RESEARCH ARTICLE

Color-Emotion Associations in Art: Fuzzy Approach

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ABSTRACT Art objects can evoke certain emotions. Color is a fundamental element of visual art and plays a significant role in how art is perceived. This paper introduces a novel approach to classifying emotions in art using Fuzzy Sets. We employ a fuzzy approach because it aligns well with human judgments' imprecise and subjective nature. Extensive fuzzy colors (n=120) and a broad emotional spectrum (n=10) allow for a more human-consistent and context-aware exploration of emotions inherent in paintings. First, we introduce the fuzzy color representation model. Then, at the fuzzification stage, we process the Wiki Art Dataset of paintings tagged with emotions, extracting fuzzy dominant colors linked to specific emotions. This results in fuzzy color distributions for ten emotions. Finally, we convert them back to a crisp domain, obtaining a knowledge base of color-emotion associations in primary colors. Our findings reveal strong associations between specific emotions and colors; for instance, gratitude strongly correlates with green, brown, and orange. Other noteworthy associations include brown and anger, orange with shame, yellow with happiness, and gray with fear. Using these associations and Jaccard similarity, we can find the emotions in the arbitrary untagged image. We conducted a 2AFC experiment involving human subjects to evaluate the proposed method. The average hit rate of 0.77 indicates a significant correlation between the method's predictions and human perception. The proposed method is simple to adapt to art painting retrieval systems. The study contributes to the theoretical understanding of color-emotion associations in art, offering valuable insights for various practical applications besides art, like marketing, design, and psychology.

INDEX TERMS Fuzzy sets, emotions in art, color palette, classification, color-emotion model, art image analysis, color perception, image processing, emotion detection.

I. INTRODUCTION

Nowadays, we observe a significant increase in the dissemination of affective information across various media worldwide [1]. Affective information refers to data that is inherently linked to human emotions. It can evoke emotional responses in the audience, such as happiness, sadness, or anger, that viewers may experience in response to certain visual stimuli, e.g., dominant color schemes used in art. The elements contributing to the sensory experience of audio and visual content include acoustic quality, facial expressions and gestures, background music, ambient noise, color schemes, and image filters. It is crucial to assess incoming data objectively, including emotional reactions [2], [3].

Color is a fundamental element of visual art and plays a big role in the emotional responses induced by the art image. Classifying art not just in terms of age or style but also in terms of the emotions it creates in a viewer is important. This can facilitate the identification of art expressing similar emotions and has a potential application in context-based image retrieval systems.

There is a growing interest in developing computational models that mimic human perception in recognizing and measuring emotions and their intensities in various domains, including art. Such a system can interpret artworks in a manner similar to human perception, overcoming the subjective nature of color perception [4] and emotional

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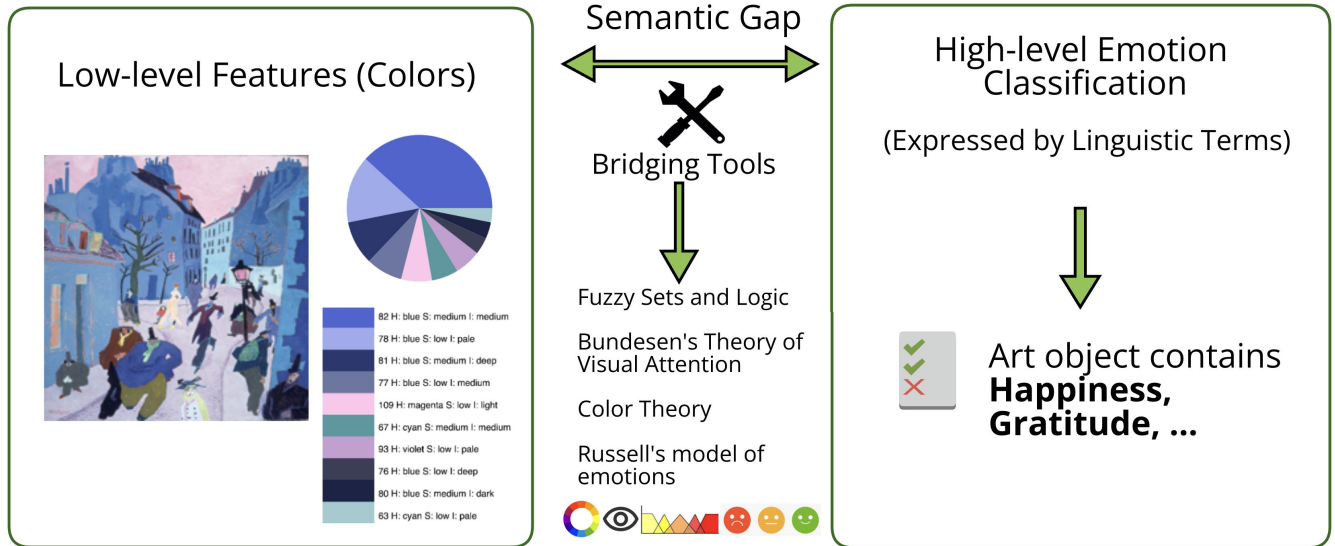
FIGURE 1. Bridging the semantic gap between low-level features in art objects and high-level semantic concepts of emotions. Lyonel Feininger "Carnival in Arcueil" painting.

interpretation. The motivation for such a system stems from its potential applications in areas like art image retrieval, art therapy, digital art creation, etc.

The relationship between color and emotion has been studied in various areas, ranging from psychology to art theory.

The colors we see can greatly impact our emotions. Researchers such as J.H. Xin have found that the lightness and chroma of colors are more influential than the hue itself [5]. Other studies, including one conducted by Banu Manav [6], have also shown that our emotional response to colors can vary based on lightness and saturation. In a related experiment, the researchers in [7] explored how changes in valence and arousal affected emotional response. They were able to accurately map four different emotions to 5 parameters: lightness, chroma, hue, valence, and arousal, with an accuracy rate of 80%.

Currently, there are several gaps in research on this topic. Technically, there is a limitation in recognizing and comprehending pictures. Aesthetically, there is no apparent correlation between the information conveyed by a picture and the response to it.

The interaction between different emotions is still poorly understood, and the studies conducted so far have been limited to a handful of emotions (usually 4 to 6). This is because emotions are difficult to represent using a specific metric. Moreover, it is important to shift the focus from the content of paintings to their forms. However, it seems impossible to achieve universal calculations in this regard.

Acknowledging that various factors influence perception is crucial and should be evaluated in different contexts. In this paper, we focus on art and present a technique to extract the emotional color palette from art objects using

fuzzy sets. This method is particularly useful as color ambiguity and perception are both subjective and inaccurate by nature. Traditional color-emotion studies have primarily relied on basic color categories, which may impact emotional experiences evoked by art.

The current paper proposes an emotion classification approach for art objects using Fuzzy Sets and Logic Approach (see Fig. 1). It matches colors in the art domain to the spectrum of human emotions. The fuzzy approach is well-suited for color and emotion detection. How people perceive color and emotion is inherently subjective and differs from person to person. The fuzzy approach can effectively represent this imprecision in the perception of color-emotion associations in a way that classical binary logic might struggle to capture.

As it can be seen in Fig. 1, we aim to bridge the gap between low-level features, specifically colors, and high-level emotion classifications (e.g., happy, fearful, etc.), utilizing a comprehensive set of bridging tools, including fuzzy sets and logic, the Russell emotion model, Bundesen's theory of visual attention, and color theory.

