, DescWC, PAD** | 0.725 | 0.733 | 0.725 |
| **BioWC, DescWC, Gray Mn** | 0.724 | 0.729 | 0.724 |
| **BioWC, DescWC, RGB Mn** | 0.723 | 0.731 | 0.724 |
| **BioWC, DescWC, Color1-4** | 0.723 | 0.731 | 0.724 |
| **BioWC, DescWC, Color1-2** | 0.721 | 0.728 | 0.722 |
| **BioWC, DescWC, Activity** | 0.721 | 0.728 | 0.722 |

Table A: 38. Based Data Classification Models. Gray 3

| | F1 | Precision | Recall |
|---|---|---|---|
| **BioWC, DescWC, Gray Mn, RGB Mn** | 0.72 | 0.726 | 0.72 |
| **BioWC, DescWC, Min 16 Max 16** | 0.72 | 0.729 | 0.72 |
| **BioWC, DescWC, Dominance** | 0.72 | 0.727 | 0.719 |
| **BioWC, DescWC, RGB Sd** | 0.718 | 0.726 | 0.719 |
| **BioWC, DescWC, Min 9 Max 9** | 0.718 | 0.725 | 0.718 |
| **BioWC, DescWC, Color1-5** | 0.716 | 0.724 | 0.716 |
| **BioWC, DescWC, Gray Sd, RGB Sd** | 0.713 | 0.719 | 0.714 |
| **BioWC, DescWC, Color1-6** | 0.713 | 0.724 | 0.713 |
| **BioWC, DescWC, Color Gray Mn, Color Gray Sd** | 0.712 | 0.721 | 0.713 |
| **BioWC, DescWC, AWH** | 0.711 | 0.718 | 0.712 |
| **BioWC, DescWC, Color1-10** | 0.705 | 0.714 | 0.705 |
| **BioWC, DescWC, Color1-7** | 0.703 | 0.713 | 0.704 |
| **BioWC, DescWC, Color1-8** | 0.703 | 0.712 | 0.703 |
| **BioNg, BioPs Facebook, Twitter, Instagram** | 0.703 | 0.705 | 0.704 |
| **BioNg, BioPs, Gray Sd** | 0.699 | 0.704 | 0.699 |
| **BioWC, DescWC, Color RGB Mn, Color RGB Sd** | 0.699 | 0.707 | 0.698 |

Table A: 39. Based Data Classification Models. Gray 3

| | F1 | Precision | Recall |
|---|---|---|---|
| **BioWC, DescWC, Color1-9** | 0.697 | 0.708 | 0.696 |
| **BioWC, DescWC, Gray Mn, RGB Mn, Gray Sd, RGB Sd** | 0.696 | 0.703 | 0.696 |
| **DescNg, DescPs** | 0.695 | 0.702 | 0.696 |
| **DescNg, DescNeu, DescPs** | 0.695 | 0.7 | 0.697 |
| **Title WC** | 0.694 | 0.699 | 0.695 |
| **BioNg, BioPs, Gray Mn** | 0.693 | 0.699 | 0.694 |
| **Facebook, Twitter, Instagram, Gray Sd** | 0.693 | 0.697 | 0.694 |
| **BioNg, BioNeu, BioPs** | 0.693 | 0.696 | 0.695 |
| **Facebook, Twitter, Instagram, Dominance** | 0.692 | 0.695 | 0.692 |
| **BioNg, BioPs, Min 9 Max 9** | 0.691 | 0.697 | 0.691 |
| **BioNg, BioPs, Pleasure** | 0.691 | 0.696 | 0.692 |
| **Facebook, Twitter, Instagram, Pleasure** | 0.691 | 0.695 | 0.691 |
| **BioNg, BioPs** | 0.69 | 0.692 | 0.691 |
| **BioNg, BioPs, Heat** | 0.69 | 0.696 | 0.69 |
| **Gray Sd** | 0.689 | 0.695 | 0.69 |
| **Facebook, Twitter, Instagram** | 0.689 | 0.692 | 0.69 |

Table A: 40. Based Data Classification Models. Gray 3

| | F1 | Precision | Recall |
|---|---|---|---|
| **BioNg, BioPs, Color1-5** | 0.689 | 0.693 | 0.691 |
| **Facebook, Twitter, Instagram, Color1** | 0.688 | 0.69 | 0.688 |
| **Facebook, Twitter, Instagram, Arousal** | 0.688 | 0.691 | 0.69 |
| **Facebook, Twitter, Instagram, RGB Mn** | 0.687 | 0.69 | 0.687 |
| **BioNeg, BioPs, RGB Mn** | 0.686 | 0.69 | 0.687 |
| **BioNg, BioPs, Color1-6** | 0.685 | 0.693 | 0.686 |
| **Facebook, Twitter, Instagram, Gray Mn** | 0.685 | 0.688 | 0.686 |
| **Facebook, Twitter, Instagram, Color1-3** | 0.685 | 0.688 | 0.686 |
| **Arousal** | 0.685 | 0.688 | 0.686 |
| **Min 9** | 0.684 | 0.689 | 0.685 |
| **Pleasure** | 0.684 | 0.689 | 0.684 |
| **Color1-3** | 0.683 | 0.69 | 0.684 |
| **Color1-5** | 0.683 | 0.69 | 0.684 |
| **BioNg, BioPs, Color1** | 0.683 | 0.686 | 0.684 |
| **Facebook, Twitter, Instagram, Color1-2** | 0.683 | 0.687 | 0.683 |
| **Facebook, Twitter, Instagram, Color1-5** | 0.683 | 0.69 | 0.684 |

Table A: 41. Based Data Classification Models. Gray 3

| | F1 | Precision | Recall |
|---|---|---|---|
| **Facebook, Twitter, Instagram, Min 16 Max 16** | 0.683 | 0.69 | 0.684 |
| **RGB Mn** | 0.682 | 0.687 | 0.683 |
| **Max 9** | 0.682 | 0.685 | 0.683 |
| **Min 16** | 0.682 | 0.687 | 0.683 |
| **Dominance** | 0.682 | 0.687 | 0.682 |
| **Base Features** | 0.681 | 0.684 | 0.682 |
| **Color1** | 0.681 | 0.684 | 0.682 |
| **Facebook, Twitter, Instagram, AWH** | 0.681 | 0.687 | 0.681 |
| **Facebook, Twitter, Instagram, Gray Mn, RGB Mn** | 0.681 | 0.687 | 0.682 |
| **Facebook, Twitter, Instagram, Heat** | 0.681 | 0.684 | 0.682 |
| **Gray Mn, RGB Mn** | 0.68 | 0.686 | 0.681 |
| **BioNg, BioPs, Arousal** | 0.68 | 0.682 | 0.682 |
| **Color1-4** | 0.679 | 0.686 | 0.68 |
| **Facebook, Twitter, Instagram, Min 9 Max 9** | 0.679 | 0.685 | 0.68 |
| **Facebook, Twitter, Instagram, Gray Sd, RGB Sd** | 0.678 | 0.685 | 0.678 |
| **BioNg, BioPs, Dominance** | 0.678 | 0.682 | 0.678 |

Table A: 42. Based Data Classification Models. Gray 3

| | F1 | Precision | Recall |
|---|---|---|---|
| **BioNg, BioPs, Color1-2** | 0.677 | 0.682 | 0.677 |
| **BioNg, BioPs, Color1-7** | 0.677 | 0.684 | 0.678 |
| **BioNg, BioPs, Color1-8** | 0.677 | 0.685 | 0.677 |
| **Facebook, Twitter, Instagram, Gray Mn, Gray Sd** | 0.677 | 0.679 | 0.678 |
| **Min 9 Max 9** | 0.677 | 0.684 | 0.677 |
| **Facebook, Twitter, Instagram, Activity** | 0.677 | 0.683 | 0.676 |
| **Facebook, Twitter, Instagram, Color1-6** | 0.676 | 0.682 | 0.677 |
| **BioNg, BioPs, Activity** | 0.676 | 0.68 | 0.676 |
| **BioNg, BioPs, AWH** | 0.675 | 0.679 | 0.675 |
| **BioNg, BioPs, Color1-3** | 0.675 | 0.681 | 0.675 |
| **BioNg, BioPs, Weight** | 0.675 | 0.676 | 0.676 |
| **RGB Sd** | 0.674 | 0.679 | 0.675 |
| **Color1-6** | 0.674 | 0.681 | 0.675 |
| **BioNg, BioPs, Gray Mn, Gray Sd** | 0.674 | 0.68 | 0.675 |
| **BioNg, BioPs, Min 16 Max 16** | 0.674 | 0.681 | 0.674 |
| **Color1-2** | 0.673 | 0.677 | 0.673 |

Table A: 43. Based Data Classification Models. Gray 3

| | F1 | Precision | Recall |
|---|---|---|---|
| **BioNg, BioPs, PAD** | 0.673 | 0.679 | 0.674 |
| **BioNg, BioPs, Color1-4** | 0.673 | 0.677 | 0.674 |
| **Facebook, Twitter, Instagram, RGB Sd** | 0.673 | 0.676 | 0.674 |
| **Facebook, Twitter, Instagram, PAD** | 0.672 | 0.677 | 0.672 |
| **Activity** | 0.672 | 0.677 | 0.672 |
| **BioNg, BioPs, Gray Sd, RGB Sd** | 0.671 | 0.677 | 0.673 |
| **Facebook, Twitter, Instagram, Color1-7** | 0.671 | 0.678 | 0.671 |
| **Gray Mn** | 0.67 | 0.674 | 0.671 |
| **BioNg, BioPs, Gray Mn, RGB Mn** | 0.67 | 0.676 | 0.672 |
| **Heat** | 0.67 | 0.675 | 0.671 |
| **Pleasure, Arousal, Dominance** | 0.669 | 0.677 | 0.67 |
| **Gray Sd, RGB Sd** | 0.669 | 0.672 | 0.671 |
| **Color1-7** | 0.669 | 0.677 | 0.669 |
| **BioNg, BioPs, RGB Sd** | 0.669 | 0.674 | 0.671 |
| **Facebook, Twitter, Instagram, Color1-8** | 0.669 | 0.679 | 0.669 |
| **Facebook, Twitter, Instagram, Weight** | 0.669 | 0.671 | 0.67 |

Table A: 44. Based Data Classification Models. Gray 3

| | F1 | Precision | Recall |
|---|---|---|---|
| **Min 16 Max 16** | 0.667 | 0.676 | 0.669 |
| **Max 16** | 0.666 | 0.673 | 0.667 |
| **Gray Mn, Gray Sd** | 0.665 | 0.67 | 0.666 |
| **BioNg, BioPs, Color1-9** | 0.665 | 0.673 | 0.666 |
| **Facebook, Twitter, Instagram, Color1-4** | 0.665 | 0.669 | 0.665 |
| **Facebook, Twitter, Instagram, Color1-10** | 0.663 | 0.669 | 0.665 |
| **BioNg, BioPs, Color1-10** | 0.662 | 0.673 | 0.664 |
| **BioNg, BioPs, Gray Mn, RGB Mn, Gray Sd, RGB Sd** | 0.661 | 0.664 | 0.664 |
| **Facebook, Twitter, Instagram, RGB Mn, RGB Sd** | 0.661 | 0.664 | 0.663 |
| **Gray Mn, RGB Mn, Gray Sd, RGB Sd** | 0.66 | 0.665 | 0.662 |
| **Activity, Weight, Heat** | 0.659 | 0.663 | 0.66 |
| **BioNg, BioPs, RGB Mn, RGB Sd** | 0.659 | 0.663 | 0.662 |
| **Weight** | 0.659 | 0.665 | 0.661 |
| **Color1-10** | 0.658 | 0.667 | 0.66 |
| **Facebook, Twitter, Instagram, Gray Mn, RGB Mn, Sd** | 0.656 | 0.66 | 0.657 |
| **RGB Mn, RGB Sd** | 0.655 | 0.658 | 0.657 |

Table A: 45. Based Data Classification Models. Gray 3

| | F1 | Precision | Recall |
|---|---|---|---|
| **Color1-8** | 0.655 | 0.662 | 0.657 |
| **Color1-9** | 0.655 | 0.662 | 0.656 |
| **Facebook, Twitter, Instagram, Color1-9** | 0.654 | 0.661 | 0.656 |

Table A: 46. Based Data Classification Models. Gray 4

| | F1 | Precision | Recall |
|---|---|---|---|
| **BioNg, BioPs BioWC, DescWC** | 0.674 | 0.673 | 0.676 |
| **Bio Word Count, Desc Word Count** | 0.672 | 0.671 | 0.674 |
| **BioWC, DescWC Facebook, Twitter, Instagram** | 0.67 | 0.67 | 0.672 |
| **BioWC, DescWC, Gray Mn** | 0.667 | 0.667 | 0.67 |
| **BioWC, DescWC, Pleasure** | 0.667 | 0.666 | 0.67 |
| **BioWC, DescWC, Activity** | 0.666 | 0.665 | 0.669 |
| **BioWC, DescWC, Color1** | 0.663 | 0.663 | 0.666 |
| **BioWC, DescWC, Gray Sd** | 0.662 | 0.661 | 0.665 |
| **BioWC, DescWC, Dominance** | 0.662 | 0.661 | 0.665 |
| **BioWC, DescWC, Color Gray Mn, Color Gray Sd** | 0.661 | 0.661 | 0.664 |
| **BioWC, DescWC, Arousal** | 0.66 | 0.659 | 0.663 |
| **BioWC, DescWC, RGB Mn** | 0.659 | 0.659 | 0.662 |
| **BioWC, DescWC, Heat** | 0.659 | 0.658 | 0.662 |
| **BioWC, DescWC, PAD** | 0.657 | 0.657 | 0.661 |
| **BioWC, DescWC, Min 9 Max 9** | 0.657 | 0.657 | 0.66 |
| **BioWC, DescWC, Weight** | 0.657 | 0.657 | 0.66 |

Table A: 47. Based Data Classification Models. Gray 4

| | F1 | Precision | Recall |
|---|---|---|---|
| **BioWC, DescWC, Gray Mn, RGB Mn** | 0.656 | 0.656 | 0.66 |
| **BioWC, DescWC, Color1-2** | 0.656 | 0.655 | 0.659 |
| **BioWC, DescWC, Color1-3** | 0.655 | 0.655 | 0.658 |
| **BioWC, DescWC, Min 16 Max 16** | 0.652 | 0.652 | 0.655 |
| **BioWC, DescWC, AWH** | 0.65 | 0.65 | 0.653 |
| **BioWC, DescWC, RGB Sd** | 0.648 | 0.647 | 0.651 |
| **BioWC, DescWC, Color1-5** | 0.648 | 0.648 | 0.652 |
| **BioNg, BioPs, Min 9 Max 9** | 0.646 | 0.645 | 0.649 |
| **BioNg, BioPs, Pleasure** | 0.646 | 0.645 | 0.649 |
| **BioNg, BioPs, Gray Sd** | 0.645 | 0.644 | 0.647 |
| **BioWC, DescWC, Color1-4** | 0.645 | 0.645 | 0.649 |
| **BioNg, BioPs, Min 16 Max 16** | 0.645 | 0.645 | 0.648 |
| **BioNg, BioPs, Weight** | 0.645 | 0.644 | 0.648 |
| **BioWC, DescWC, Gray Sd, RGB Sd** | 0.644 | 0.645 | 0.647 |
| **BioNg, BioPs, Activity** | 0.644 | 0.643 | 0.646 |
| **BioNg, BioNeu, BioPs** | 0.644 | 0.643 | 0.646 |