The contributions of this paper are the following:

- *Enhanced emotional spectrum.* We consider a broad range of emotions (N=10) with contextual relevance in art.
- *Increased granularity.* Basic colors provide a general understanding of color-emotion relationships, but using a wider array of fuzzy colors (N=120), our model imitates human perception of colors. This enables a richer exploration of emotions and their connections to specific color variations and combinations.
- *Rich color expressiveness of emotions.* We employ 10-color palettes to depict the complexity inherent in art images better, but we also consider color proportion.
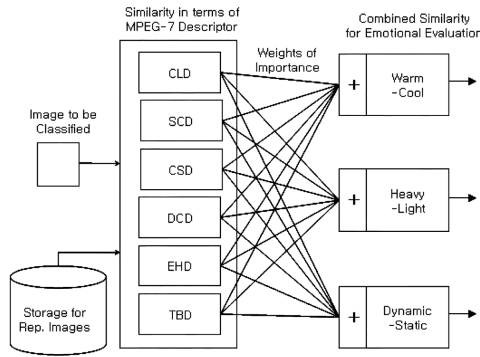
FIGURE 2. Lee J. Emotional classification of color images [8].

FIGURE 3. Kang's study color image scale [14].

Most studies concentrate on emotions within two or three color palettes.

- *Proof of concept.* We also provided a method for automatically tagging the art objects for Art Gallery Systems for emotion-based image retrieval.

The paper has the following structure. Section I is this Introduction. Section II presents a review of prior research on color-emotion associations. In Section III, various methods we use in this study, including fuzzy sets, logic, and theory of visual attention, are detailed, along with explanations of data collection and proposed approach details. The subsequent section, Section IV, showcases the sample application and experimental results. Next, the Discussion is presented in Section V. Finally, Section VI concludes the paper and offers recommendations for future enhancements to the methodology.

II. RELATED WORK
A. COLOR-EMOTION ASSOCIATION STUDIES

This section presents an overview of the literature related to emotion detection in Art. Several studies have examined color-emotion associations in various contexts, including art. Prior work can be divided into three main directions: context dependency investigation, machine learning algorithms, and a fuzzy approach.

The earliest studies were highly interested in the human perception subjectivity level. Color perception depends on factors such as sex, nationality, culture, etc. Authors of [9] decided to find out to what extent human perception is influenced by cultural background. They compared people's emotional responses in 7 different regions of Europe and Asia. They found out that regardless of their national differences, people of different cultures reacted to colors quite similarly. So, the cultural context has very limited influence on human perception. However, the human response to color is mainly influenced by lightness, chroma, and hue.

Several studies have examined that the aesthetics of art objects depends on their texture, cultural context, and the viewer's emotional state [10], [11]. The work proposed in [11] uses Kansei engineering to translate feelings into specific parameters for frequently encountered subjects in
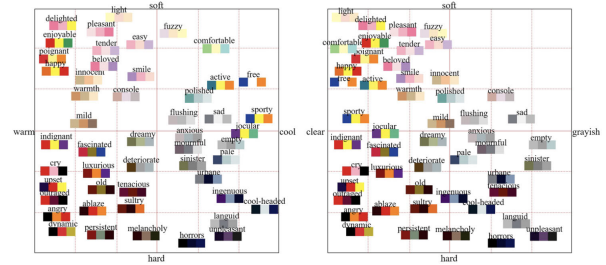
aesthetics and emotion. The paper by [12] conducted several psychological experiments to evaluate how the perception differs for single-color and multiple-color paintings. They used different scale types and concluded that the emotional response to color is more universal. Two more critical factors influence the outcome of emotional perception: order and learning. The initial factor involves components like symmetry, rhythm, repetition, and contrast. The second factor, learning, highlights that individuals tend to perceive something as aesthetically pleasing when it aligns with their previous experiences [13].

From the perspective of the proposed approach, previous works can be divided into machine learning algorithms and fuzzy logic approaches.

Advanced search engines are mostly based on text, keywords, or face recognition algorithms. References [15] and [16] proposed to use a color as a new metric for image retrieval and classification. The work of [17] extended emotion recognition methods by adding the relationship between neighboring emotions. Their algorithm considers that emotion and transitions between emotion regions may influence human perception.

The study [8] provided several classification methods for emotions, such as Decision trees, support vector machines, and Naive Bayes. Additionally, it stressed the importance of selecting emotional adjectives based on four criteria: universality, distinctiveness, utility, and comprehensiveness (see Fig. 2). From the viewpoint of affective computing, it is currently understood that emotional states can only be described explicitly and not implicitly. The primary objective of affective computing is to identify and classify emotions accordingly. Several approaches have been reported in the literature: knowledge base, statistical methods, and hybrid [1]. Some of them lack semantic strength.

In their theory, Kobayashi created a graph to identify the combination of most similar colors and determine the leading emotion from it [18]. The work proposed in [14] uses Kobayashi's color theories to extract complex emotions from paintings by adding a grayish/clear factor for improved accuracy. However, the probability of error increases with many emotions in the picture. Fig. 3 illustrates this approach.

The authors of the other study designed a machine-learning algorithm for emotion classification in images, utilizing color
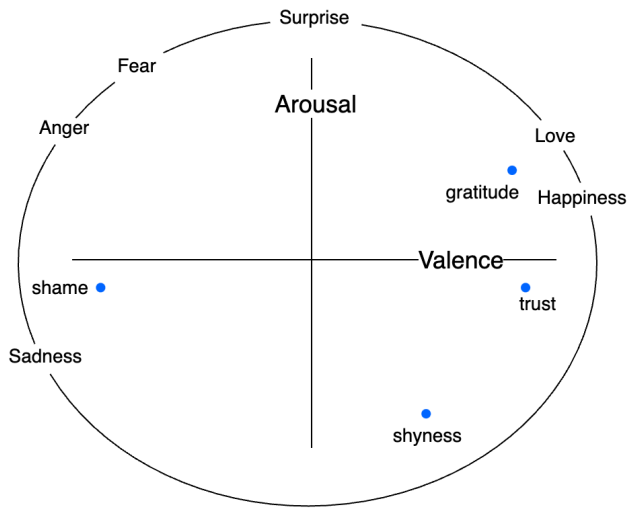
FIGURE 4. Russell emotional model adapted to the art context [19].

information and categorizing emotions into three distinct classes: negative, positive, and neutral [20]. Another study proposed the L-EEP method, utilizing Culture Technology, to automatically extract eight emotions from Iranian-Islamic paintings through color analysis and the automated Luscher test [21]. Recent work proposed a network for recognizing emotions in images, utilizing a weakly supervised approach to learn emotion intensity [22].

Fuzzy logic has been used to address these concerns, specifically targeting diverse contexts such as gender, age, ethnic group, and environmental factors when computing the outcome of an emotional assessment. Several works stressed the importance of the fuzzy sets approach to imitate human perception of high-level color concepts:

- Researchers introduced fuzzy color spaces defined using RGB and Euclidean distance, with examples from the well-known ISCC-NBS color naming system [23].
- The other works introduced fuzzy granular colors constructed by consolidating fuzzy colors that share semantic relationships within a specific color category [24], a method centered on images for constructing fuzzy color spaces within defined contexts [25].
- Nachtegael introduced a formula for calculating the similarity of fuzzy color histograms [26].
- In the other work, the connection between colors and emotions was investigated by employing fuzzy feature vectors derived from fuzzy color histograms and emotion vectors obtained through surveys [4].
- Another model employed fuzzy logic and L*a*b* color space for emotional semantic queries. The generation of semantic terms was facilitated by applying a fuzzy clustering algorithm [27].
- Recent research [28] and [29] used fuzzy logic to explore the universality of color palettes concerning specific associations. The study revealed that color harmony demonstrates a universal aspect within specific contexts.

Generally, certain impressions maintain universal color palettes across diverse settings, while others are context-dependent. There are universally accepted color palettes noted for their considerable aesthetic appeal and several universally perceived color associations. The perception of aesthetics is partly general and partly domain-specific.

As we can see from the above, the level of interest in this field appears to be substantial. However, there are also some technical and semantic limitations to research. One important constraint on most works discussed in this area is the limited number of colors and their crisp nature, which is in contrast to human color perception. Some of the experiments were conducted without a validated dataset, and psychological experiments were conducted without controlling participants' conditions.

B. MODELS OF EMOTION

Several emotion models have been proposed to describe and categorize human emotions. Here are a few examples of well-known ones: Russell's Circumplex Model [19], Ekman's Six Basic Emotions [30], Plutchik's Wheel of Emotions, James-Lange Theory [31], Cannon-Bard Theory [32], [33], Barrett's Conceptual Act Theory [34], The Geneva Emotion Wheel [35], Schachter-Singer Two-Factor Theory [36], Mehrabian's PAD Model [37].

In our research, we are using Russell's emotional model. Russell's Circumplex Model is a two-dimensional model organizing emotions based on two primary dimensions: valence (pleasure-displeasure axis) and arousal (activation-deactivation axis) [19]. According to Russell's approach, emotions don't exist in discrete categories but along continuous dimensions. This is consistent with the fuzzy approach, which allows for the fuzziness and transitionality of emotional borders. Color and emotion relationships in art may be difficult to categorize using rigid boundaries. Thus, any emotion can be, to some extent, pleasant/unpleasant and active/passive.

The model was developed based on subjective feelings [19]. Participants were asked to group 28 emotion words based on perceived similarity, and a statistical technique was used to group related words.

We have adapted Russell's model for the art context by using the most relevant emotions from the dataset (discussed below in subsection III-A). As shown in Fig. 4, a set of emotions is distributed on the wheel. We are using them as tags for art paintings. This figure positions ten chosen emotions - anger, shyness, happiness, sadness, gratitude, shame, fear, trust, love, and surprise - within the model's primary dimensions: valence (pleasure-displeasure) and arousal (activation-deactivation).

III. METHODS

In this paper, we propose a classification system that takes an art piece and predicts the emotional response it can generate.

FIGURE 5. WikiArts Emotions Dataset [38]. Sample images.

We aim to enhance the current image emotion classification and retrieval algorithms using fuzzy logic. Our approach comprises several stages. Firstly, we will identify the most relevant emotions within the art domain and acquire a relevant dataset. We will then proceed to process the images by smoothing and normalizing them. Subsequently, we will retrieve color palettes from the prepared data and map them to image emotion tags. To increase the precision of the mapping process, we will convert the RGB color palettes into fuzzy palettes.

A. DATASET

To proceed, we must first locate a set of paintings previously tagged with specific emotions. This step can be divided into two parts: training and testing. We use Wiki Art Dataset. This resource contains works from 195 artists, 42129 images for training, and 10628 images for testing [38]. This dataset has classified 20 emotions into three categories: positive, negative, and other/mixed.

The images in this dataset were manually tagged with the emotions they evoke in humans. At least ten annotators annotated each work of art. There are three sets of annotations: based on title, image, and combined (image and title). For our study, we selected annotations based on the image only (without a title) because our analysis is based on colors in the image, ignoring any associated text, including author, title, and genre.

The labeled dataset is divided into three variants according to aggregation thresholds of 30%, 40%, and 50%, respectively. A label is selected if at least 30%, 40%, and 50% of the responses, or three out of every ten respondents, suggest that a particular emotion is applicable. The authors claim that 40% of the dataset is generous aggregation criteria; nonetheless, we selected 50% of the dataset for nine emotions and 30% of the dataset for the emotion of *shyness*, which only contains one image in the 50% of the dataset (see Table 1).

Using this dataset and comparing it with Russell's emotional model, we chose the main emotions for our model. As you can see in Table 1, these are the ten most relevant emotional words and their distribution in the dataset. Refer to Table 1 for details.

Sample art images from the WikiArts Emotions Dataset are presented in Fig. 5.

TABLE 1. Distribution of emotions in dataset.

Emotion	Dataset	Image count
happiness	50%	773
love	50%	160
anger	50%	21
sadness	50%	159
gratitude	50%	8
fear	50%	202
shame	50%	5
surprise	50%	532
shyness	30%	6
trust	50%	358

It already has some annotations. As mentioned, we can compare these results to determine how much the proposed method corresponds to emotion recognition accuracy.

B. THEORY OF VISUAL ATTENTION

Color perception involves categorizing colors through visual recognition and attentional selection [39], [40].

Let us go over the main ideas from a theory of visual attention. Bundesen introduces three types of perceptual categories in his work: color, shape, and location categories [40]. Our model is primarily based on color analysis. Using Bundesen's notation, colors represent emotions as perceptual categories.

According to Bundesen's theory of visual attention (TVA), perceptual categorization involves identifying whether an input element x belongs to a certain category i. This is expressed as $E(x, i)$, with $E(x, i) \in [0, 1]$ representing the certainty of x belonging to i. The set of all perceptual units is denoted by S, and the set of all categories is denoted by R.

The concept of *saliency* refers to the strength of sensory evidence that suggests an element belongs to a perceptual category. This is denoted by the notation $\eta(x, i)$, where x is the element and i is the perceptual category. Additionally, each category is assigned a pertinence value, denoted by π_i, representing its importance for a specific task T. We can calculate the attentional weight of x using pertinence and
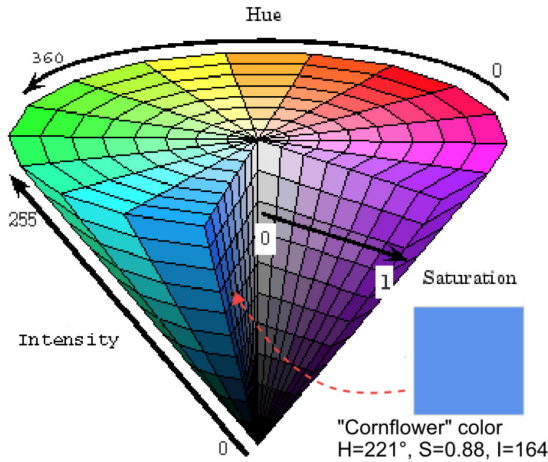
salience values:

$$\omega_x = \sum_{i \in R} \eta(x, i)\pi_i \quad (1)$$

It is important to note that in Equation (1), only categories that have positive pertinence values have an impact on ω_x.

When it comes to visual attention, two mechanisms are often used—filtering and pigeonholing. *Filtering* refers to selecting an item, denoted by x, from a set of items, denoted by S, that belongs to a particular category, denoted by i. For example, a client might search for a dark and dramatic art object, and filtering can narrow down the art catalog to show only those that fit this description.

On the other hand, *Pigeonholing* refers to identifying a suitable category, denoted by i, for a given item, denoted by x, that belongs to a set of categories, denoted by R. In other words, if we have an item, we can use pigeonholing to determine its category. For example, when a manager of the art gallery collects artists' or experts' judgments on some art object and then categorizes them as being, e.g., *happy, romantic, fearful*, etc.

C. FUZZY SETS THEORY

Emotion ambiguity and a few emotion classes compared to human feelings are some difficulties distinguishing emotions [42]. The fuzzy approach represents a valuable method for dealing with imprecision. It has been utilized in several studies to represent emotions and their intensity in audio, speech, and video [43], [44], [45], [46], color image [4], [8], [27], [28], [29], [47], text [48], [49], [50], [51], face [44], [45], [52], [53] and product [54], [55] emotion analysis.

Fuzzy colors are suitable for contextual relevance: they are often associated with specific contexts or cultural domains, greatly influencing emotional responses. By incorporating a fuzzy sets approach, accounting for the cultural, contextual, and individual variations in color-emotion associations leads

to a more comprehensive analysis. The next section presents fundamental concepts from fuzzy theory utilized in our study.