Table A: 48. Based Data Classification Models. Gray 4

| | F1 | Precision | Recall |
|---|---|---|---|
| **BioNg, BioPs, RGB Sd** | 0.643 | 0.642 | 0.646 |
| **BioNg, BioPs, Arousal** | 0.643 | 0.642 | 0.645 |
| **BioNg, BioPs Facebook, Twitter, Instagram** | 0.643 | 0.642 | 0.645 |
| **BioWC, DescWC, Color RGB Mn, Color RGB Sd** | 0.642 | 0.643 | 0.646 |
| **DescNg, DescPs** | 0.641 | 0.64 | 0.645 |
| **BioNg, BioPs, PAD** | 0.641 | 0.641 | 0.643 |
| **BioNg, BioPs, Gray Mn** | 0.64 | 0.639 | 0.643 |
| **BioNg, BioPs, Heat** | 0.64 | 0.64 | 0.643 |
| **BioNg, BioPs, Color1** | 0.639 | 0.639 | 0.642 |
| **BioNg, BioPs, Dominance** | 0.639 | 0.638 | 0.642 |
| **BioNeg, BioPs, RGB Mn** | 0.638 | 0.639 | 0.641 |
| **BioWC, DescWC, Color1-6** | 0.638 | 0.638 | 0.642 |
| **BioNg, BioPs** | 0.637 | 0.635 | 0.639 |
| **BioNg, BioPs, RGB Mn, RGB Sd** | 0.637 | 0.638 | 0.641 |
| **BioNg, BioPs, Color1-2** | 0.637 | 0.637 | 0.64 |
| **BioWC, DescWC, Color1-7** | 0.637 | 0.638 | 0.642 |

Table A: 49. Based Data Classification Models. Gray 4

| | F1 | Precision | Recall |
|---|---|---|---|
| **BioNg, BioPs, Gray Mn, RGB Mn** | 0.636 | 0.636 | 0.639 |
| **BioNg, BioPs, Color1-3** | 0.636 | 0.636 | 0.639 |
| **BioWC, DescWC, Color1-8** | 0.636 | 0.637 | 0.64 |
| **BioNg, BioPs, Gray Sd, RGB Sd** | 0.635 | 0.635 | 0.639 |
| **BioWC, DescWC, Color1-9** | 0.635 | 0.636 | 0.641 |
| **DescNg, DescNeu, DescPs** | 0.635 | 0.634 | 0.639 |
| **BioNg, BioPs, AWH** | 0.634 | 0.634 | 0.637 |
| **BioNg, BioPs, Gray Mn, Gray Sd** | 0.634 | 0.635 | 0.636 |
| **BioWC, DescWC, Gray Mn, RGB Mn, Gray Sd, RGB Sd** | 0.634 | 0.635 | 0.639 |
| **BioNg, BioPs, Color1-5** | 0.632 | 0.632 | 0.635 |
| **BioNg, BioPs, Color1-9** | 0.631 | 0.631 | 0.635 |
| **BioNg, BioPs, Color1-4** | 0.63 | 0.629 | 0.633 |
| **BioNg, BioPs, Color1-8** | 0.629 | 0.63 | 0.633 |
| **BioNg, BioPs, Gray Mn, RGB Mn, Gray Sd, RGB Sd** | 0.628 | 0.63 | 0.632 |
| **BioNg, BioPs, Color1-7** | 0.627 | 0.628 | 0.631 |
| **BioWC, DescWC, Color1-10** | 0.627 | 0.629 | 0.632 |

Table A: 50. Based Data Classification Models. Gray 4

| | F1 | Precision | Recall |
|---|---|---|---|
| **BioNg, BioPs, Color1-6** | 0.626 | 0.627 | 0.63 |
| **BioNg, BioPs, Color1-10** | 0.624 | 0.626 | 0.629 |
| **Facebook, Twitter, Instagram, Color1-2** | 0.612 | 0.611 | 0.616 |
| **Facebook, Twitter, Instagram, Min 9 Max 9** | 0.612 | 0.61 | 0.617 |
| **Facebook, Twitter, Instagram, Arousal** | 0.612 | 0.61 | 0.616 |
| **Facebook, Twitter, Instagram, Pleasure** | 0.611 | 0.609 | 0.614 |
| **Facebook, Twitter, Instagram, Weight** | 0.611 | 0.609 | 0.615 |
| **Facebook, Twitter, Instagram, Gray Mn** | 0.61 | 0.608 | 0.613 |
| **Facebook, Twitter, Instagram, Gray Sd** | 0.61 | 0.609 | 0.614 |
| **Facebook, Twitter, Instagram, Dominance** | 0.609 | 0.608 | 0.612 |
| **Facebook, Twitter, Instagram** | 0.606 | 0.604 | 0.609 |
| **Facebook, Twitter, Instagram, Min 16 Max 16** | 0.605 | 0.604 | 0.61 |
| **Facebook, Twitter, Instagram, RGB Mn** | 0.604 | 0.604 | 0.608 |
| **Facebook, Twitter, Instagram, RGB Sd** | 0.604 | 0.604 | 0.609 |
| **Facebook, Twitter, Instagram, Gray Mn, Gray Sd** | 0.604 | 0.603 | 0.607 |
| **Facebook, Twitter, Instagram, AWH** | 0.603 | 0.603 | 0.607 |

Table A: 51. Based Data Classification Models. Gray 4

| | F1 | Precision | Recall |
|---|---|---|---|
| **Facebook, Twitter, Instagram, Gray Sd, RGB Sd** | 0.601 | 0.601 | 0.605 |
| **Facebook, Twitter, Instagram, PAD** | 0.6 | 0.599 | 0.604 |
| **Facebook, Twitter, Instagram, RGB Mn, RGB Sd** | 0.6 | 0.601 | 0.605 |
| **Facebook, Twitter, Instagram, Color1** | 0.6 | 0.598 | 0.604 |
| **Facebook, Twitter, Instagram, Activity** | 0.6 | 0.599 | 0.604 |
| **Facebook, Twitter, Instagram, Heat** | 0.6 | 0.598 | 0.604 |
| **Facebook, Twitter, Instagram, Gray Mn, RGB Mn** | 0.599 | 0.598 | 0.604 |
| **Facebook, Twitter, Instagram, Color1-5** | 0.598 | 0.598 | 0.603 |
| **Facebook, Twitter, Instagram, Color1-3** | 0.596 | 0.594 | 0.6 |
| **Facebook, Twitter, Instagram, Color1-4** | 0.596 | 0.595 | 0.601 |
| **Facebook, Twitter, Instagram, Gray Mn, RGB Mn, Sd** | 0.594 | 0.595 | 0.6 |
| **Facebook, Twitter, Instagram, Color1-7** | 0.593 | 0.593 | 0.598 |
| **Title WC** | 0.591 | 0.591 | 0.595 |
| **Facebook, Twitter, Instagram, Color1-6** | 0.588 | 0.588 | 0.593 |
| **Facebook, Twitter, Instagram, Color1-8** | 0.587 | 0.587 | 0.592 |
| **Arousal** | 0.585 | 0.583 | 0.589 |

Table A: 52. Based Data Classification Models. Gray 4

| | F1 | Precision | Recall |
|---|---|---|---|
| **Min 9** | 0.583 | 0.582 | 0.587 |
| **Pleasure** | 0.583 | 0.582 | 0.588 |
| **Heat** | 0.582 | 0.58 | 0.586 |
| **Gray Sd** | 0.581 | 0.579 | 0.586 |
| **Color1-2** | 0.581 | 0.579 | 0.585 |
| **Max 16** | 0.581 | 0.578 | 0.585 |
| **Min 9 Max 9** | 0.581 | 0.579 | 0.586 |
| **Gray Mn, Gray Sd** | 0.58 | 0.578 | 0.585 |
| **Color1** | 0.58 | 0.578 | 0.585 |
| **Base Features** | 0.579 | 0.577 | 0.584 |
| **Pleasure, Arousal, Dominance** | 0.578 | 0.577 | 0.583 |
| **Dominance** | 0.578 | 0.576 | 0.582 |
| **Weight** | 0.578 | 0.576 | 0.582 |
| **RGB Sd** | 0.577 | 0.575 | 0.582 |
| **Min 16 Max 16** | 0.577 | 0.575 | 0.583 |
| **Facebook, Twitter, Instagram, Color1-9** | 0.576 | 0.576 | 0.583 |

Table A: 53. Based Data Classification Models. Gray 4

| | F1 | Precision | Recall |
|---|---|---|---|
| **Color1-3** | 0.575 | 0.573 | 0.58 |
| **Facebook, Twitter, Instagram, Color1-10** | 0.575 | 0.575 | 0.581 |
| **Min 16** | 0.575 | 0.572 | 0.579 |
| **Gray Mn** | 0.573 | 0.57 | 0.577 |
| **Max 9** | 0.573 | 0.57 | 0.577 |
| **Activity** | 0.573 | 0.572 | 0.579 |
| **Gray Sd, RGB Sd** | 0.572 | 0.571 | 0.577 |
| **RGB Mn** | 0.571 | 0.569 | 0.575 |
| **RGB Mn, RGB Sd** | 0.571 | 0.57 | 0.577 |
| **Color1-4** | 0.57 | 0.568 | 0.575 |
| **Activity, Weight, Heat** | 0.569 | 0.568 | 0.575 |
| **Gray Mn, RGB Mn** | 0.568 | 0.567 | 0.572 |
| **Gray Mn, RGB Mn, Gray Sd, RGB Sd** | 0.564 | 0.563 | 0.57 |
| **Color1-5** | 0.564 | 0.563 | 0.569 |
| **Color1-6** | 0.563 | 0.562 | 0.569 |
| **Color1-8** | 0.563 | 0.563 | 0.569 |

Table A: 54. Based Data Classification Models. Gray 4

| | F1 | Precision | Recall |
|---|---|---|---|
| **Color1-7** | 0.562 | 0.562 | 0.568 |
| **Color1-9** | 0.558 | 0.556 | 0.565 |
| **Color1-10** | 0.551 | 0.55 | 0.558 |

Table A: 55. Based Data Classification Models. Gray 5

| | F1 | Precision | Recall |
|---|---|---|---|
| **BioNg, BioPs, Arousal** | 0.608 | 0.607 | 0.61 |
| **BioWC, DescWC, Color1-2** | 0.601 | 0.6 | 0.604 |
| **BioWC, DescWC Facebook, Twitter, Instagram** | 0.598 | 0.597 | 0.6 |
| **BioNg, BioPs, Color1-3** | 0.597 | 0.597 | 0.598 |
| **BioNg, BioPs, Activity** | 0.597 | 0.596 | 0.598 |
| **BioNg, BioPs Facebook, Twitter, Instagram** | 0.597 | 0.598 | 0.598 |
| **BioNg, BioPs, PAD** | 0.596 | 0.596 | 0.598 |
| **BioNg, BioPs, Color1** | 0.596 | 0.596 | 0.597 |
| **BioWC, DescWC, PAD** | 0.596 | 0.595 | 0.599 |
| **BioWC, DescWC, Pleasure** | 0.596 | 0.596 | 0.598 |
| **Facebook, Twitter, Instagram, Arousal** | 0.596 | 0.595 | 0.597 |
| **BioNg, BioPs, Dominance** | 0.595 | 0.595 | 0.597 |
| **BioWC, DescWC, Weight** | 0.595 | 0.594 | 0.597 |
| **BioWC, DescWC, Arousal** | 0.594 | 0.594 | 0.597 |
| **Facebook, Twitter, Instagram, Pleasure** | 0.594 | 0.593 | 0.596 |
| **Facebook, Twitter, Instagram, Dominance** | 0.594 | 0.593 | 0.596 |

Table A: 56. Based Data Classification Models. Gray 5

| | F1 | Precision | Recall |
|---|---|---|---|
| **BioNg, BioPs, Gray Sd, RGB Sd** | 0.593 | 0.593 | 0.594 |
| **BioNg, BioPs, Color1-2** | 0.593 | 0.591 | 0.595 |
| **BioWC, DescWC, Color1** | 0.593 | 0.593 | 0.596 |
| **BioNg, BioPs, Weight** | 0.593 | 0.593 | 0.595 |
| **BioNg, BioPs, RGB Sd** | 0.592 | 0.591 | 0.594 |
| **DescNg, DescPs** | 0.591 | 0.59 | 0.593 |
| **BioWC, DescWC, Color1-3** | 0.591 | 0.591 | 0.594 |
| **BioNg, BioPs BioWC, DescWC** | 0.591 | 0.591 | 0.594 |
| **BioNg, BioPs, Gray Sd** | 0.59 | 0.59 | 0.591 |
| **BioNg, BioPs, Gray Mn, Gray Sd** | 0.59 | 0.589 | 0.592 |
| **Facebook, Twitter, Instagram, Color1-4** | 0.59 | 0.588 | 0.592 |
| **BioNg, BioPs, Pleasure** | 0.59 | 0.59 | 0.59 |
| **BioNg, BioPs, Min 16 Max 16** | 0.589 | 0.589 | 0.591 |
| **BioNg, BioPs, Heat** | 0.589 | 0.588 | 0.591 |
| **BioWC, DescWC, Activity** | 0.589 | 0.589 | 0.591 |
| **BioNeg, BioPs, RGB Mn** | 0.588 | 0.588 | 0.59 |

Table A: 57. Based Data Classification Models. Gray 5

| | F1 | Precision | Recall |
|---|---|---|---|
| **BioNg, BioPs, Color1-4** | 0.588 | 0.588 | 0.59 |
| **Facebook, Twitter, Instagram, PAD** | 0.588 | 0.587 | 0.591 |
| **Facebook, Twitter, Instagram, Gray Sd** | 0.588 | 0.588 | 0.59 |
| **Title WC** | 0.588 | 0.588 | 0.589 |
| **Bio Word Count, Desc Word Count** | 0.587 | 0.585 | 0.588 |
| **BioWC, DescWC, Color1-6** | 0.587 | 0.586 | 0.591 |
| **BioNg, BioPs, Min 9 Max 9** | 0.587 | 0.587 | 0.588 |
| **BioNg, BioNeu, BioPs** | 0.587 | 0.587 | 0.588 |
| **DescNg, DescNeu, DescPs** | 0.587 | 0.586 | 0.59 |
| **Facebook, Twitter, Instagram** | 0.586 | 0.585 | 0.588 |
| **BioNg, BioPs** | 0.586 | 0.586 | 0.587 |
| **BioWC, DescWC, Gray Sd** | 0.586 | 0.585 | 0.589 |
| **Facebook, Twitter, Instagram, RGB Sd** | 0.586 | 0.586 | 0.588 |
| **Facebook, Twitter, Instagram, Color1** | 0.586 | 0.585 | 0.588 |
| **Facebook, Twitter, Instagram, Activity** | 0.586 | 0.585 | 0.587 |
| **BioNg, BioPs, Gray Mn, RGB Mn** | 0.585 | 0.586 | 0.586 |