1) FUZZY SETS

Fuzzy sets, first introduced by Zadeh [56], allow membership degrees to be indicated by a number between 0 and 1. In Boolean logic, we only deal with a pair of numbers, 0,1. However, when it comes to fuzzy sets, we consider all the numbers within a range of [0,1]. This range is called a *membership function* (MF) and is denoted as $\mu_A(x)$, which can be used to represent fuzzy sets.

MFs are mathematical techniques for modeling the meaning of symbols by indicating flexible membership to a set. We can use it to represent uncertain concepts like age, performance, building height, etc. Therefore, MF's key function is to convert a crisp value to a membership level in a fuzzy set. We also need to show triangular and trapezoidal MF here.

2) LINGUISTIC VARIABLES

Zadeh [57] defined a linguistic variable as a variable whose values are words or sentences in a natural or artificial language rather than numbers. For instance, the label 'deep' can be considered a linguistic value of the variable 'Color Intensity,' similar to a number but with less precision. A linguistic variable's set of all linguistic values is called a *term set*.

3) FUZZY HEDGES

There are two types of modifiers or hedges: reinforcing and weakening modifiers. These modifiers are used to either strengthen or weaken a statement. The hedge ''very'' represents the reinforcing modifier:

$$t_{very}(u) = u^2 \quad (2)$$

Weakening modifiers are the second type of modifiers. For example, ''more-or-less'' is a hedge that indicates a degree of uncertainty.

$$t_{more\text{-}or\text{-}less}(u) = \sqrt{u} \quad (3)$$

Additionally, the hedge of ''not'' can be expressed as:

$$t_{not}(u) = 1 - u \quad (4)$$

Hedges can be applied several times. For example, *not very good performance* is the example of a combined hedge consisting of two atomic hedges *not* and *very*.

4) FUZZY OPERATIONS

In fuzzy logic, the α-cut (alpha cut) is a crisp set that contains all the members of a given fuzzy subset f whose values are greater than or equal to a certain threshold α (which ranges from 0 to 1). Mathematically, we can represent the α-cut of the fuzzy subset f as:
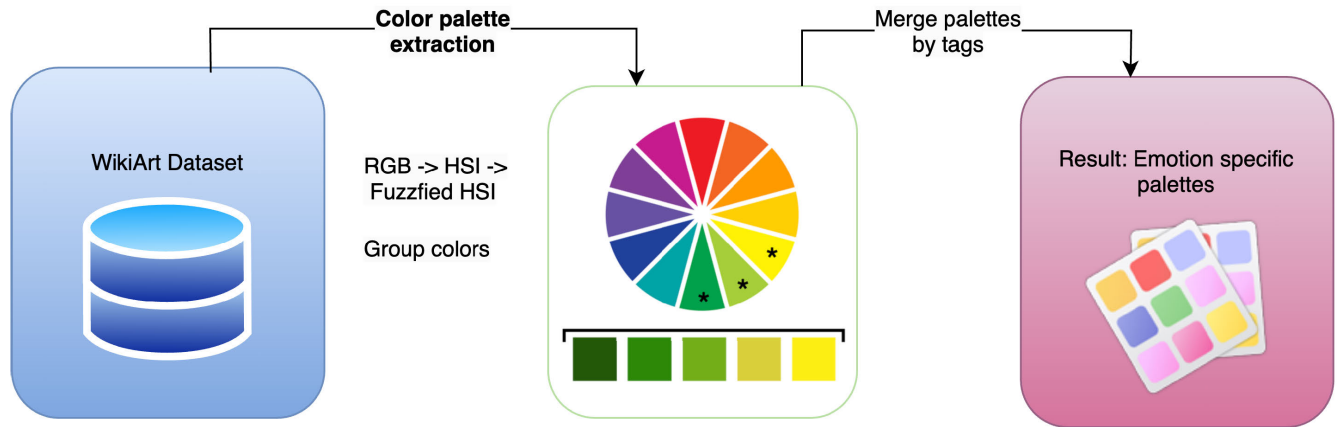
$$f_\alpha = \{x : \mu_f(x) \geq \alpha\}$$

FIGURE 7. Proposed Approach: Fuzzy colors palette extraction.

We can use the α-cuts to perform set operations on fuzzy sets. For instance, given two fuzzy sets A and B, we can obtain their union and intersection by taking the union and intersection of their respective α-cuts. That is:

$$(A \cup B)_\alpha = A_\alpha \cup B_\alpha, \quad (A \cap B)_\alpha = A_\alpha \cap B_\alpha$$

Fuzzy logic is suitable to cope with subjective metrics, such as emotions and broad concepts, like color, because it is consistent with human perception [41]. Initially, we get the color palette in RGB format and translate it into HSI and FHSI.

D. HSI COLOR MODEL

Because of the high correlation between RGB color space attributes and their failure to replicate human color perception, other color spaces, such as HS* (HSL, HSI, HSV), are favored for modeling human color perception [39], [58].

Three attributes—*hue* (H, such as yellow, cyan, or blue), *intensity* (I, pale vs. dark), and *saturation* (S, saturated vs. dull)–are used in the HSI paradigm to express colors (see Fig. 6). As a result, it is more in line with how colors are perceived by the human visual system, which is predicated on three interpretations of color: brightness, purity, and category. All three interpretations perfectly correspond to HSI.

The Hue describes the color in terms of an angle between 0 and 360 degrees. The Saturation describes how much the color is mixed with light, ranging between 0 and 100. The Intensity component ranges from 0 to 255, where 0 represents black and 255 represents white.

E. PROPOSED APPROACH

The main idea of the proposed approach can be seen in Fig. 7. First, we process a dataset comprising art images. We extract fuzzy dominant colors and their frequencies associated with certain emotions for each image in the dataset. As a result, we get a fuzzy color distribution for each of the ten emotions. Finally, we convert them back to a crisp domain, obtaining color-emotion associations in the form of basic colors.

We employ a fuzzy approach because it enables us to evaluate emotions in a way consistent with human judgment. We obtain a more logical and human-consistent output by partitioning the set of potential emotions into subsets corresponding to linguistic tags [59]. Similarly, fuzzy sets make it simple to show how an emotion gradually changes from one label to another [57].

In the theory of visual attention, an art image is represented by the variable x, while S represents a database of all images. The variable i represents an emotion category, such as fear or happiness, which can be composite (e.g. love and anger). The collection of all emotion categories is represented by R.

1) FUZZIFICATION OF HSI COLORS
Triangular Membership Function:

$$\mu(x) = \begin{cases} 0, & x \leq a \\ \dfrac{x-a}{b-a}, & a \leq x \leq b \\ \dfrac{c-x}{c-b}, & b \leq x \leq c \\ 0, & x \geq c \end{cases}$$

Trapezoidal Membership Function:

$$\mu(x) = \begin{cases} 0, & x \leq a \\ \dfrac{x-a}{b-a}, & a \leq x \leq b \\ 1, & b \leq x \leq c \\ \dfrac{d-x}{d-c}, & c \leq x \leq d \\ 0, & x \geq d \end{cases}$$

Fuzzy partitions were adapted from [39], [55], [58], and [59], but the changes were done to the "Low" Saturation because we don't have "Any" Category. These partitions were obtained based on a survey on human color categorization.

Table 2 shows the information about term sets and domains of each fuzzy variable in our color model (H, S, I). Fig. 8 presents the membership functions for fuzzy H, S, and I

TABLE 2. Fuzzy attributes of the fuzzy color model. Adapted from [39] and [55].