Table A: 58. Based Data Classification Models. Gray 5

| | F1 | Precision | Recall |
|---|---|---|---|
| **BioWC, DescWC, RGB Sd** | 0.585 | 0.585 | 0.585 |
| **BioNg, BioPs, Gray Mn** | 0.584 | 0.584 | 0.585 |
| **BioNg, BioPs, Color1-6** | 0.584 | 0.584 | 0.585 |
| **BioWC, DescWC, AWH** | 0.583 | 0.582 | 0.585 |
| **BioWC, DescWC, RGB Mn** | 0.583 | 0.581 | 0.586 |
| **BioWC, DescWC, Gray Sd, RGB Sd** | 0.583 | 0.584 | 0.585 |
| **BioWC, DescWC, Color Gray Mn, Color Gray Sd** | 0.583 | 0.582 | 0.585 |
| **BioWC, DescWC, Dominance** | 0.583 | 0.582 | 0.586 |
| **Facebook, Twitter, Instagram, AWH** | 0.582 | 0.581 | 0.583 |
| **Facebook, Twitter, Instagram, Color1-2** | 0.582 | 0.581 | 0.585 |
| **Facebook, Twitter, Instagram, Color1-3** | 0.581 | 0.58 | 0.585 |
| **BioWC, DescWC, Min 9 Max 9** | 0.581 | 0.581 | 0.584 |
| **Arousal** | 0.581 | 0.581 | 0.584 |
| **Facebook, Twitter, Instagram, Weight** | 0.581 | 0.58 | 0.583 |
| **Facebook, Twitter, Instagram, Gray Mn** | 0.58 | 0.579 | 0.582 |
| **Facebook, Twitter, Instagram, RGB Mn** | 0.58 | 0.58 | 0.582 |

Table A: 59. Based Data Classification Models. Gray 5

| | F1 | Precision | Recall |
|---|---|---|---|
| **Facebook, Twitter, Instagram, Gray Sd, RGB Sd** | 0.58 | 0.58 | 0.582 |
| **BioWC, DescWC, Min 16 Max 16** | 0.58 | 0.58 | 0.584 |
| **BioWC, DescWC, Heat** | 0.58 | 0.579 | 0.582 |
| **Facebook, Twitter, Instagram, Heat** | 0.58 | 0.579 | 0.581 |
| **BioNg, BioPs, AWH** | 0.579 | 0.58 | 0.582 |
| **BioWC, DescWC, Gray Mn** | 0.579 | 0.578 | 0.582 |
| **Color1** | 0.578 | 0.578 | 0.58 |
| **BioNg, BioPs, Color1-5** | 0.578 | 0.577 | 0.58 |
| **BioWC, DescWC, Gray Mn, RGB Mn** | 0.578 | 0.577 | 0.581 |
| **Gray Sd** | 0.577 | 0.576 | 0.579 |
| **Color1-2** | 0.577 | 0.577 | 0.581 |
| **Base Features** | 0.576 | 0.575 | 0.578 |
| **BioWC, DescWC, Color RGB Mn, Color RGB Sd** | 0.576 | 0.577 | 0.579 |
| **Facebook, Twitter, Instagram, Gray Mn, Gray Sd** | 0.576 | 0.574 | 0.579 |
| **Facebook, Twitter, Instagram, Color1-8** | 0.576 | 0.575 | 0.58 |
| **BioWC, DescWC, Color1-4** | 0.575 | 0.575 | 0.578 |

Table A: 60. Based Data Classification Models. Gray 5

| | F1 | Precision | Recall |
|---|---|---|---|
| **BioWC, DescWC, Color1-5** | 0.575 | 0.574 | 0.579 |
| **BioWC, DescWC, Color1-9** | 0.575 | 0.573 | 0.579 |
| **Activity** | 0.575 | 0.574 | 0.576 |
| **Pleasure, Arousal, Dominance** | 0.574 | 0.574 | 0.576 |
| **BioWC, DescWC, Gray Mn, RGB Mn, Gray Sd, RGB Sd** | 0.574 | 0.573 | 0.577 |
| **RGB Mn** | 0.573 | 0.572 | 0.576 |
| **Facebook, Twitter, Instagram, Color1-5** | 0.573 | 0.572 | 0.575 |
| **Color1-3** | 0.572 | 0.571 | 0.575 |
| **BioNg, BioPs, Color1-8** | 0.572 | 0.572 | 0.574 |
| **Facebook, Twitter, Instagram, Gray Mn, RGB Mn** | 0.572 | 0.571 | 0.576 |
| **Facebook, Twitter, Instagram, Min 16 Max 16** | 0.572 | 0.571 | 0.574 |
| **BioNg, BioPs, RGB Mn, RGB Sd** | 0.571 | 0.57 | 0.573 |
| **BioNg, BioPs, Color1-10** | 0.57 | 0.569 | 0.573 |
| **Facebook, Twitter, Instagram, Color1-6** | 0.57 | 0.568 | 0.574 |
| **Min 9** | 0.57 | 0.568 | 0.572 |
| **Max 16** | 0.57 | 0.569 | 0.572 |

Table A: 61. Based Data Classification Models. Gray 5

| | F1 | Precision | Recall |
|---|---|---|---|
| **Dominance** | 0.57 | 0.569 | 0.573 |
| **Gray Mn** | 0.569 | 0.567 | 0.571 |
| **BioNg, BioPs, Color1-7** | 0.569 | 0.568 | 0.57 |
| **BioNg, BioPs, Color1-9** | 0.569 | 0.568 | 0.572 |
| **BioWC, DescWC, Color1-8** | 0.569 | 0.569 | 0.573 |
| **Facebook, Twitter, Instagram, Min 9 Max 9** | 0.569 | 0.569 | 0.572 |
| **Pleasure** | 0.569 | 0.568 | 0.571 |
| **RGB Sd** | 0.568 | 0.568 | 0.57 |
| **BioWC, DescWC, Color1-10** | 0.568 | 0.568 | 0.572 |
| **Facebook, Twitter, Instagram, RGB Mn, RGB Sd** | 0.568 | 0.566 | 0.571 |
| **Facebook, Twitter, Instagram, Color1-7** | 0.568 | 0.565 | 0.572 |
| **Heat** | 0.568 | 0.567 | 0.57 |
| **Gray Sd, RGB Sd** | 0.567 | 0.568 | 0.569 |
| **BioNg, BioPs, Gray Mn, RGB Mn, Gray Sd, RGB Sd** | 0.567 | 0.566 | 0.569 |
| **Weight** | 0.567 | 0.566 | 0.57 |
| **Gray Mn, Gray Sd** | 0.565 | 0.564 | 0.568 |

Table A: 62. Based Data Classification Models. Gray 5

| | F1 | Precision | Recall |
|---|---|---|---|
| **BioWC, DescWC, Color1-7** | 0.565 | 0.563 | 0.569 |
| **Min 9 Max 9** | 0.565 | 0.564 | 0.568 |
| **Gray Mn, RGB Mn** | 0.564 | 0.563 | 0.566 |
| **Max 9** | 0.564 | 0.563 | 0.566 |
| **Min 16 Max 16** | 0.564 | 0.563 | 0.567 |
| **Activity, Weight, Heat** | 0.562 | 0.56 | 0.565 |
| **Color1-4** | 0.561 | 0.56 | 0.565 |
| **Color1-6** | 0.56 | 0.559 | 0.564 |
| **Facebook, Twitter, Instagram, Color1-9** | 0.56 | 0.558 | 0.565 |
| **Min 16** | 0.559 | 0.557 | 0.562 |
| **RGB Mn, RGB Sd** | 0.558 | 0.557 | 0.56 |
| **Color1-5** | 0.557 | 0.556 | 0.561 |
| **Facebook, Twitter, Instagram, Gray Mn, RGB Mn, Sd** | 0.556 | 0.555 | 0.559 |
| **Color1-7** | 0.554 | 0.554 | 0.557 |
| **Color1-10** | 0.554 | 0.553 | 0.559 |
| **Facebook, Twitter, Instagram, Color1-10** | 0.554 | 0.553 | 0.558 |

Table A: 63. Based Data Classification Models. Gray 5

| | F1 | Precision | Recall |
|---|---|---|---|
| **Color1-8** | 0.547 | 0.546 | 0.552 |
| **Gray Mn, RGB Mn, Gray Sd, RGB Sd** | 0.546 | 0.545 | 0.549 |
| **Color1-9** | 0.542 | 0.54 | 0.547 |

Table A: 64. Based Data Classification Models. Gray 6

| | F1 | Precision | Recall |
|---|---|---|---|
| **BioNg, BioPs BioWC, DescWC** | 0.69 | 0.69 | 0.69 |
| **BioWC, DescWC Facebook, Twitter, Instagram** | 0.685 | 0.686 | 0.686 |
| **BioWC, DescWC, Arousal** | 0.681 | 0.681 | 0.682 |
| **Bio Word Count, Desc Word Count** | 0.678 | 0.679 | 0.679 |
| **BioWC, DescWC, Color Gray Mn, Color Gray Sd** | 0.678 | 0.678 | 0.679 |
| **BioWC, DescWC, Dominance** | 0.678 | 0.678 | 0.679 |
| **BioWC, DescWC, Pleasure** | 0.677 | 0.677 | 0.678 |
| **BioWC, DescWC, Gray Mn** | 0.676 | 0.676 | 0.677 |
| **BioWC, DescWC, PAD** | 0.674 | 0.675 | 0.675 |
| **BioWC, DescWC, Gray Sd** | 0.674 | 0.674 | 0.675 |
| **BioWC, DescWC, Color1-3** | 0.674 | 0.675 | 0.676 |
| **BioWC, DescWC, Color1-4** | 0.674 | 0.676 | 0.675 |
| **BioWC, DescWC, Min 9 Max 9** | 0.674 | 0.675 | 0.676 |
| **BioWC, DescWC, Activity** | 0.674 | 0.674 | 0.675 |
| **BioWC, DescWC, Weight** | 0.674 | 0.675 | 0.675 |
| **BioWC, DescWC, AWH** | 0.673 | 0.674 | 0.674 |

Table A: 65. Based Data Classification Models. Gray 6

| | F1 | Precision | Recall |
|---|---|---|---|
| **BioWC, DescWC, Color1-2** | 0.673 | 0.674 | 0.675 |
| **BioNg, BioPs Facebook, Twitter, Instagram** | 0.673 | 0.673 | 0.675 |
| **BioNg, BioPs, Gray Sd** | 0.672 | 0.672 | 0.673 |
| **BioWC, DescWC, RGB Mn** | 0.672 | 0.672 | 0.673 |
| **BioNg, BioPs, Activity** | 0.672 | 0.672 | 0.673 |
| **BioNg, BioPs, Weight** | 0.672 | 0.673 | 0.673 |
| **BioWC, DescWC, Heat** | 0.672 | 0.673 | 0.673 |
| **BioNg, BioPs, PAD** | 0.671 | 0.672 | 0.673 |
| **BioNg, BioPs, Color1-2** | 0.671 | 0.671 | 0.672 |
| **BioNg, BioPs, Color1-3** | 0.671 | 0.671 | 0.673 |
| **BioNg, BioPs, Color1-4** | 0.671 | 0.672 | 0.673 |
| **BioWC, DescWC, Color1** | 0.671 | 0.671 | 0.672 |
| **BioNg, BioPs, Arousal** | 0.671 | 0.671 | 0.672 |
| **BioNg, BioNeu, BioPs** | 0.671 | 0.671 | 0.672 |
| **BioNg, BioPs, AWH** | 0.67 | 0.671 | 0.672 |
| **BioNg, BioPs, Gray Mn** | 0.67 | 0.671 | 0.672 |

Table A: 66. Based Data Classification Models. Gray 6

| | F1 | Precision | Recall |
|---|---|---|---|
| **BioNg, BioPs, Gray Mn, Gray Sd** | 0.67 | 0.67 | 0.672 |
| **BioWC, DescWC, RGB Sd** | 0.67 | 0.671 | 0.672 |
| **BioWC, DescWC, Min 16 Max 16** | 0.67 | 0.671 | 0.672 |
| **BioNg, BioPs** | 0.669 | 0.668 | 0.67 |
| **BioNg, BioPs, RGB Sd** | 0.669 | 0.669 | 0.67 |
| **BioNg, BioPs, Color1-5** | 0.669 | 0.67 | 0.671 |
| **BioWC, DescWC, Gray Mn, RGB Mn** | 0.669 | 0.67 | 0.671 |
| **BioWC, DescWC, Color RGB Mn, Color RGB Sd** | 0.669 | 0.67 | 0.671 |
| **BioNg, BioPs, Min 9 Max 9** | 0.669 | 0.669 | 0.67 |
| **BioNeg, BioPs, RGB Mn** | 0.668 | 0.668 | 0.67 |
| **BioNg, BioPs, Gray Sd, RGB Sd** | 0.668 | 0.669 | 0.67 |
| **BioNg, BioPs, Color1** | 0.668 | 0.668 | 0.67 |
| **BioNg, BioPs, Dominance** | 0.668 | 0.668 | 0.669 |
| **BioWC, DescWC, Color1-6** | 0.667 | 0.668 | 0.669 |
| **BioNg, BioPs, Pleasure** | 0.667 | 0.667 | 0.669 |
| **BioWC, DescWC, Gray Sd, RGB Sd** | 0.666 | 0.667 | 0.668 |

Table A: 67. Based Data Classification Models. Gray 6

| | F1 | Precision | Recall |
|---|---|---|---|
| **BioWC, DescWC, Color1-5** | 0.666 | 0.667 | 0.668 |
| **BioNg, BioPs, Heat** | 0.666 | 0.666 | 0.667 |
| **BioNg, BioPs, RGB Mn, RGB Sd** | 0.665 | 0.665 | 0.667 |
| **BioNg, BioPs, Color1-7** | 0.665 | 0.666 | 0.667 |
| **BioWC, DescWC, Color1-7** | 0.665 | 0.666 | 0.667 |
| **BioNg, BioPs, Min 16 Max 16** | 0.665 | 0.665 | 0.666 |
| **BioNg, BioPs, Gray Mn, RGB Mn** | 0.664 | 0.665 | 0.666 |
| **BioWC, DescWC, Gray Mn, RGB Mn, Gray Sd, RGB Sd** | 0.663 | 0.665 | 0.665 |
| **BioNg, BioPs, Color1-6** | 0.662 | 0.663 | 0.664 |
| **BioNg, BioPs, Color1-9** | 0.661 | 0.663 | 0.663 |
| **BioWC, DescWC, Color1-9** | 0.661 | 0.663 | 0.663 |
| **BioNg, BioPs, Gray Mn, RGB Mn, Gray Sd, RGB Sd** | 0.66 | 0.661 | 0.662 |
| **BioNg, BioPs, Color1-8** | 0.66 | 0.661 | 0.662 |
| **BioWC, DescWC, Color1-10** | 0.66 | 0.661 | 0.662 |
| **BioNg, BioPs, Color1-10** | 0.659 | 0.66 | 0.661 |
| **BioWC, DescWC, Color1-8** | 0.657 | 0.659 | 0.659 |

Table A: 68. Based Data Classification Models. Gray 6

| | F1 | Precision | Recall |
|---|---|---|---|
| **Facebook, Twitter, Instagram, Gray Sd** | 0.649 | 0.649 | 0.65 |
| **Facebook, Twitter, Instagram, Gray Mn, Gray Sd** | 0.648 | 0.648 | 0.649 |
| **Facebook, Twitter, Instagram, Color1** | 0.648 | 0.648 | 0.649 |
| **Facebook, Twitter, Instagram, Arousal** | 0.648 | 0.647 | 0.649 |
| **Facebook, Twitter, Instagram, Activity** | 0.648 | 0.648 | 0.649 |
| **Facebook, Twitter, Instagram, Pleasure** | 0.646 | 0.646 | 0.647 |
| **Facebook, Twitter, Instagram, Weight** | 0.646 | 0.647 | 0.648 |
| **DescNg, DescPs** | 0.645 | 0.644 | 0.646 |
| **Facebook, Twitter, Instagram, Gray Mn** | 0.645 | 0.645 | 0.646 |
| **Facebook, Twitter, Instagram, Color1-3** | 0.645 | 0.645 | 0.646 |
| **Facebook, Twitter, Instagram, Dominance** | 0.645 | 0.645 | 0.647 |
| **Facebook, Twitter, Instagram, PAD** | 0.644 | 0.644 | 0.646 |
| **Facebook, Twitter, Instagram, AWH** | 0.644 | 0.645 | 0.646 |
| **Facebook, Twitter, Instagram, Color1-2** | 0.644 | 0.644 | 0.646 |
| **Facebook, Twitter, Instagram** | 0.643 | 0.643 | 0.644 |
| **Facebook, Twitter, Instagram, RGB Mn** | 0.643 | 0.643 | 0.644 |

Table A: 69. Based Data Classification Models. Gray 6

| | F1 | Precision | Recall |
|---|---|---|---|
| **Facebook, Twitter, Instagram, Color1-4** | 0.643 | 0.643 | 0.645 |
| **Facebook, Twitter, Instagram, Gray Sd, RGB Sd** | 0.642 | 0.642 | 0.643 |
| **Facebook, Twitter, Instagram, Min 9 Max 9** | 0.642 | 0.642 | 0.644 |
| **DescNg, DescNeu, DescPs** | 0.641 | 0.641 | 0.644 |
| **Facebook, Twitter, Instagram, RGB Sd** | 0.64 | 0.64 | 0.642 |
| **Facebook, Twitter, Instagram, Color1-6** | 0.64 | 0.641 | 0.642 |
| **Facebook, Twitter, Instagram, RGB Mn, RGB Sd** | 0.639 | 0.639 | 0.641 |
| **Facebook, Twitter, Instagram, Color1-5** | 0.638 | 0.639 | 0.64 |
| **Facebook, Twitter, Instagram, Min 16 Max 16** | 0.638 | 0.638 | 0.64 |
| **Facebook, Twitter, Instagram, Heat** | 0.638 | 0.638 | 0.639 |
| **Facebook, Twitter, Instagram, Gray Mn, RGB Mn** | 0.637 | 0.638 | 0.639 |
| **Facebook, Twitter, Instagram, Gray Mn, RGB Mn, Sd** | 0.637 | 0.638 | 0.639 |
| **Facebook, Twitter, Instagram, Color1-7** | 0.636 | 0.637 | 0.638 |
| **Facebook, Twitter, Instagram, Color1-9** | 0.635 | 0.636 | 0.637 |
| **Facebook, Twitter, Instagram, Color1-8** | 0.633 | 0.634 | 0.635 |
| **Facebook, Twitter, Instagram, Color1-10** | 0.632 | 0.634 | 0.635 |

Table A: 70. Based Data Classification Models. Gray 6

| | F1 | Precision | Recall |
|---|---|---|---|
| **Title WC** | 0.625 | 0.625 | 0.627 |
| **Gray Mn** | 0.62 | 0.619 | 0.622 |
| **Activity** | 0.619 | 0.619 | 0.621 |
| **Activity, Weight, Heat** | 0.618 | 0.617 | 0.62 |
| **Gray Mn, Gray Sd** | 0.618 | 0.618 | 0.62 |
| **Dominance** | 0.618 | 0.618 | 0.62 |
| **Arousal** | 0.617 | 0.616 | 0.619 |
| **Gray Sd** | 0.616 | 0.615 | 0.618 |
| **Color1** | 0.616 | 0.615 | 0.618 |
| **Color1-2** | 0.616 | 0.616 | 0.619 |
| **Pleasure** | 0.616 | 0.615 | 0.618 |
| **Weight** | 0.616 | 0.615 | 0.618 |
| **Pleasure, Arousal, Dominance** | 0.615 | 0.615 | 0.618 |
| **Base Features** | 0.614 | 0.613 | 0.616 |
| **Color1-3** | 0.614 | 0.613 | 0.616 |
| **Color1-4** | 0.613 | 0.612 | 0.615 |

Table A: 71. Based Data Classification Models. Gray 6

| | F1 | Precision | Recall |
|---|---|---|---|
| **Color1-5** | 0.613 | 0.614 | 0.616 |
| **Min 9** | 0.612 | 0.612 | 0.614 |
| **Max 9** | 0.612 | 0.611 | 0.614 |
| **Min 16 Max 16** | 0.612 | 0.612 | 0.614 |
| **RGB Mn** | 0.611 | 0.61 | 0.613 |
| **Color1-6** | 0.61 | 0.61 | 0.612 |
| **Max 16** | 0.61 | 0.61 | 0.612 |
| **Gray Mn, RGB Mn** | 0.609 | 0.608 | 0.611 |
| **Gray Sd, RGB Sd** | 0.609 | 0.609 | 0.612 |
| **RGB Mn, RGB Sd** | 0.609 | 0.609 | 0.612 |
| **Min 16** | 0.608 | 0.608 | 0.61 |
| **Min 9 Max 9** | 0.608 | 0.608 | 0.61 |
| **RGB Sd** | 0.607 | 0.607 | 0.61 |
| **Gray Mn, RGB Mn, Gray Sd, RGB Sd** | 0.606 | 0.606 | 0.609 |
| **Heat** | 0.606 | 0.606 | 0.608 |
| **Color1-7** | 0.604 | 0.604 | 0.607 |

Table A: 72. Based Data Classification Models. Gray 6

| | F1 | Precision | Recall |
|---|---|---|---|
| **Color1-8** | 0.601 | 0.601 | 0.604 |
| **Color1-10** | 0.601 | 0.601 | 0.605 |
| **Color1-9** | 0.599 | 0.599 | 0.603 |

Table A: 73. Based Data Classification Models. Gray 7

| | F1 | Precision | Recall |
|---|---|---|---|
| **DescNg, DescNeu, DescPs** | 0.658 | 0.66 | 0.662 |
| **BioNg, BioPs BioWC, DescWC** | 0.643 | 0.648 | 0.646 |
| **BioNg, BioPs, Dominance** | 0.642 | 0.65 | 0.646 |
| **Facebook, Twitter, Instagram, Weight** | 0.642 | 0.642 | 0.646 |
| **Dominance** | 0.636 | 0.643 | 0.642 |
| **Gray Mn, Gray Sd** | 0.634 | 0.64 | 0.637 |
| **DescNg, DescPs** | 0.634 | 0.635 | 0.637 |
| **BioWC, DescWC, Gray Sd** | 0.634 | 0.642 | 0.637 |
| **BioWC, DescWC, RGB Sd** | 0.634 | 0.645 | 0.637 |
| **BioWC, DescWC, Pleasure** | 0.634 | 0.641 | 0.637 |
| **Facebook, Twitter, Instagram, Dominance** | 0.633 | 0.64 | 0.637 |
| **Facebook, Twitter, Instagram, Activity** | 0.632 | 0.633 | 0.637 |
| **BioWC, DescWC Facebook, Twitter, Instagram** | 0.631 | 0.64 | 0.633 |
| **BioWC, DescWC, Activity** | 0.63 | 0.646 | 0.633 |
| **BioNg, BioPs** | 0.629 | 0.631 | 0.633 |
| **BioWC, DescWC, Gray Sd, RGB Sd** | 0.628 | 0.633 | 0.633 |

Table A: 74. Based Data Classification Models. Gray 7

| | F1 | Precision | Recall |
|---|---|---|---|
| **BioNg, BioPs, Activity** | 0.628 | 0.639 | 0.633 |
| **BioWC, DescWC, Heat** | 0.627 | 0.631 | 0.633 |
| **Bio Word Count, Desc Word Count** | 0.626 | 0.631 | 0.629 |
| **BioWC, DescWC, PAD** | 0.626 | 0.632 | 0.629 |
| **Base Features** | 0.625 | 0.628 | 0.629 |
| **Gray Sd** | 0.625 | 0.631 | 0.629 |
| **BioWC, DescWC, Gray Mn** | 0.623 | 0.63 | 0.625 |
| **BioWC, DescWC, Color1** | 0.622 | 0.637 | 0.629 |
| **Facebook, Twitter, Instagram, Gray Mn** | 0.621 | 0.63 | 0.625 |
| **Facebook, Twitter, Instagram, Gray Sd** | 0.621 | 0.628 | 0.625 |
| **Min 9 Max 9** | 0.621 | 0.628 | 0.625 |
| **Gray Sd, RGB Sd** | 0.62 | 0.626 | 0.625 |
| **Min 9** | 0.62 | 0.632 | 0.625 |
| **Pleasure** | 0.62 | 0.622 | 0.625 |
| **Weight** | 0.62 | 0.621 | 0.625 |
| **Facebook, Twitter, Instagram, Color1** | 0.619 | 0.63 | 0.625 |

Table A: 75. Based Data Classification Models. Gray 7

| | F1 | Precision | Recall |
|---|---|---|---|
| **BioWC, DescWC, Weight** | 0.617 | 0.62 | 0.621 |
| **Title WC** | 0.617 | 0.621 | 0.621 |
| **Pleasure, Arousal, Dominance** | 0.616 | 0.627 | 0.621 |
| **BioNg, BioPs, Weight** | 0.616 | 0.621 | 0.621 |
| **BioWC, DescWC, Dominance** | 0.615 | 0.622 | 0.621 |
| **BioWC, DescWC, Min 9 Max 9** | 0.614 | 0.617 | 0.617 |
| **BioWC, DescWC, Arousal** | 0.614 | 0.619 | 0.617 |
| **Facebook, Twitter, Instagram, Pleasure** | 0.614 | 0.619 | 0.621 |
| **BioWC, DescWC, AWH** | 0.609 | 0.613 | 0.613 |
| **BioNg, BioPs, Min 9 Max 9** | 0.609 | 0.614 | 0.613 |
| **BioWC, DescWC, Color RGB Mn, Color RGB Sd** | 0.608 | 0.611 | 0.613 |
| **Arousal** | 0.608 | 0.618 | 0.608 |
| **Facebook, Twitter, Instagram** | 0.607 | 0.611 | 0.613 |
| **BioNg, BioPs, Gray Sd, RGB Sd** | 0.607 | 0.618 | 0.613 |
| **Facebook, Twitter, Instagram, Gray Mn, RGB Mn, Sd** | 0.606 | 0.61 | 0.613 |
| **BioNg, BioPs, RGB Sd** | 0.605 | 0.609 | 0.608 |

Table A: 76. Based Data Classification Models. Gray 7

| | F1 | Precision | Recall |
|---|---|---|---|
| **BioNg, BioPs Facebook, Twitter, Instagram** | 0.605 | 0.613 | 0.608 |
| **BioNg, BioNeu, BioPs** | 0.605 | 0.611 | 0.608 |
| **BioWC, DescWC, Color Gray Mn, Color Gray Sd** | 0.604 | 0.607 | 0.608 |
| **Facebook, Twitter, Instagram, RGB Mn** | 0.604 | 0.614 | 0.608 |
| **Min 16** | 0.604 | 0.609 | 0.608 |
| **Heat** | 0.604 | 0.61 | 0.608 |
| **BioWC, DescWC, Gray Mn, RGB Mn** | 0.603 | 0.621 | 0.613 |
| **Facebook, Twitter, Instagram, Gray Mn, Gray Sd** | 0.603 | 0.614 | 0.608 |
| **BioWC, DescWC, Min 16 Max 16** | 0.603 | 0.616 | 0.608 |
| **BioNg, BioPs, Gray Mn, Gray Sd** | 0.602 | 0.603 | 0.608 |
| **Activity** | 0.602 | 0.607 | 0.608 |
| **RGB Sd** | 0.601 | 0.605 | 0.604 |
| **Facebook, Twitter, Instagram, PAD** | 0.601 | 0.603 | 0.608 |
| **BioNg, BioPs, Gray Sd** | 0.6 | 0.605 | 0.604 |
| **BioNg, BioPs, Pleasure** | 0.6 | 0.609 | 0.604 |
| **BioNg, BioPs, AWH** | 0.599 | 0.599 | 0.608 |

Table A: 77. Based Data Classification Models. Gray 7

| | F1 | Precision | Recall |
|---|---|---|---|
| **BioNg, BioPs, Color1-2** | 0.599 | 0.609 | 0.604 |
| **Facebook, Twitter, Instagram, Gray Sd, RGB Sd** | 0.599 | 0.603 | 0.604 |
| **Max 9** | 0.599 | 0.61 | 0.604 |
| **Gray Mn, RGB Mn** | 0.598 | 0.598 | 0.604 |
| **BioNg, BioPs, PAD** | 0.598 | 0.604 | 0.604 |
| **Facebook, Twitter, Instagram, Min 9 Max 9** | 0.597 | 0.605 | 0.6 |
| **BioNg, BioPs, Heat** | 0.597 | 0.601 | 0.604 |
| **Gray Mn** | 0.596 | 0.6 | 0.604 |
| **Facebook, Twitter, Instagram, RGB Mn, RGB Sd** | 0.596 | 0.604 | 0.604 |
| **Facebook, Twitter, Instagram, Min 16 Max 16** | 0.596 | 0.61 | 0.604 |
| **Facebook, Twitter, Instagram, Arousal** | 0.595 | 0.598 | 0.6 |
| **BioNg, BioPs, Arousal** | 0.594 | 0.605 | 0.6 |
| **BioWC, DescWC, RGB Mn** | 0.593 | 0.601 | 0.6 |
| **BioNg, BioPs, Min 16 Max 16** | 0.593 | 0.608 | 0.596 |
| **Facebook, Twitter, Instagram, Color1-2** | 0.592 | 0.599 | 0.596 |
| **BioNg, BioPs, Gray Mn, RGB Mn** | 0.591 | 0.6 | 0.6 |