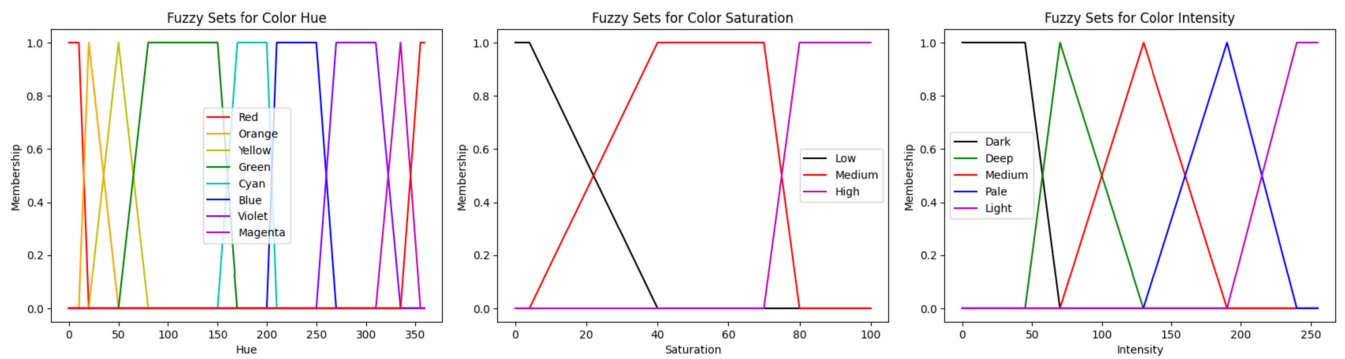| Fuzzy Variable	Term set	Domain
Hue	T = { Red, Orange, Yellow, Green, Cyan, Blue, Violet, Magenta }	X = [0, 360]
Saturation	T = { Low, Medium, High }	X = [0, 100]
Intensity	T = { Dark, Deep, Medium, Pale, Light }	X = [0, 255]

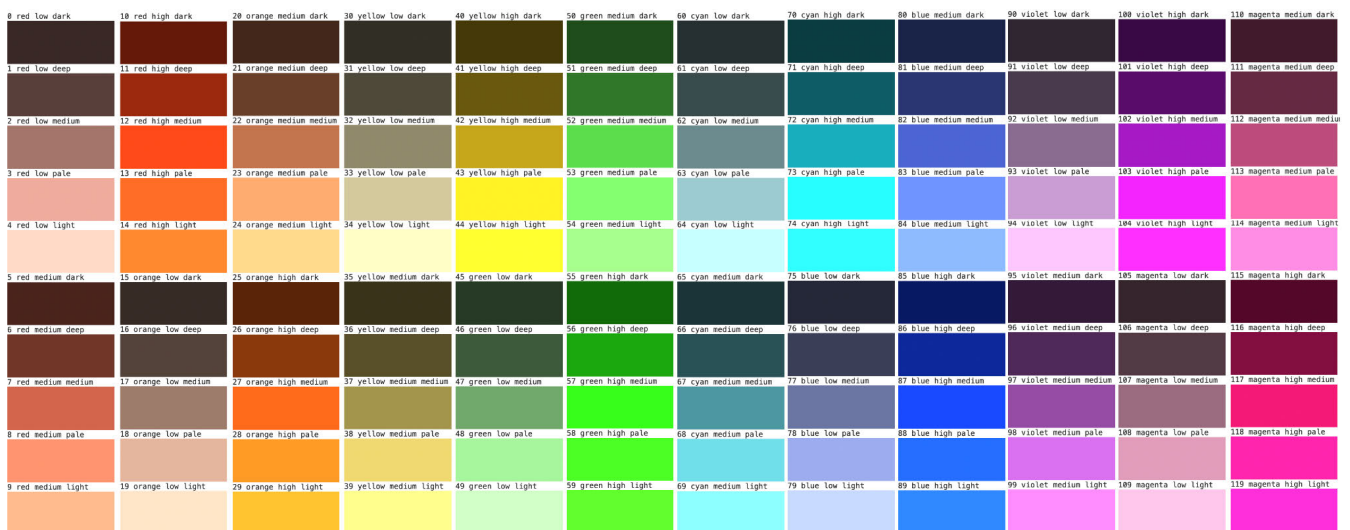**FIGURE 8.** Fuzzy Sets for Hue, Saturation, and Intensity attributes.

FIGURE 9. Fuzzy color representation model, which incorporates 120 hues, each characterized by three linguistic terms: hue, saturation, and intensity.

variables. Fig. 9 presents the fuzzy colors of the proposed representation model, which incorporates 120 distinct fuzzy colors. We have divided the intensity into five fuzzy sets, namely "Low," "Medium," and "High," with the domain $X = [0, 100]$ and the universal set $U = 0, 1, 2,\dots, 99, 100$. Similarly, the attribute of hue has been divided into eight fuzzy sets, including "Red," "Orange," "Yellow," "Green," "Cyan," "Blue," "Violet," and "Magenta," with the domain $X = [0, 360]$ and the universal set $U = 0, 1, 2,\dots, 359, 360$. Lastly, the attribute of saturation has been divided into three fuzzy sets, namely "Dark," "Deep," "Medium," "Pale," and

"Light," with the domains $X = [0, 255]$, and the respective universal set $U = 0, 1, 2,\dots, 254, 255$. By doing this, we have created a comprehensive and accurate spectrum of fuzzy colors.

Some color representatives can be seen in Fig 10. On the figure, we have a table like Hue: red, Intensity: deep, etc., and an explanation that a fuzzy color is a region, not a point.

A fuzzy color is a subset of points within a crisp color space, which is the HSI space in our case, as mentioned in [39], [55], [60]. We define the domains of the attributes H, S, and I as D_H, D_S, and D_I, respectively.
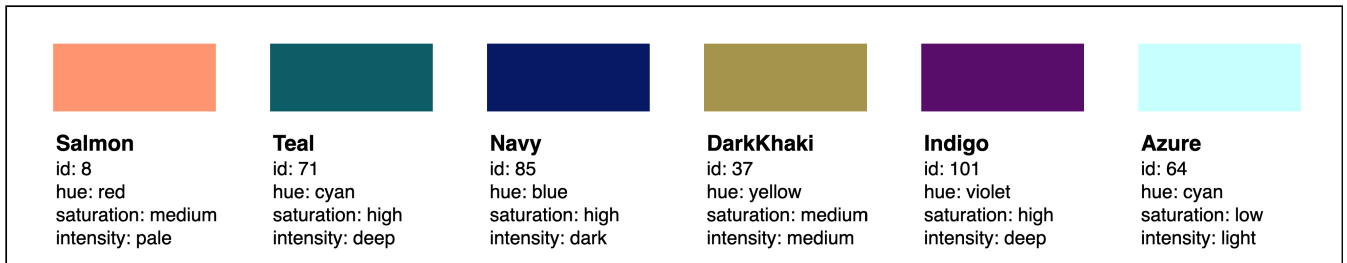
FIGURE 10. Fuzzy colors examples from the proposed fuzzy color model.

Definition 1: **Fuzzy color** *C is a linguistic label whose semantic is represented in crisp HSI color space by a normalized fuzzy subset of* $D_H \times D_S \times D_I$.

It can be inferred from Definition 1 that there is always at least one crisp color that fully belongs to any given fuzzy color C. This prompts us to extend the concept of fuzzy color to the notion of fuzzy color space. As per the fundamental idea of a fuzzy color space [60]:

Definition 2: **Fuzzy color space** *is a set of fuzzy colors that define a partition of* $D_H \times D_S \times D_I$.

Definition 3: **Fuzzy color palette** *is a combination of several fuzzy colors [28].*

Each element in a fuzzy color palette is a fuzzy color (area) rather than a sharp color (point) [28]. Let us take *Salmon* color as an example (see Fig. 10). We convert crisp inputs into fuzzy sets for the fuzzification process. For example, if the color is in RGB format (*Salmon*: R=255, G=160, B=122), we first convert it into HSI model (H = 17, S = 32%, I = 179%), then to the fuzzy color model (H = *Red*, S = *Medium*, I = *Pale*. In this case, Hue is partial 'Red' and 'Orange', while Saturation is partially 'Medium' and partially 'Low'.