Table A: 78. Based Data Classification Models. Gray 7

| | F1 | Precision | Recall |
|---|---|---|---|
| **BioNg, BioPs, Color1** | 0.591 | 0.593 | 0.596 |
| **BioWC, DescWC, Color1-8** | 0.591 | 0.613 | 0.596 |
| **Facebook, Twitter, Instagram, Heat** | 0.59 | 0.593 | 0.596 |
| **BioNg, BioPs, Gray Mn** | 0.589 | 0.594 | 0.596 |
| **Min 16 Max 16** | 0.589 | 0.592 | 0.592 |
| **Color1** | 0.588 | 0.595 | 0.592 |
| **BioWC, DescWC, Color1-4** | 0.588 | 0.59 | 0.592 |
| **BioNg, BioPs, Gray Mn, RGB Mn, Gray Sd, RGB Sd** | 0.586 | 0.594 | 0.596 |
| **BioWC, DescWC, Color1-3** | 0.586 | 0.591 | 0.592 |
| **BioNeg, BioPs, RGB Mn** | 0.585 | 0.589 | 0.592 |
| **BioWC, DescWC, Color1-2** | 0.584 | 0.591 | 0.588 |
| **Facebook, Twitter, Instagram, Color1-7** | 0.584 | 0.597 | 0.592 |
| **Activity, Weight, Heat** | 0.581 | 0.588 | 0.588 |
| **Facebook, Twitter, Instagram, Color1-9** | 0.581 | 0.603 | 0.588 |
| **BioWC, DescWC, Color1-5** | 0.58 | 0.595 | 0.583 |
| **Facebook, Twitter, Instagram, AWH** | 0.58 | 0.584 | 0.588 |

Table A: 79. Based Data Classification Models. Gray 7

| | F1 | Precision | Recall |
|---|---|---|---|
| **Color1-2** | 0.578 | 0.587 | 0.583 |
| **BioWC, DescWC, Gray Mn, RGB Mn, Gray Sd, RGB Sd** | 0.578 | 0.581 | 0.583 |
| **RGB Mn** | 0.577 | 0.579 | 0.588 |
| **Facebook, Twitter, Instagram, RGB Sd** | 0.577 | 0.582 | 0.583 |
| **RGB Mn, RGB Sd** | 0.576 | 0.583 | 0.583 |
| **BioNg, BioPs, Color1-3** | 0.576 | 0.582 | 0.583 |
| **Gray Mn, RGB Mn, Gray Sd, RGB Sd** | 0.575 | 0.583 | 0.579 |
| **Color1-4** | 0.574 | 0.578 | 0.579 |
| **BioWC, DescWC, Color1-6** | 0.574 | 0.594 | 0.579 |
| **BioNg, BioPs, Color1-4** | 0.572 | 0.587 | 0.579 |
| **BioNg, BioPs, RGB Mn, RGB Sd** | 0.571 | 0.584 | 0.579 |
| **BioNg, BioPs, Color1-5** | 0.57 | 0.576 | 0.575 |
| **Max 16** | 0.57 | 0.576 | 0.575 |
| **Color1-9** | 0.569 | 0.58 | 0.579 |
| **Facebook, Twitter, Instagram, Color1-5** | 0.567 | 0.579 | 0.575 |
| **BioNg, BioPs, Color1-6** | 0.566 | 0.576 | 0.575 |

Table A: 80. Based Data Classification Models. Gray 7

| | F1 | Precision | Recall |
|---|---|---|---|
| **Color1-10** | 0.565 | 0.581 | 0.575 |
| **Facebook, Twitter, Instagram, Color1-3** | 0.565 | 0.572 | 0.571 |
| **BioNg, BioPs, Color1-7** | 0.562 | 0.57 | 0.571 |
| **Color1-8** | 0.56 | 0.586 | 0.571 |
| **Facebook, Twitter, Instagram, Color1-10** | 0.56 | 0.575 | 0.571 |
| **Facebook, Twitter, Instagram, Gray Mn, RGB Mn** | 0.558 | 0.571 | 0.567 |
| **Facebook, Twitter, Instagram, Color1-6** | 0.558 | 0.565 | 0.562 |
| **BioWC, DescWC, Color1-9** | 0.555 | 0.573 | 0.562 |
| **Facebook, Twitter, Instagram, Color1-8** | 0.555 | 0.568 | 0.567 |
| **Color1-7** | 0.554 | 0.573 | 0.567 |
| **Color1-5** | 0.553 | 0.558 | 0.558 |
| **BioWC, DescWC, Color1-10** | 0.553 | 0.565 | 0.562 |
| **BioWC, DescWC, Color1-7** | 0.552 | 0.562 | 0.562 |
| **BioNg, BioPs, Color1-10** | 0.548 | 0.563 | 0.558 |
| **Color1-3** | 0.547 | 0.555 | 0.55 |
| **Color1-6** | 0.543 | 0.547 | 0.554 |

Table A: 81. Based Data Classification Models. Gray 7

| | F1 | Precision | Recall |
|---|---|---|---|
| **Facebook, Twitter, Instagram, Color1-4** | 0.541 | 0.551 | 0.546 |
| **BioNg, BioPs, Color1-8** | 0.536 | 0.551 | 0.546 |
| **BioNg, BioPs, Color1-9** | 0.532 | 0.551 | 0.546 |

Table A: 82. Based Data Classification Models. Gray 8

| | F1 | Precision | Recall |
|---|---|---|---|
| **BioNg, BioPs BioWC, DescWC** | 0.614 | 0.613 | 0.616 |
| **BioNg, BioPs Facebook, Twitter, Instagram** | 0.602 | 0.601 | 0.603 |
| **BioWC, DescWC Facebook, Twitter, Instagram** | 0.598 | 0.597 | 0.599 |
| **BioNg, BioNeu, BioPs** | 0.595 | 0.594 | 0.597 |
| **BioNg, BioPs, Pleasure** | 0.586 | 0.585 | 0.588 |
| **BioNg, BioPs, Arousal** | 0.586 | 0.585 | 0.588 |
| **BioNg, BioPs** | 0.585 | 0.584 | 0.587 |
| **BioNg, BioPs, Gray Mn** | 0.585 | 0.584 | 0.587 |
| **BioNg, BioPs, Dominance** | 0.585 | 0.584 | 0.587 |
| **BioNg, BioPs, Weight** | 0.585 | 0.584 | 0.586 |
| **BioNg, BioPs, Gray Sd** | 0.584 | 0.583 | 0.585 |
| **BioNg, BioPs, Color1** | 0.584 | 0.583 | 0.586 |
| **BioNg, BioPs, Activity** | 0.583 | 0.582 | 0.585 |
| **BioNg, BioPs, Gray Mn, Gray Sd** | 0.582 | 0.581 | 0.584 |
| **BioNg, BioPs, Min 16 Max 16** | 0.582 | 0.58 | 0.584 |
| **BioNg, BioPs, Color1-2** | 0.581 | 0.58 | 0.583 |

Table A: 83. Based Data Classification Models. Gray 8

| | F1 | Precision | Recall |
|---|---|---|---|
| **BioNg, BioPs, Min 9 Max 9** | 0.581 | 0.58 | 0.583 |
| **BioNg, BioPs, Heat** | 0.581 | 0.58 | 0.583 |
| **BioNg, BioPs, PAD** | 0.578 | 0.577 | 0.581 |
| **BioNeg, BioPs, RGB Mn** | 0.578 | 0.577 | 0.58 |
| **BioNg, BioPs, Color1-3** | 0.578 | 0.577 | 0.58 |
| **BioNg, BioPs, AWH** | 0.577 | 0.576 | 0.579 |
| **BioNg, BioPs, Color1-4** | 0.577 | 0.576 | 0.579 |
| **BioNg, BioPs, Gray Mn, RGB Mn** | 0.575 | 0.574 | 0.577 |
| **Bio Word Count, Desc Word Count** | 0.574 | 0.573 | 0.576 |
| **BioNg, BioPs, RGB Sd** | 0.574 | 0.573 | 0.576 |
| **BioWC, DescWC, Pleasure** | 0.573 | 0.572 | 0.575 |
| **BioWC, DescWC, Activity** | 0.573 | 0.572 | 0.575 |
| **BioNg, BioPs, Color1-5** | 0.572 | 0.571 | 0.574 |
| **BioWC, DescWC, Color1** | 0.572 | 0.571 | 0.574 |
| **BioWC, DescWC, Arousal** | 0.572 | 0.571 | 0.574 |
| **BioWC, DescWC, Dominance** | 0.572 | 0.571 | 0.575 |

Table A: 84. Based Data Classification Models. Gray 8

| | F1 | Precision | Recall |
|---|---|---|---|
| **BioNg, BioPs, Gray Sd, RGB Sd** | 0.571 | 0.57 | 0.573 |
| **BioNg, BioPs, RGB Mn, RGB Sd** | 0.571 | 0.57 | 0.574 |
| **BioNg, BioPs, Color1-6** | 0.571 | 0.57 | 0.574 |
| **BioWC, DescWC, Gray Mn** | 0.571 | 0.57 | 0.573 |
| **BioWC, DescWC, Gray Sd** | 0.571 | 0.57 | 0.573 |
| **BioWC, DescWC, Color Gray Mn, Color Gray Sd** | 0.57 | 0.569 | 0.572 |
| **BioWC, DescWC, Weight** | 0.57 | 0.569 | 0.572 |
| **BioWC, DescWC, Min 16 Max 16** | 0.569 | 0.568 | 0.571 |
| **BioWC, DescWC, Heat** | 0.569 | 0.567 | 0.571 |
| **BioWC, DescWC, Color1-2** | 0.568 | 0.567 | 0.571 |
| **BioNg, BioPs, Color1-7** | 0.566 | 0.565 | 0.569 |
| **BioWC, DescWC, Color1-3** | 0.566 | 0.564 | 0.568 |
| **BioWC, DescWC, Min 9 Max 9** | 0.565 | 0.563 | 0.567 |
| **BioWC, DescWC, PAD** | 0.564 | 0.562 | 0.566 |
| **BioNg, BioPs, Gray Mn, RGB Mn, Gray Sd, RGB Sd** | 0.563 | 0.562 | 0.566 |
| **BioNg, BioPs, Color1-8** | 0.563 | 0.562 | 0.566 |

Table A: 85. Based Data Classification Models. Gray 8

| | F1 | Precision | Recall |
|---|---|---|---|
| **BioWC, DescWC, AWH** | 0.563 | 0.562 | 0.566 |
| **BioWC, DescWC, RGB Mn** | 0.563 | 0.562 | 0.566 |
| **BioWC, DescWC, Gray Mn, RGB Mn** | 0.561 | 0.56 | 0.563 |
| **BioWC, DescWC, RGB Sd** | 0.561 | 0.559 | 0.563 |
| **BioWC, DescWC, Color1-4** | 0.56 | 0.559 | 0.563 |
| **BioNg, BioPs, Color1-9** | 0.559 | 0.558 | 0.562 |
| **BioNg, BioPs, Color1-10** | 0.559 | 0.558 | 0.562 |
| **BioWC, DescWC, Color1-5** | 0.558 | 0.557 | 0.561 |
| **BioWC, DescWC, Gray Sd, RGB Sd** | 0.556 | 0.554 | 0.558 |
| **BioWC, DescWC, Color1-6** | 0.554 | 0.553 | 0.557 |
| **BioWC, DescWC, Color RGB Mn, Color RGB Sd** | 0.552 | 0.551 | 0.555 |
| **BioWC, DescWC, Color1-7** | 0.549 | 0.548 | 0.552 |
| **BioWC, DescWC, Color1-8** | 0.548 | 0.547 | 0.551 |
| **BioWC, DescWC, Gray Mn, RGB Mn, Gray Sd, RGB Sd** | 0.547 | 0.546 | 0.55 |
| **BioWC, DescWC, Color1-9** | 0.544 | 0.542 | 0.547 |
| **BioWC, DescWC, Color1-10** | 0.538 | 0.537 | 0.542 |

Table A: 86. Based Data Classification Models. Gray 8

| | F1 | Precision | Recall |
|---|---|---|---|
| **Facebook, Twitter, Instagram, Color1** | 0.532 | 0.53 | 0.534 |
| **Facebook, Twitter, Instagram, Gray Mn** | 0.531 | 0.53 | 0.534 |
| **Facebook, Twitter, Instagram, Dominance** | 0.531 | 0.53 | 0.534 |
| **Facebook, Twitter, Instagram, Color1-2** | 0.53 | 0.528 | 0.532 |
| **Facebook, Twitter, Instagram, Gray Sd** | 0.529 | 0.527 | 0.531 |
| **Facebook, Twitter, Instagram, Gray Mn, Gray Sd** | 0.529 | 0.527 | 0.532 |
| **Facebook, Twitter, Instagram, Arousal** | 0.529 | 0.527 | 0.531 |
| **Facebook, Twitter, Instagram, Weight** | 0.529 | 0.527 | 0.532 |
| **Facebook, Twitter, Instagram, Pleasure** | 0.528 | 0.527 | 0.531 |
| **Facebook, Twitter, Instagram, Activity** | 0.527 | 0.526 | 0.53 |
| **Facebook, Twitter, Instagram** | 0.526 | 0.525 | 0.528 |
| **Facebook, Twitter, Instagram, PAD** | 0.526 | 0.525 | 0.53 |
| **Facebook, Twitter, Instagram, Color1-3** | 0.526 | 0.524 | 0.529 |
| **Facebook, Twitter, Instagram, RGB Mn** | 0.525 | 0.524 | 0.528 |
| **Facebook, Twitter, Instagram, Min 9 Max 9** | 0.525 | 0.523 | 0.528 |
| **Facebook, Twitter, Instagram, Min 16 Max 16** | 0.524 | 0.522 | 0.527 |

Table A: 87. Based Data Classification Models. Gray 8

| | F1 | Precision | Recall |
|---|---|---|---|
| **Facebook, Twitter, Instagram, AWH** | 0.523 | 0.522 | 0.526 |
| **Facebook, Twitter, Instagram, Gray Mn, RGB Mn** | 0.522 | 0.52 | 0.525 |
| **Facebook, Twitter, Instagram, Color1-4** | 0.522 | 0.521 | 0.525 |
| **Facebook, Twitter, Instagram, Heat** | 0.522 | 0.52 | 0.524 |
| **Facebook, Twitter, Instagram, RGB Mn, RGB Sd** | 0.521 | 0.519 | 0.525 |
| **Facebook, Twitter, Instagram, Color1-5** | 0.521 | 0.519 | 0.524 |
| **Facebook, Twitter, Instagram, RGB Sd** | 0.519 | 0.517 | 0.522 |
| **Facebook, Twitter, Instagram, Gray Sd, RGB Sd** | 0.518 | 0.517 | 0.522 |
| **DescNg, DescNeu, DescPs** | 0.518 | 0.517 | 0.521 |
| **DescNg, DescPs** | 0.516 | 0.514 | 0.519 |
| **Facebook, Twitter, Instagram, Color1-6** | 0.516 | 0.514 | 0.52 |
| **Facebook, Twitter, Instagram, Gray Mn, RGB Mn, Sd** | 0.513 | 0.512 | 0.517 |
| **Facebook, Twitter, Instagram, Color1-7** | 0.513 | 0.512 | 0.517 |
| **Facebook, Twitter, Instagram, Color1-8** | 0.511 | 0.51 | 0.516 |
| **Facebook, Twitter, Instagram, Color1-9** | 0.507 | 0.505 | 0.511 |
| **Facebook, Twitter, Instagram, Color1-10** | 0.504 | 0.503 | 0.509 |

Table A: 88. Based Data Classification Models. Gray 8

| | F1 | Precision | Recall |
|---|---|---|---|
| **Title WC** | 0.49 | 0.488 | 0.493 |
| **Gray Mn, Gray Sd** | 0.48 | 0.478 | 0.483 |
| **Color1-2** | 0.48 | 0.478 | 0.482 |
| **RGB Mn** | 0.478 | 0.476 | 0.481 |
| **Color1-3** | 0.477 | 0.476 | 0.48 |
| **Pleasure, Arousal, Dominance** | 0.475 | 0.473 | 0.478 |
| **Gray Mn** | 0.475 | 0.473 | 0.478 |
| **RGB Mn, RGB Sd** | 0.475 | 0.473 | 0.479 |
| **Dominance** | 0.475 | 0.473 | 0.478 |
| **Gray Sd** | 0.474 | 0.472 | 0.477 |
| **Color1** | 0.474 | 0.473 | 0.477 |
| **Color1-4** | 0.474 | 0.472 | 0.477 |
| **Weight** | 0.474 | 0.473 | 0.477 |
| **Activity, Weight, Heat** | 0.473 | 0.472 | 0.477 |
| **Gray Mn, RGB Mn** | 0.473 | 0.471 | 0.476 |
| **Pleasure** | 0.473 | 0.471 | 0.476 |

Table A: 89. Based Data Classification Models. Gray 8

| | F1 | Precision | Recall |
|---|---|---|---|
| **Activity** | 0.472 | 0.47 | 0.475 |
| **Color1-5** | 0.471 | 0.469 | 0.475 |
| **Max 16** | 0.471 | 0.469 | 0.474 |
| **Min 16 Max 16** | 0.471 | 0.469 | 0.474 |
| **Arousal** | 0.471 | 0.469 | 0.474 |
| **Color1-6** | 0.47 | 0.468 | 0.474 |
| **Max 9** | 0.47 | 0.468 | 0.473 |
| **Gray Mn, RGB Mn, Gray Sd, RGB Sd** | 0.469 | 0.467 | 0.473 |
| **Min 16** | 0.469 | 0.468 | 0.472 |
| **Min 9** | 0.468 | 0.466 | 0.471 |
| **Min 9 Max 9** | 0.468 | 0.466 | 0.471 |
| **Base Features** | 0.467 | 0.465 | 0.469 |
| **Color1-7** | 0.467 | 0.465 | 0.471 |
| **RGB Sd** | 0.466 | 0.464 | 0.47 |
| **Gray Sd, RGB Sd** | 0.464 | 0.462 | 0.468 |
| **Color1-8** | 0.464 | 0.462 | 0.468 |

Table A: 90 Based Data Classification Models. Gray 8

| | F1 | Precision | Recall |
|---|---|---|---|
| **Heat** | 0.464 | 0.462 | 0.466 |
| **Color1-9** | 0.46 | 0.458 | 0.464 |
| **Color1-10** | 0.459 | 0.457 | 0.464 |

Table A: 91. Based Data Classification Models. Gray 9

| | F1 | Precision | Recall |
|---|---|---|---|
| **BioNg, BioPs BioWC, DescWC** | 0.612 | 0.61 | 0.614 |
| **BioWC, DescWC Facebook, Twitter, Instagram** | 0.604 | 0.603 | 0.606 |
| **BioWC, DescWC, Gray Mn** | 0.599 | 0.598 | 0.601 |
| **BioNg, BioPs Facebook, Twitter, Instagram** | 0.599 | 0.597 | 0.601 |
| **BioNg, BioPs, Color1** | 0.598 | 0.597 | 0.6 |
| **BioNg, BioPs, Min 16 Max 16** | 0.598 | 0.597 | 0.6 |
| **BioWC, DescWC, Activity** | 0.598 | 0.598 | 0.6 |
| **BioNg, BioPs, Gray Mn** | 0.597 | 0.596 | 0.6 |
| **BioWC, DescWC, Color Gray Mn, Color Gray Sd** | 0.597 | 0.597 | 0.599 |
| **BioNg, BioPs, Min 9 Max 9** | 0.597 | 0.596 | 0.599 |
| **BioNg, BioPs, Activity** | 0.597 | 0.597 | 0.6 |
| **BioWC, DescWC, Heat** | 0.597 | 0.597 | 0.599 |
| **BioNg, BioNeu, BioPs** | 0.597 | 0.596 | 0.599 |
| **Bio Word Count, Desc Word Count** | 0.596 | 0.595 | 0.598 |
| **BioNg, BioPs, PAD** | 0.596 | 0.595 | 0.599 |
| **BioNg, BioPs, Color1-2** | 0.596 | 0.595 | 0.599 |

Table A: 92. Based Data Classification Models. Gray 9

| | F1 | Precision | Recall |
|---|---|---|---|
| **BioWC, DescWC, Min 16 Max 16** | 0.596 | 0.597 | 0.599 |
| **BioWC, DescWC, Arousal** | 0.596 | 0.595 | 0.598 |
| **BioWC, DescWC, Dominance** | 0.596 | 0.596 | 0.598 |
| **BioNeg, BioPs, RGB Mn** | 0.595 | 0.594 | 0.598 |
| **BioNg, BioPs, Gray Mn, Gray Sd** | 0.595 | 0.598 | 0.598 |
| **BioWC, DescWC, Gray Sd** | 0.595 | 0.594 | 0.597 |
| **BioNg, BioPs, Arousal** | 0.595 | 0.594 | 0.598 |
| **BioNg, BioPs, Heat** | 0.595 | 0.594 | 0.597 |
| **BioNg, BioPs, RGB Sd** | 0.594 | 0.594 | 0.597 |
| **BioNg, BioPs, RGB Mn, RGB Sd** | 0.594 | 0.593 | 0.596 |
| **BioNg, BioPs, Dominance** | 0.594 | 0.593 | 0.596 |
| **BioWC, DescWC, Pleasure** | 0.594 | 0.594 | 0.597 |
| **BioNg, BioPs** | 0.593 | 0.592 | 0.595 |
| **BioNg, BioPs, AWH** | 0.593 | 0.593 | 0.596 |
| **BioNg, BioPs, Gray Sd** | 0.593 | 0.592 | 0.595 |
| **BioWC, DescWC, AWH** | 0.593 | 0.594 | 0.596 |

Table A: 93. Based Data Classification Models. Gray 9

| | F1 | Precision | Recall |
|---|---|---|---|
| **BioWC, DescWC, Color1** | 0.593 | 0.593 | 0.595 |
| **BioWC, DescWC, Color1-2** | 0.593 | 0.593 | 0.595 |
| **BioWC, DescWC, Min 9 Max 9** | 0.593 | 0.593 | 0.595 |
| **BioNg, BioPs, Pleasure** | 0.593 | 0.591 | 0.595 |
| **BioNg, BioPs, Weight** | 0.593 | 0.592 | 0.595 |
| **BioWC, DescWC, Color1-3** | 0.592 | 0.592 | 0.594 |
| **BioWC, DescWC, Weight** | 0.592 | 0.591 | 0.594 |
| **BioNg, BioPs, Gray Sd, RGB Sd** | 0.591 | 0.59 | 0.594 |
| **BioNg, BioPs, Color1-4** | 0.591 | 0.59 | 0.593 |
| **BioNg, BioPs, Color1-5** | 0.591 | 0.591 | 0.594 |
| **BioWC, DescWC, RGB Mn** | 0.591 | 0.591 | 0.593 |
| **BioNg, BioPs, Color1-3** | 0.59 | 0.59 | 0.593 |
| **BioWC, DescWC, Gray Mn, RGB Mn** | 0.59 | 0.59 | 0.592 |
| **BioWC, DescWC, Color1-4** | 0.59 | 0.591 | 0.593 |
| **BioWC, DescWC, Color1-5** | 0.59 | 0.591 | 0.593 |
| **BioWC, DescWC, PAD** | 0.589 | 0.589 | 0.592 |

Table A: 94. Based Data Classification Models. Gray 9

| | F1 | Precision | Recall |
|---|---|---|---|
| **BioWC, DescWC, RGB Sd** | 0.589 | 0.59 | 0.591 |
| **BioNg, BioPs, Gray Mn, RGB Mn** | 0.588 | 0.587 | 0.591 |
| **BioWC, DescWC, Color RGB Mn, Color RGB Sd** | 0.588 | 0.589 | 0.59 |
| **BioNg, BioPs, Color1-6** | 0.587 | 0.587 | 0.59 |
| **BioNg, BioPs, Gray Mn, RGB Mn, Gray Sd, RGB Sd** | 0.586 | 0.586 | 0.589 |
| **BioNg, BioPs, Color1-7** | 0.586 | 0.586 | 0.589 |
| **BioWC, DescWC, Gray Sd, RGB Sd** | 0.584 | 0.584 | 0.586 |
| **BioWC, DescWC, Gray Mn, RGB Mn, Gray Sd, RGB Sd** | 0.584 | 0.585 | 0.587 |
| **BioNg, BioPs, Color1-8** | 0.582 | 0.582 | 0.585 |
| **BioNg, BioPs, Color1-10** | 0.582 | 0.582 | 0.585 |
| **BioNg, BioPs, Color1-9** | 0.581 | 0.58 | 0.584 |
| **BioWC, DescWC, Color1-7** | 0.581 | 0.582 | 0.584 |
| **BioWC, DescWC, Color1-8** | 0.581 | 0.582 | 0.584 |
| **BioWC, DescWC, Color1-6** | 0.58 | 0.58 | 0.583 |
| **BioWC, DescWC, Color1-10** | 0.576 | 0.577 | 0.579 |
| **BioWC, DescWC, Color1-9** | 0.574 | 0.575 | 0.577 |

Table A: 95. Based Data Classification Models. Gray 9

| | F1 | Precision | Recall |
|---|---|---|---|
| Facebook, Twitter, Instagram, Color1 | 0.573 | 0.572 | 0.575 |
| Facebook, Twitter, Instagram, Dominance | 0.57 | 0.57 | 0.572 |
| Facebook, Twitter, Instagram, Activity | 0.57 | 0.569 | 0.572 |
| Facebook, Twitter, Instagram, AWH | 0.569 | 0.569 | 0.571 |
| Facebook, Twitter, Instagram, Gray Mn | 0.569 | 0.569 | 0.572 |
| Facebook, Twitter, Instagram, Gray Sd | 0.569 | 0.568 | 0.571 |
| Facebook, Twitter, Instagram, RGB Mn, RGB Sd | 0.569 | 0.569 | 0.571 |
| Facebook, Twitter, Instagram, Min 16 Max 16 | 0.569 | 0.569 | 0.571 |
| Facebook, Twitter, Instagram, Arousal | 0.569 | 0.568 | 0.571 |
| Facebook, Twitter, Instagram, Gray Mn, Gray Sd | 0.568 | 0.568 | 0.571 |
| Facebook, Twitter, Instagram, Weight | 0.568 | 0.567 | 0.57 |
| DescNg, DescPs | 0.567 | 0.567 | 0.569 |
| Facebook, Twitter, Instagram, RGB Mn | 0.567 | 0.567 | 0.569 |
| Facebook, Twitter, Instagram, Color1-2 | 0.566 | 0.566 | 0.569 |
| Facebook, Twitter, Instagram, Color1-3 | 0.566 | 0.566 | 0.568 |
| Facebook, Twitter, Instagram, Gray Mn, RGB Mn | 0.565 | 0.565 | 0.568 |

Table A: 96 Based Data Classification Models. Gray 9

| | F1 | Precision | Recall |
|---|---|---|---|
| **Facebook, Twitter, Instagram, Min 9 Max 9** | 0.565 | 0.565 | 0.568 |
| **DescNg, DescNeu, DescPs** | 0.565 | 0.565 | 0.567 |
| **Facebook, Twitter, Instagram** | 0.564 | 0.563 | 0.566 |
| **Facebook, Twitter, Instagram, PAD** | 0.564 | 0.564 | 0.566 |
| **Facebook, Twitter, Instagram, Pleasure** | 0.564 | 0.564 | 0.567 |
| **Facebook, Twitter, Instagram, Heat** | 0.564 | 0.564 | 0.567 |
| **Facebook, Twitter, Instagram, Gray Sd, RGB Sd** | 0.563 | 0.563 | 0.566 |
| **Facebook, Twitter, Instagram, RGB Sd** | 0.563 | 0.563 | 0.565 |
| **Facebook, Twitter, Instagram, Color1-5** | 0.562 | 0.562 | 0.564 |
| **Facebook, Twitter, Instagram, Gray Mn, RGB Mn, Sd** | 0.561 | 0.562 | 0.564 |
| **Facebook, Twitter, Instagram, Color1-4** | 0.561 | 0.561 | 0.563 |
| **Facebook, Twitter, Instagram, Color1-7** | 0.56 | 0.561 | 0.562 |
| **Facebook, Twitter, Instagram, Color1-8** | 0.56 | 0.561 | 0.563 |
| **Facebook, Twitter, Instagram, Color1-6** | 0.557 | 0.558 | 0.56 |
| **Facebook, Twitter, Instagram, Color1-10** | 0.554 | 0.555 | 0.557 |
| **Facebook, Twitter, Instagram, Color1-9** | 0.553 | 0.554 | 0.556 |

Table A: 97. Based Data Classification Models. Gray 9

| | F1 | Precision | Recall |
|---|---|---|---|
| **Title WC** | 0.546 | 0.546 | 0.548 |
| **Gray Mn, Gray Sd** | 0.543 | 0.544 | 0.545 |
| **Activity, Weight, Heat** | 0.542 | 0.543 | 0.544 |
| **Color1-2** | 0.542 | 0.542 | 0.544 |
| **Max 16** | 0.542 | 0.542 | 0.543 |
| **RGB Mn** | 0.541 | 0.542 | 0.543 |
| **Color1** | 0.541 | 0.54 | 0.543 |
| **Gray Mn** | 0.54 | 0.541 | 0.542 |
| **Color1-3** | 0.54 | 0.541 | 0.542 |
| **Arousal** | 0.54 | 0.54 | 0.542 |
| **Activity** | 0.54 | 0.54 | 0.543 |
| **Min 16 Max 16** | 0.539 | 0.539 | 0.541 |
| **Dominance** | 0.539 | 0.539 | 0.541 |
| **RGB Mn, RGB Sd** | 0.538 | 0.54 | 0.541 |
| **Pleasure, Arousal, Dominance** | 0.537 | 0.538 | 0.539 |
| **Gray Mn, RGB Mn, Gray Sd, RGB Sd** | 0.537 | 0.538 | 0.539 |