2) SELECTED EMOTIONS

This research aims to explore the connection between color palettes and human emotions. As emotions are highly subjective and influenced by various factors such as gender, race, mood, and life experiences [61], we have chosen to focus on the context of art to obtain a more objective assessment. To achieve this, we have examined various online galleries, articles, and datasets to identify which emotions are most commonly associated with paintings. Additionally, Kang et al. have already researched color and emotion pairings, as detailed in their article [14].

We have extensively researched this topic and analyzed various psychological articles, including [62] and [63]. Our goal was to select a comprehensive list of emotions based on previous studies, which is crucial for comparing our model's accuracy with existing results.

The selected dominant emotions in an art context are gratitude, happiness, anger, love, trust, fear, surprise, sadness, and shame. As a result, we will conduct further research on these emotions.

Algorithm 1 Finding the Image Dominant Colors [39], [55]

Data: image M_1 in RGB format
Result: The histogram that represents the most prominent color in image M_1

```
/* The image's dominant color
   histogram, C_H(image) is a vector
   (h_C1,…,h_Cn), where each element h_Ci
   represents the frequency of color
   C_i in the image.                  */
```
Function *FindFuzzyDomColors (image)*

  FuzzyColors ← an empty dictionary;
  FuzzyDomColors ← an empty array;
```
   /* initialize the frequency of
      each fuzzy color to 0        */
```
  while *not at end of image* **do**
    read current pixel;
    process current pixel;
```
      /* convert a pixel from RGB to
         HSI, then fuzzify – convert
         to fuzzy HSI                */
```
    fc ← computed fuzzy color;
    FuzzyColors[*fc*] ++;
  end
```
   /* Return the five most frequent
      fuzzy colors. The number of
      colors returned depends on the
      context of the application.  */
```
  FuzzyDomColors ← 5 keys from *FuzzyColors* with max frequency;
  return *FuzzyDomColors*;

---

3) IMAGE PREPROCESSING

The original art images were in various sizes but have been normalized to (200,200) and converted to RGB mode. Next, we transformed each pixel to HSI and then fuzzy HSI. The algorithm for fuzzy dominant color extraction (or fuzzy color histogram) can be seen in Algorithm 1.

4) DETECTION OF EMOTION COLOR PALETTE

Algorithm 1 aims to compute the dominant color palette of an image represented in RGB format. This process involves

Algorithm 2 Receiving Emotion Fuzzy Colors Palette.

Data: Dataset of images $M_1, \ldots, M_n$ of some Emotion E

Result: fuzzy colors palette FP for Emotion E

```
/* This function calculates the
   dominant color histogram of the
   given emotion image, denoted by
   E_H(image). The resulting output is
   a vector (h_{C_1}, ..., h_{C_n}) where each h_{C_i}
   element represents the frequency
   of the fuzzy color C_i in the
   emotion image.                    */
```

Function *GetEmotionFuzzyColorsPalette (emotion)*

    emotionFuzzyColors ← an empty dictionary;

    emotionFuzzyDomColors ← an empty array;

```
    /* Set the frequency count for
       each fuzzy color to zero.   */
```

    for *each M_i in dataset* **do**

        FC_i ← FindFuzzyDomColors(M_i);

```
        /* calculate the frequency of
           each fuzzy color for
           emotion.                */
```

        for *each fc in FC_i* **do**

            emotionFuzzyColors[fc]++;

        end

    end

```
    /* Return the 15 most frequently
       occurring fuzzy colors.     */
```

    emotionFuzzyDomColors ← 15 keys from *emotionFuzzyColors* with max frequency;

    return *emotionFuzzyDomColors*;
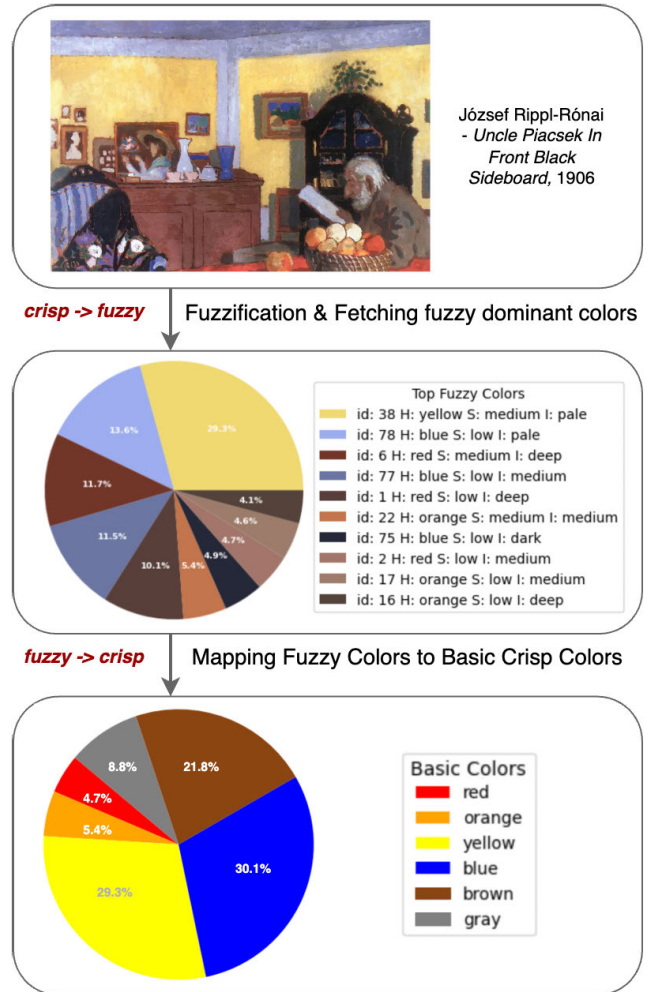
FIGURE 11. Extracting the fuzzy dominant colors from art images and mapping them to basic crisp colors.

converting the RGB image to HSI (Hue, Saturation, Intensity) color space, fuzzifying these colors, and then generating a fuzzy dominant color palette based on the frequency of these fuzzy colors.

Algorithm 2 is designed to generate a fuzzy color histogram specific to an emotion E based on a labeled dataset of images representing that emotion. For each image M_i in this dataset, the function extracts the dominant fuzzy colors within that specific image. This extraction process is executed by employing the method *FindFuzzyDomColors(M_i)*, which returns the top 5 most frequent fuzzy colors of this image denoted as FC_i.

Next, we increment each color in FC_i's frequency for the emotion palette. After processing each dataset image, the algorithm identifies the 15 most frequently occurring fuzzy colors within the emotion dictionary. These top 15 fuzzy colors, determined by their respective frequencies, are considered the dominant representations of this specific emotion.

Some of the obtained fuzzy palettes contain fewer than 15 fuzzy colors. This is because we also considered the proportion of colors; specifically, we filtered out those that constituted less than 3.5% of the image from the top 15 fuzzy colors. Note that these parameters (5 top fuzzy colors in each image, top 15 fuzzy colors for each emotion, threshold 3.5%) were determined based on our preliminary experiments and offer a balance between capturing essential color-emotional art data and computational feasibility. However, they can be modified for different contexts to capture the nature of emotions in this particular context effectively.