Table A: 98. Based Data Classification Models. Gray 9

| | F1 | Precision | Recall |
|---|---|---|---|
| **Max 9** | 0.537 | 0.537 | 0.539 |
| **Min 16** | 0.537 | 0.538 | 0.539 |
| **Gray Mn, RGB Mn** | 0.536 | 0.537 | 0.538 |
| **Gray Sd** | 0.536 | 0.536 | 0.539 |
| **Base Features** | 0.535 | 0.535 | 0.537 |
| **RGB Sd** | 0.535 | 0.535 | 0.536 |
| **Weight** | 0.535 | 0.535 | 0.537 |
| **Color1-4** | 0.534 | 0.535 | 0.536 |
| **Color1-5** | 0.534 | 0.536 | 0.536 |
| **Color1-6** | 0.534 | 0.535 | 0.536 |
| **Min 9 Max 9** | 0.534 | 0.534 | 0.536 |
| **Gray Sd, RGB Sd** | 0.533 | 0.534 | 0.535 |
| **Color1-7** | 0.533 | 0.535 | 0.536 |
| **Min 9** | 0.533 | 0.534 | 0.535 |
| **Pleasure** | 0.532 | 0.532 | 0.534 |
| **Heat** | 0.532 | 0.533 | 0.535 |

Table A: 99. Based Data Classification Models. Gray 9

| | F1 | Precision | Recall |
|---|---|---|---|
| **Color1-8** | 0.531 | 0.533 | 0.533 |
| **Color1-9** | 0.527 | 0.529 | 0.53 |
| **Color1-10** | 0.524 | 0.526 | 0.526 |

Table A: 100. Based Data Classification Models. Edge 0

| | F1 | Precision | Recall |
|---|---|---|---|
| **BioNg, BioPs, Arousal** | 0.733 | 0.698 | 0.772 |
| **BioWC, DescWC, Dominance** | 0.732 | 0.695 | 0.774 |
| **BioWC, DescWC, Activity** | 0.729 | 0.691 | 0.773 |
| **BioWC, DescWC, Pleasure** | 0.728 | 0.69 | 0.77 |
| **BioWC, DescWC, Arousal** | 0.728 | 0.689 | 0.773 |
| **BioWC, DescWC, Weight** | 0.726 | 0.688 | 0.769 |
| **BioWC, DescWC, Heat** | 0.725 | 0.684 | 0.77 |
| **Facebook, Twitter, Instagram, Dominance** | 0.718 | 0.682 | 0.758 |
| **Facebook, Twitter, Instagram, Arousal** | 0.708 | 0.671 | 0.75 |
| **Facebook, Twitter, Instagram, Pleasure** | 0.707 | 0.671 | 0.748 |
| **Facebook, Twitter, Instagram, Activity** | 0.707 | 0.67 | 0.749 |
| **Facebook, Twitter, Instagram, Heat** | 0.707 | 0.673 | 0.746 |
| **Facebook, Twitter, Instagram, Weight** | 0.702 | 0.667 | 0.741 |
| **BioNg, BioPs BioWC, DescWC** | 0.6 | 0.599 | 0.602 |
| **BioNg, BioPs Facebook, Twitter, Instagram** | 0.586 | 0.585 | 0.588 |
| **BioWC, DescWC Facebook, Twitter, Instagram** | 0.583 | 0.581 | 0.585 |

Table A: 101. Based Data Classification Models. Edge 0

| | F1 | Precision | Recall |
|---|---|---|---|
| **BioNg, BioNeu, BioPs** | 0.576 | 0.575 | 0.578 |
| **BioNg, BioPs** | 0.567 | 0.565 | 0.569 |
| **BioNg, BioPs, Color1** | 0.565 | 0.563 | 0.567 |
| **BioNg, BioPs, Dominance** | 0.564 | 0.562 | 0.566 |
| **BioNg, BioPs, Pleasure** | 0.563 | 0.561 | 0.565 |
| **BioNg, BioPs, Gray Mn** | 0.562 | 0.561 | 0.565 |
| **BioNg, BioPs, Gray Sd** | 0.562 | 0.561 | 0.565 |
| **BioNg, BioPs, Color1-2** | 0.561 | 0.559 | 0.564 |
| **BioNg, BioPs, Activity** | 0.561 | 0.56 | 0.564 |
| **BioNg, BioPs, Weight** | 0.561 | 0.56 | 0.564 |
| **BioNg, BioPs, Gray Mn, Gray Sd** | 0.56 | 0.558 | 0.562 |
| **BioNg, BioPs, Heat** | 0.559 | 0.558 | 0.562 |
| **BioNg, BioPs, Min 16 Max 16** | 0.558 | 0.557 | 0.561 |
| **BioNg, BioPs, PAD** | 0.557 | 0.555 | 0.56 |
| **BioNg, BioPs, Color1-3** | 0.557 | 0.556 | 0.56 |
| **BioNg, BioPs, Min 9 Max 9** | 0.557 | 0.555 | 0.56 |

Table A: 102. Based Data Classification Models. Edge 0

| | F1 | Precision | Recall |
|---|---|---|---|
| **Bio Word Count, Desc Word Count** | 0.556 | 0.555 | 0.559 |
| **BioNg, BioPs, AWH** | 0.556 | 0.554 | 0.559 |
| **BioNeg, BioPs, RGB Mn** | 0.556 | 0.555 | 0.559 |
| **BioNg, BioPs, RGB Sd** | 0.553 | 0.552 | 0.556 |
| **BioNg, BioPs, Color1-4** | 0.553 | 0.551 | 0.556 |
| **BioWC, DescWC, Gray Mn** | 0.552 | 0.551 | 0.555 |
| **BioWC, DescWC, Color1** | 0.552 | 0.551 | 0.555 |
| **BioNg, BioPs, Gray Mn, RGB Mn** | 0.551 | 0.549 | 0.553 |
| **BioWC, DescWC, Gray Sd** | 0.551 | 0.55 | 0.554 |
| **BioWC, DescWC, Color Gray Mn, Color Gray Sd** | 0.551 | 0.55 | 0.554 |
| **BioWC, DescWC, Color1-2** | 0.549 | 0.547 | 0.552 |
| **BioNg, BioPs, Gray Sd, RGB Sd** | 0.548 | 0.547 | 0.551 |
| **BioNg, BioPs, Color1-5** | 0.548 | 0.547 | 0.552 |
| **BioNg, BioPs, RGB Mn, RGB Sd** | 0.547 | 0.545 | 0.55 |
| **BioNg, BioPs, Color1-6** | 0.547 | 0.545 | 0.55 |
| **BioWC, DescWC, Min 16 Max 16** | 0.546 | 0.545 | 0.55 |

Table A: 103. Based Data Classification Models. Edge 0

| | F1 | Precision | Recall |
|---|---|---|---|
| **BioWC, DescWC, PAD** | 0.545 | 0.543 | 0.548 |
| **BioWC, DescWC, Min 9 Max 9** | 0.545 | 0.544 | 0.548 |
| **BioWC, DescWC, Color1-3** | 0.543 | 0.542 | 0.546 |
| **BioWC, DescWC, RGB Mn** | 0.542 | 0.541 | 0.546 |
| **BioWC, DescWC, Color1-4** | 0.542 | 0.541 | 0.546 |
| **BioNg, BioPs, Color1-7** | 0.541 | 0.54 | 0.545 |
| **BioWC, DescWC, AWH** | 0.54 | 0.539 | 0.544 |
| **BioWC, DescWC, Gray Mn, RGB Mn** | 0.539 | 0.537 | 0.542 |
| **BioNg, BioPs, Color1-8** | 0.538 | 0.536 | 0.542 |
| **BioWC, DescWC, RGB Sd** | 0.538 | 0.536 | 0.541 |
| **BioNg, BioPs, Gray Mn, RGB Mn, Gray Sd, RGB Sd** | 0.537 | 0.535 | 0.541 |
| **BioNg, BioPs, Color1-9** | 0.535 | 0.534 | 0.539 |
| **BioWC, DescWC, Gray Sd, RGB Sd** | 0.535 | 0.534 | 0.539 |
| **BioWC, DescWC, Color1-5** | 0.534 | 0.532 | 0.538 |
| **BioNg, BioPs, Color1-10** | 0.533 | 0.532 | 0.537 |
| **BioWC, DescWC, Color RGB Mn, Color RGB Sd** | 0.532 | 0.531 | 0.536 |

Table A: 104. Based Data Classification Models. Edge 0

| | F1 | Precision | Recall |
|---|---|---|---|
| **BioWC, DescWC, Color1-6** | 0.531 | 0.53 | 0.535 |
| **BioWC, DescWC, Color1-7** | 0.529 | 0.527 | 0.533 |
| **BioWC, DescWC, Color1-8** | 0.524 | 0.522 | 0.528 |
| **BioWC, DescWC, Gray Mn, RGB Mn, Gray Sd, RGB Sd** | 0.523 | 0.521 | 0.527 |
| **BioWC, DescWC, Color1-9** | 0.521 | 0.519 | 0.525 |
| **BioWC, DescWC, Color1-10** | 0.518 | 0.517 | 0.533 |
| **Facebook, Twitter, Instagram, Gray Mn, Gray Sd** | 0.512 | 0.51 | 0.515 |
| **Facebook, Twitter, Instagram, Gray Mn** | 0.511 | 0.509 | 0.514 |
| **Facebook, Twitter, Instagram, Color1** | 0.511 | 0.51 | 0.514 |
| **Facebook, Twitter, Instagram** | 0.509 | 0.507 | 0.511 |
| **Facebook, Twitter, Instagram, Gray Sd** | 0.509 | 0.507 | 0.512 |
| **Facebook, Twitter, Instagram, PAD** | 0.508 | 0.506 | 0.511 |
| **Facebook, Twitter, Instagram, Color1-2** | 0.508 | 0.506 | 0.511 |
| **Facebook, Twitter, Instagram, RGB Mn** | 0.506 | 0.504 | 0.509 |
| **Facebook, Twitter, Instagram, Color1-3** | 0.506 | 0.504 | 0.509 |
| **Facebook, Twitter, Instagram, Min 16 Max 16** | 0.505 | 0.504 | 0.509 |

Table A: 105. Based Data Classification Models. Edge 0

| | F1 | Precision | Recall |
|---|---|---|---|
| **Facebook, Twitter, Instagram, AWH** | 0.504 | 0.502 | 0.508 |
| **Facebook, Twitter, Instagram, Min 9 Max 9** | 0.504 | 0.502 | 0.507 |
| **Facebook, Twitter, Instagram, Color1-4** | 0.503 | 0.502 | 0.507 |
| **Facebook, Twitter, Instagram, Gray Mn, RGB Mn** | 0.501 | 0.499 | 0.504 |
| **DescNg, DescNeu, DescPs** | 0.501 | 0.499 | 0.505 |
| **Facebook, Twitter, Instagram, RGB Sd** | 0.499 | 0.497 | 0.502 |
| **Facebook, Twitter, Instagram, Color1-5** | 0.499 | 0.497 | 0.503 |
| **DescNg, DescPs** | 0.497 | 0.496 | 0.501 |
| **Facebook, Twitter, Instagram, RGB Mn, RGB Sd** | 0.497 | 0.495 | 0.501 |
| **Facebook, Twitter, Instagram, Color1-6** | 0.495 | 0.493 | 0.499 |
| **Facebook, Twitter, Instagram, Gray Sd, RGB Sd** | 0.493 | 0.491 | 0.497 |
| **Facebook, Twitter, Instagram, Color1-7** | 0.492 | 0.49 | 0.496 |
| **Facebook, Twitter, Instagram, Gray Mn, RGB Mn, Sd** | 0.49 | 0.488 | 0.494 |
| **Facebook, Twitter, Instagram, Color1-8** | 0.49 | 0.488 | 0.494 |
| **Facebook, Twitter, Instagram, Color1-9** | 0.487 | 0.485 | 0.492 |
| **Facebook, Twitter, Instagram, Color1-10** | 0.484 | 0.482 | 0.489 |

Table A: 106. Based Data Classification Models. Edge 0

| | F1 | Precision | Recall |
|---|---|---|---|
| **Title WC** | 0.469 | 0.467 | 0.472 |
| **Gray Mn, Gray Sd** | 0.46 | 0.458 | 0.464 |
| **Pleasure, Arousal, Dominance** | 0.458 | 0.456 | 0.461 |
| **Gray Mn** | 0.457 | 0.455 | 0.461 |
| **Color1** | 0.456 | 0.454 | 0.459 |
| **Pleasure** | 0.456 | 0.454 | 0.459 |
| **RGB Mn** | 0.455 | 0.453 | 0.458 |
| **Color1-2** | 0.455 | 0.453 | 0.459 |
| **Color1-3** | 0.455 | 0.453 | 0.459 |
| **Dominance** | 0.455 | 0.453 | 0.459 |
| **Max 16** | 0.454 | 0.451 | 0.457 |
| **Gray Sd** | 0.453 | 0.451 | 0.456 |
| **Color1-4** | 0.453 | 0.45 | 0.457 |
| **Min 16 Max 16** | 0.453 | 0.451 | 0.457 |
| **Arousal** | 0.453 | 0.451 | 0.457 |
| **Weight** | 0.453 | 0.451 | 0.457 |

Table A: 107. Based Data Classification Models. Edge 0

| | F1 | Precision | Recall |
|---|---|---|---|
| **Max 9** | 0.452 | 0.45 | 0.456 |
| **Activity** | 0.452 | 0.45 | 0.456 |
| **Activity, Weight, Heat** | 0.451 | 0.449 | 0.455 |
| **Gray Mn, RGB Mn** | 0.451 | 0.449 | 0.455 |
| **Base Features** | 0.45 | 0.448 | 0.453 |
| **RGB Mn, RGB Sd** | 0.45 | 0.448 | 0.455 |
| **Min 16** | 0.45 | 0.448 | 0.454 |
| **Min 9 Max 9** | 0.45 | 0.448 | 0.454 |
| **Color1-5** | 0.449 | 0.447 | 0.454 |
| **Color1-6** | 0.447 | 0.445 | 0.452 |
| **Gray Mn, RGB Mn, Gray Sd, RGB Sd** | 0.446 | 0.444 | 0.451 |
| **Gray Sd, RGB Sd** | 0.445 | 0.443 | 0.449 |
| **RGB Sd** | 0.445 | 0.443 | 0.449 |
| **Color1-7** | 0.445 | 0.443 | 0.45 |
| **Heat** | 0.445 | 0.443 | 0.449 |
| **Color1-8** | 0.442 | 0.44 | 0.447 |

Table A: 108. Based Data Classification Models. Edge 0

| | F1 | Precision | Recall |
|---|---|---|---|
| **Color1-9** | 0.44 | 0.438 | 0.446 |
| **Color1-10** | 0.437 | 0.435 | 0.443 |
| **Min 9** | 0.0449 | 0.447 | 0.452 |

Table A: 109. Based Data Classification Models. Edge 1

| | F1 | Precision | Recall |
|---|---|---|---|
| **BioWC, DescWC, Gray Mn** | 0.658 | 0.658 | 0.66 |
| **BioWC, DescWC, PAD** | 0.657 | 0.657 | 0.659 |
| **BioWC, DescWC, Weight** | 0.657 | 0.657 | 0.659 |
| **BioWC, DescWC, Arousal** | 0.656 | 0.656 | 0.658 |
| **DescNg, DescNeu, DescPs** | 0.656 | 0.656 | 0.658 |
| **BioWC, DescWC, Color Gray Mn, Color Gray Sd** | 0.655 | 0.654 | 0.657 |
| **BioWC, DescWC, Dominance** | 0.655 | 0.655 | 0.656 |
| **BioWC, DescWC, AWH** | 0.653 | 0.653 | 0.655 |
| **BioWC, DescWC, RGB Mn** | 0.653 | 0.653 | 0.654 |
| **BioWC, DescWC, Color1** | 0.653 | 0.653 | 0.655 |
| **BioWC, DescWC, Min 9 Max 9** | 0.653 | 0.653 | 0.655 |
| **BioWC, DescWC, Pleasure** | 0.653 | 0.653 | 0.655 |
| **BioNg, BioPs BioWC, DescWC** | 0.653 | 0.653 | 0.655 |
| **BioWC, DescWC Facebook, Twitter, Instagram** | 0.653 | 0.652 | 0.654 |
| **BioWC, DescWC, Min 16 Max 16** | 0.652 | 0.652 | 0.654 |
| **BioWC, DescWC, Activity** | 0.652 | 0.652 | 0.654 |

Table A: 110. Based Data Classification Models. Edge 1

| | F1 | Precision | Recall |
|---|---|---|---|
| **BioWC, DescWC, Gray Mn** | 0.658 | 0.658 | 0.66 |
| **BioWC, DescWC, PAD** | 0.657 | 0.657 | 0.659 |
| **BioWC, DescWC, Weight** | 0.657 | 0.657 | 0.659 |
| **BioWC, DescWC, Arousal** | 0.656 | 0.656 | 0.658 |
| **DescNg, DescNeu, DescPs** | 0.656 | 0.656 | 0.658 |
| **BioWC, DescWC, Color Gray Mn, Color Gray Sd** | 0.655 | 0.654 | 0.657 |
| **BioWC, DescWC, Dominance** | 0.655 | 0.655 | 0.656 |
| **BioWC, DescWC, AWH** | 0.653 | 0.653 | 0.655 |
| **BioWC, DescWC, RGB Mn** | 0.653 | 0.653 | 0.654 |
| **BioWC, DescWC, Color1** | 0.653 | 0.653 | 0.655 |
| **BioWC, DescWC, Min 9 Max 9** | 0.653 | 0.653 | 0.655 |
| **BioWC, DescWC, Pleasure** | 0.653 | 0.653 | 0.655 |
| **BioNg, BioPs BioWC, DescWC** | 0.653 | 0.653 | 0.655 |
| **BioWC, DescWC Facebook, Twitter, Instagram** | 0.653 | 0.652 | 0.654 |
| **BioWC, DescWC, Min 16 Max 16** | 0.652 | 0.652 | 0.654 |
| **BioWC, DescWC, Activity** | 0.652 | 0.652 | 0.654 |

Table A: 111. Based Data Classification Models. Edge 1

| | F1 | Precision | Recall |
|---|---|---|---|
| **BioWC, DescWC, Gray Mn, RGB Mn** | 0.651 | 0.651 | 0.653 |
| **BioWC, DescWC, Color1-2** | 0.651 | 0.651 | 0.653 |
| **Bio Word Count, Desc Word Count** | 0.65 | 0.649 | 0.651 |
| **BioWC, DescWC, Gray Sd** | 0.649 | 0.649 | 0.651 |
| **BioWC, DescWC, Color RGB Mn, Color RGB Sd** | 0.649 | 0.65 | 0.651 |
| **BioWC, DescWC, RGB Sd** | 0.648 | 0.648 | 0.65 |
| **BioWC, DescWC, Color1-3** | 0.648 | 0.647 | 0.65 |
| **BioWC, DescWC, Heat** | 0.648 | 0.648 | 0.649 |
| **BioWC, DescWC, Color1-4** | 0.647 | 0.647 | 0.65 |
| **BioWC, DescWC, Color1-5** | 0.646 | 0.646 | 0.648 |
| **DescNg, DescPs** | 0.644 | 0.644 | 0.645 |
| **BioWC, DescWC, Gray Sd, RGB Sd** | 0.643 | 0.643 | 0.646 |
| **BioWC, DescWC, Color1-6** | 0.643 | 0.643 | 0.645 |
| **BioWC, DescWC, Gray Mn, RGB Mn, Gray Sd, RGB Sd** | 0.642 | 0.643 | 0.644 |
| **BioWC, DescWC, Color1-7** | 0.642 | 0.641 | 0.644 |
| **BioWC, DescWC, Color1-8** | 0.642 | 0.643 | 0.645 |

Table A: 112. Based Data Classification Models. Edge 1

| | F1 | Precision | Recall |
|---|---|---|---|
| **BioNg, BioPs, PAD** | 0.641 | 0.641 | 0.643 |
| **BioWC, DescWC, Color1-9** | 0.641 | 0.642 | 0.644 |
| **BioNg, BioPs, Dominance** | 0.641 | 0.641 | 0.643 |
| **BioNg, BioPs, Gray Mn, Gray Sd** | 0.64 | 0.639 | 0.641 |
| **BioNg, BioPs, Min 9 Max 9** | 0.64 | 0.639 | 0.642 |
| **BioNeg, BioPs, RGB Mn** | 0.639 | 0.639 | 0.641 |
| **BioNg, BioPs, Arousal** | 0.637 | 0.637 | 0.639 |
| **BioNg, BioPs, Min 16 Max 16** | 0.636 | 0.636 | 0.638 |
| **BioNg, BioPs, Activity** | 0.636 | 0.635 | 0.638 |
| **BioNg, BioPs, Color1** | 0.635 | 0.634 | 0.637 |
| **Title WC** | 0.635 | 0.634 | 0.636 |
| **BioNg, BioPs, Gray Mn** | 0.634 | 0.633 | 0.635 |
| **BioNg, BioPs, Gray Sd** | 0.634 | 0.634 | 0.636 |
| **BioWC, DescWC, Color1-10** | 0.634 | 0.635 | 0.637 |
| **BioNg, BioPs, RGB Sd** | 0.633 | 0.632 | 0.635 |
| **BioNg, BioPs, RGB Mn, RGB Sd** | 0.633 | 0.633 | 0.635 |

Table A: 113. Based Data Classification Models. Edge 1

| | F1 | Precision | Recall |
|---|---|---|---|
| **Facebook, Twitter, Instagram, RGB Mn, RGB Sd** | 0.633 | 0.633 | 0.635 |
| **BioNg, BioPs, Weight** | 0.633 | 0.633 | 0.635 |
| **Facebook, Twitter, Instagram, Arousal** | 0.633 | 0.632 | 0.634 |
| **BioNg, BioPs, Color1-2** | 0.632 | 0.631 | 0.634 |
| **Facebook, Twitter, Instagram, Gray Mn** | 0.632 | 0.631 | 0.633 |
| **Facebook, Twitter, Instagram, Min 9 Max 9** | 0.632 | 0.631 | 0.634 |
| **BioNg, BioPs, Heat** | 0.632 | 0.632 | 0.634 |
| **BioNg, BioNeu, BioPs** | 0.632 | 0.631 | 0.634 |
| **BioNg, BioPs, AWH** | 0.631 | 0.63 | 0.633 |
| **BioNg, BioPs, Gray Mn, RGB Mn** | 0.631 | 0.631 | 0.633 |
| **Facebook, Twitter, Instagram, PAD** | 0.631 | 0.631 | 0.633 |
| **Facebook, Twitter, Instagram, Gray Mn, Gray Sd** | 0.631 | 0.631 | 0.633 |
| **BioNg, BioPs, Color1-4** | 0.63 | 0.63 | 0.633 |
| **Facebook, Twitter, Instagram, Pleasure** | 0.63 | 0.629 | 0.632 |
| **BioNg, BioPs, Color1-5** | 0.629 | 0.629 | 0.632 |
| **Facebook, Twitter, Instagram, Gray Mn, RGB Mn** | 0.629 | 0.629 | 0.631 |

Table A: 114. Based Data Classification Models. Edge 1

| | F1 | Precision | Recall |
|---|---|---|---|
| **BioNg, BioPs, Pleasure** | 0.629 | 0.628 | 0.63 |
| **Facebook, Twitter, Instagram, Activity** | 0.629 | 0.629 | 0.631 |
| **BioNg, BioPs Facebook, Twitter, Instagram** | 0.629 | 0.628 | 0.631 |
| **BioNg, BioPs** | 0.628 | 0.627 | 0.629 |
| **BioNg, BioPs, Gray Sd, RGB Sd** | 0.628 | 0.628 | 0.63 |
| **BioNg, BioPs, Gray Mn, RGB Mn, Gray Sd, RGB Sd** | 0.628 | 0.628 | 0.63 |
| **Facebook, Twitter, Instagram, RGB Mn** | 0.628 | 0.628 | 0.63 |
| **Facebook, Twitter, Instagram, Color1** | 0.628 | 0.628 | 0.63 |
| **Facebook, Twitter, Instagram, Min 16 Max 16** | 0.628 | 0.628 | 0.63 |
| **Facebook, Twitter, Instagram, Dominance** | 0.628 | 0.628 | 0.63 |
| **BioNg, BioPs, Color1-7** | 0.627 | 0.627 | 0.63 |
| **Facebook, Twitter, Instagram, Weight** | 0.627 | 0.627 | 0.629 |
| **BioNg, BioPs, Color1-3** | 0.626 | 0.625 | 0.628 |
| **BioNg, BioPs, Color1-6** | 0.626 | 0.627 | 0.629 |
| **BioNg, BioPs, Color1-10** | 0.626 | 0.626 | 0.629 |
| **Facebook, Twitter, Instagram, Gray Sd** | 0.626 | 0.626 | 0.628 |

Table A: 115. Based Data Classification Models. Edge 1

| | F1 | Precision | Recall |
|---|---|---|---|
| **BioNg, BioPs, Color1-8** | 0.625 | 0.625 | 0.628 |
| **Facebook, Twitter, Instagram, Gray Mn, RGB Mn, Sd** | 0.625 | 0.626 | 0.627 |
| **BioNg, BioPs, Color1-9** | 0.624 | 0.624 | 0.627 |
| **Facebook, Twitter, Instagram, RGB Sd** | 0.624 | 0.624 | 0.626 |
| **Facebook, Twitter, Instagram, Color1-3** | 0.624 | 0.624 | 0.627 |
| **Facebook, Twitter, Instagram, Color1-5** | 0.624 | 0.624 | 0.627 |
| **Facebook, Twitter, Instagram, AWH** | 0.623 | 0.623 | 0.626 |
| **Facebook, Twitter, Instagram, Color1-2** | 0.623 | 0.623 | 0.626 |
| **Facebook, Twitter, Instagram, Color1-6** | 0.623 | 0.623 | 0.626 |
| **Facebook, Twitter, Instagram** | 0.622 | 0.621 | 0.624 |
| **Facebook, Twitter, Instagram, Color1-7** | 0.622 | 0.622 | 0.624 |
| **Facebook, Twitter, Instagram, Color1-4** | 0.621 | 0.621 | 0.624 |
| **Facebook, Twitter, Instagram, Color1-9** | 0.621 | 0.622 | 0.624 |
| **Facebook, Twitter, Instagram, Heat** | 0.621 | 0.62 | 0.623 |
| **Facebook, Twitter, Instagram, Color1-8** | 0.62 | 0.62 | 0.623 |
| **Gray Mn, Gray Sd** | 0.617 | 0.618 | 0.62 |

Table A: 116. Based Data Classification Models. Edge 1

| | F1 | Precision | Recall |
|---|---|---|---|
| **Facebook, Twitter, Instagram, Gray Sd, RGB Sd** | 0.617 | 0.617 | 0.619 |
| **Facebook, Twitter, Instagram, Color1-10** | 0.617 | 0.618 | 0.621 |
| **Arousal** | 0.617 | 0.617 | 0.619 |
| **Min 9 Max 9** | 0.616 | 0.616 | 0.619 |
| **Pleasure, Arousal, Dominance** | 0.615 | 0.615 | 0.618 |
| **Gray Mn** | 0.615 | 0.615 | 0.617 |
| **Max 9** | 0.615 | 0.615 | 0.618 |
| **Dominance** | 0.615 | 0.614 | 0.617 |
| **RGB Mn** | 0.614 | 0.614 | 0.616 |
| **Min 9** | 0.614 | 0.613 | 0.616 |
| **Max 16** | 0.614 | 0.613 | 0.616 |
| **Color1** | 0.613 | 0.612 | 0.615 |
| **Min 16** | 0.613 | 0.612 | 0.615 |
| **Weight** | 0.612 | 0.611 | 0.614 |
| **Color1-2** | 0.611 | 0.61 | 0.613 |
| **Min 16 Max 16** | 0.611 | 0.611 | 0.614 |

Table A: 117. Based Data Classification Models. Edge 1

| | F1 | Precision | Recall |
|---|---|---|---|
| **Pleasure** | 0.611 | 0.61 | 0.614 |
| **Activity** | 0.611 | 0.611 | 0.614 |
| **Gray Sd** | 0.61 | 0.61 | 0.612 |
| **Activity, Weight, Heat** | 0.609 | 0.608 | 0.611 |
| **RGB Sd** | 0.609 | 0.609 | 0.611 |
| **RGB Mn, RGB Sd** | 0.609 | 0.61 | 0.612 |
| **Color1-3** | 0.609 | 0.608 | 0.611 |
| **Base Features** | 0.608 | 0.606 | 0.61 |
| **Gray Mn, RGB Mn** | 0.608 | 0.608 | 0.611 |
| **Gray Mn, RGB Mn, Gray Sd, RGB Sd** | 0.605 | 0.605 | 0.607 |
| **Color1-4** | 0.605 | 0.605 | 0.608 |
| **Color1-5** | 0.605 | 0.606 | 0.608 |
| **Color1-8** | 0.605 | 0.606 | 0.609 |
| **Color1-6** | 0.604 | 0.605 | 0.607 |
| **Color1-7** | 0.604 | 0.605 | 0.607 |
| **Heat** | 0.604 | 0.603 | 0.606 |

Table A: 118. Based Data Classification Models. Edge 1

| | F1 | Precision | Recall |
|---|---|---|---|
| **Color1-9** | 0.602 | 0.603 | 0.606 |
| **Gray Sd, RGB Sd** | 0.601 | 0.601 | 0.604 |
| **Color1-10** | 0.601 | 0.602 | 0.605 |