As an alternative color representation and for a comparative evaluation of the obtained color-emotion associations with the results of other researchers, we mapped fuzzy dominant colors for each emotion to basic crisp colors akin to defuzzification. The set of basic color categories we employed included 'red', 'orange', 'yellow', 'green', 'cyan', 'blue', 'black', 'brown', 'beige', 'purple', 'gray'. Fuzzy colors with 'dark' intensity were aligned with 'black', while colors with 'low' saturation are shades of gray, so they were associated with 'gray' basic color. Considering the contextual relevance and popularity of beige and brown colors in the
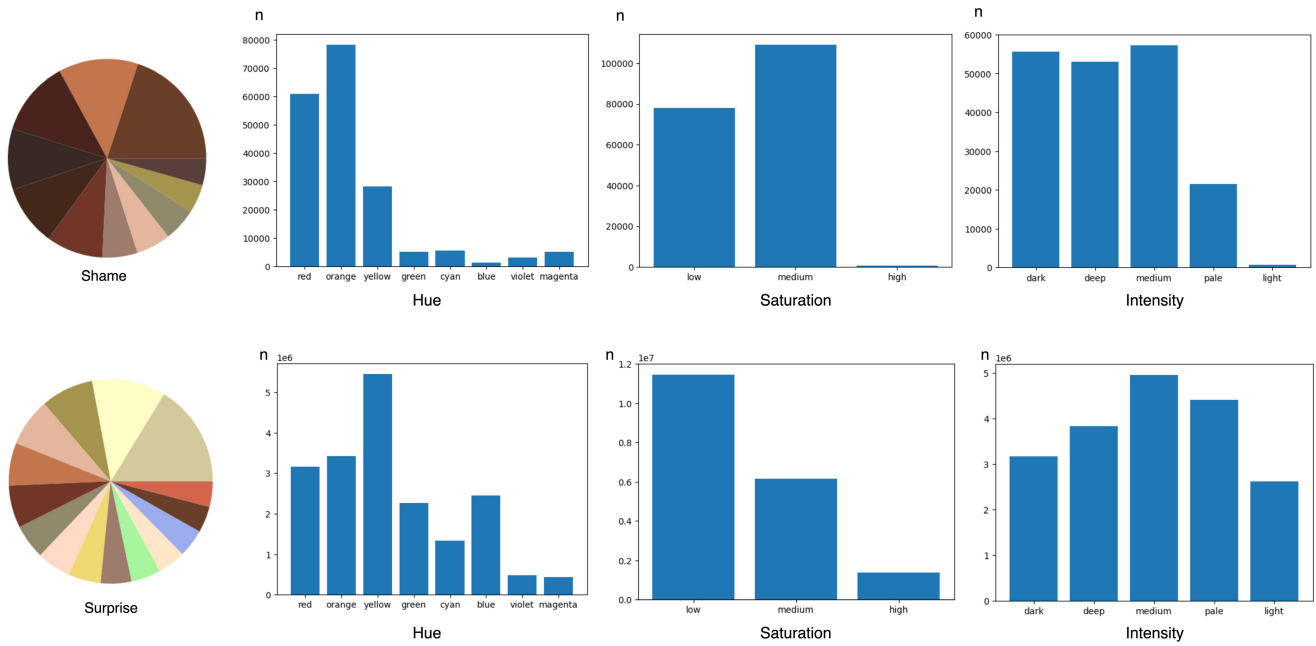
FIGURE 12. Distribution of HSI attributes across certain emotion.

domain of art paintings, we separated them from fuzzy colors with 'red', 'orange', and 'yellow' hues. Fuzzy colors with 'violet' and 'magenta' hues were mapped to 'purple'. The remaining fuzzy colors with hues 'red', 'orange', 'yellow', 'green', 'cyan', 'blue' were mapped to their respective crisp colors.

Fig. 11 illustrates the fuzzification process and the subsequent mapping of fuzzy dominant colors to basic crisp colors. The dominant colors are identified using a fuzzy color representation model in the fuzzification phase. These fuzzy colors, indicative of emotional responses, are then systematically mapped to a set of basic crisp colors.

IV. EXPERIMENTAL RESULTS
A. COLOR-EMOTION ASSOCIATIONS RESULTS
Fig. 12 illustrates the distribution of hue, saturation, and intensity attributes across certain emotions. One can mention the obvious difference between color palettes for shame and surprise. The two palettes under consideration evoke distinct emotional responses. The first palette, rich in reds, oranges, and yellows, exudes a vibrant and energetic aura with its medium saturation levels and deep, dark intensity. In contrast, the second palette contains a wider range of hues, featuring shades of yellow, green, cyan, and blue. It offers a softer appearance due to its lower saturation and a blend of medium to pale intensities. The surprise palette provides cooler tones compared to the intense warmth of the shame palette.

Our findings suggest that specific emotions exhibit strong associations with certain colors; for example, the 'gratitude' emotion is strongly associated with *green, brown,* and *orange* colors. Table 3 shows the association of all studied emotions

with basic colors. Fig. 13 and Fig. 14 provide the visual support for this association.

The associations between emotions and colors reveal interesting patterns. *Happiness* and *love* share similar color associations, prominently featuring brown, green, and orange. *Gratitude* is distinctly linked to brown, green, and orange. *Surprise* stands out as the sole emotion associated with light colors, with an absence of black and a prevalence of beige. *Shyness* is unique, incorporating purple and cyan as basic colors. Shame exhibits a more limited palette, with brown dominating. *Anger* is characterized by brown, gray, black, and red. Gray is notably intertwined with *fear*, and *fear* shares similar color associations with *sadness*. For *trust*, brown and gray take the lead in color associations. Brown consistently appears as the most frequent color in these emotional associations.

Table 3 illustrates our experimental results. It shows an association between emotions and corresponding basic colors, accompanied by estimated percentages denoting the prevalence or intensity of each color within the representation of those emotions.

Based on our results, prominent color-emotion associations were brown and *gratitude*, brown and *anger*, orange and *shame*, yellow and *happiness*, gray and *fear*. The full spectrum of color associations and emotions can be seen on the heatmap (Fig. 15).

It can be observed that brown is a prominent color across almost all emotions. The historical and natural prevalence of brown and its symbolic use in different cultures explain its frequent appearance and varied associations in art [64], [65]. However, its specific association with 'love' could be influenced by the representation of people, such as

TABLE 3. Basic colors distribution across emotions (measures indicated in percents).

| Emotion	Red	Orange	Yellow	Green	Cyan	Blue	Black	Brown	Beige	Purple	Gray
Gratitude	8.7	17.4	0	17.4	0	0	13.0	43.5	0	0	0
Anger	9.5	14.3	7.9	0	0	0	12.8	31.7	4.8	0	19.0
Shyness	0	0	11.1	22.2	11.1	22.2	0	11.1	0	11.1	11.1
Shame	13.3	26.7	0	0	0	0	20.0	40.0	0	0	0
Sadness	4.1	9.3	18.3	5.8	0	4.3	12.7	20.3	0	0	25.2
Love	6.1	12.9	14.5	4.4	0	4.2	13.2	28.9	5.3	0	10.5
Fear	6.4	8.0	10.7	5.9	0	5.2	8.6	18.2	5.2	0	31.8
Surprise	0	8.6	14.5	5.0	0	8.6	0	12.4	26.4	0	24.4
Trust	6.3	9.9	11.4	0	0	5.3	14.1	31.7	4.0	0	17.3
Happiness	4.1	10.6	20.9	8.8	0	3.8	5.6	20.3	5.7	0	20.2
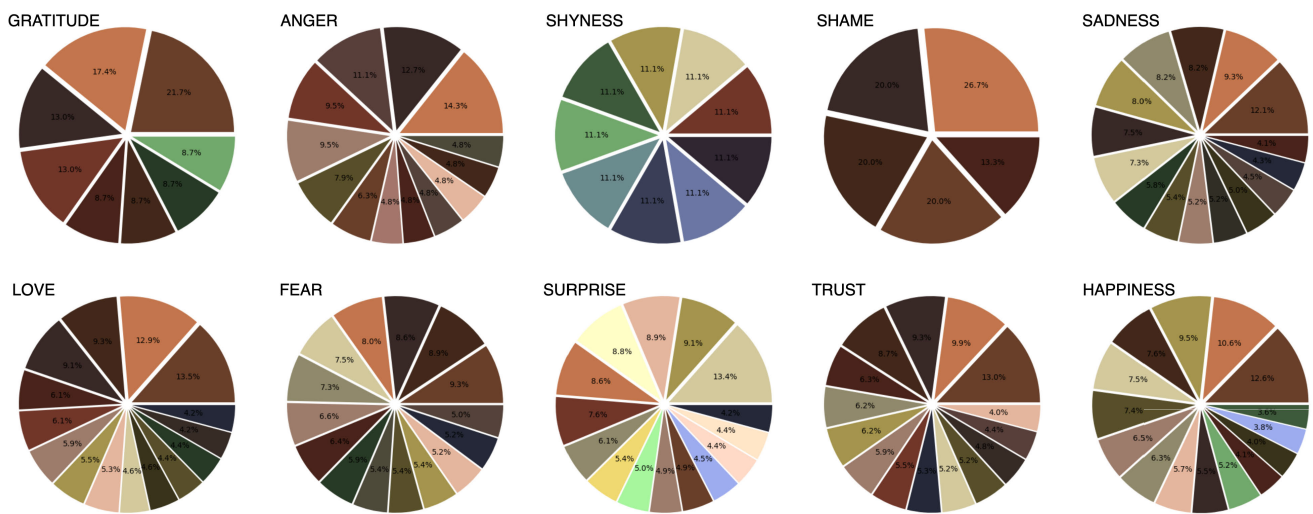
FIGURE 13. Color-emotion association results: Fuzzy color palettes.

maternal or romantic scenes, often depicted in brown tones. Therefore, its frequent usage, particularly as a background or natural color, makes it less distinctive in representing distinct emotions. Additionally, according to [28], brown hues are among the top fuzzy colors in art images.

Our methodology doesn't just focus on the presence of colors but also their proportions. This leads to a higher frequency of standard colors such as gray, black, and brown, often seen in nature and art. Our results reflect this emphasis on proportions. As a result, even small proportions of less common colors like red become notably significant in associating with specific emotions.

An interesting observation was made regarding emotionally neutral art images. Fig. 16 illustrates color-emotion association palettes received from images tagged as neutral. In contrast to other emotions, a neutral fuzzy palette is light and has low saturation. In the primary colors, hues such as brown and black are absent, typically occupying a significant part in other palettes. The dominant color in this palette is

green, which is considered neutral for taking place in both the cool and warm spectrum. Moreover, the basic color palette contains all the colors except purple, which may be due to the specifics of the context.

Brown color is the representation of human skin in art objects in the dataset, and thereby we can conclude that people tagged images as neutral if there weren't any people drawn.

B. PERFORMANCE EVALUATION
In this section, we present the performance evaluation results of the model.

1) THE JACCARD SIMILARITY
The Jaccard similarity is used to measure the similarity between the two palettes, namely Emotion Palette (E) and Image Palette (I). It calculates the similarity between two sets by comparing their intersection and union. In this case, the intersection is the set of common colors that appear in
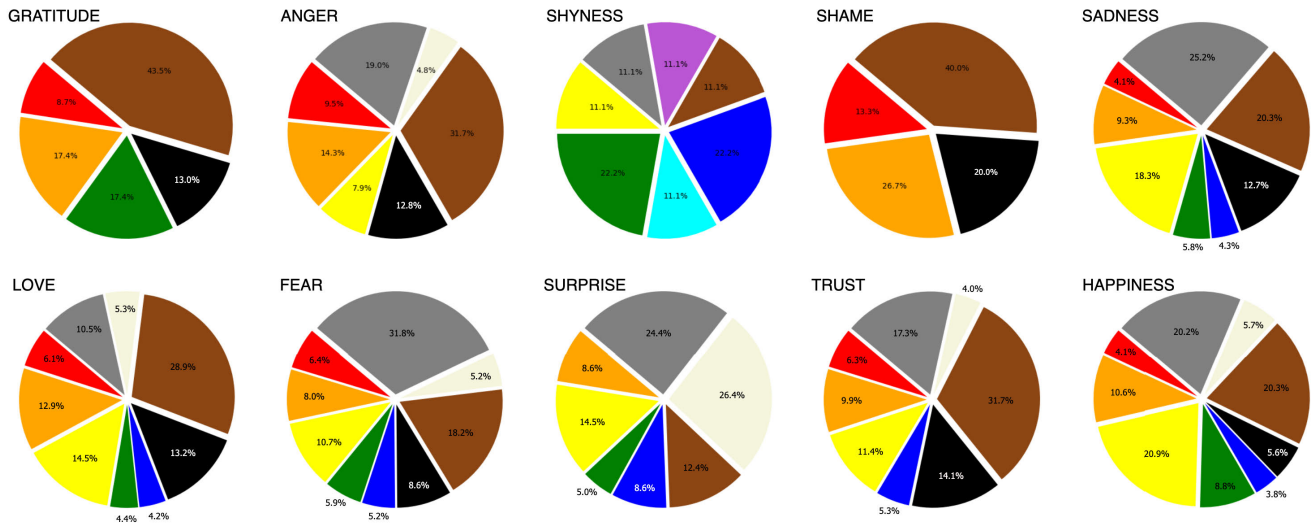
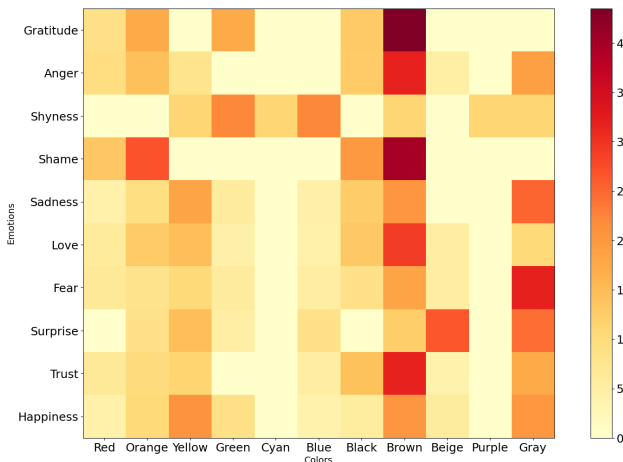**FIGURE 14.** Color-emotion association results: Crisp, basic color palettes.

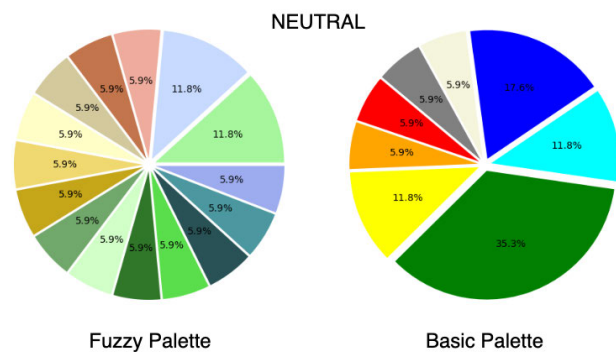
FIGURE 15. Heatmap of color-emotion association.

FIGURE 16. Fuzzy and Basic color palettes for neutral emotions.

both palettes, while the union is the total number of unique colors in both palettes. The Jaccard similarity is calculated by dividing the intersection's size by the union's size.

The Jaccard similarity value ranges from 0 (completely dissimilar) to 1 (completely similar). A higher Jaccard similarity indicates a greater association between the image and emotion color palettes. Equation (5) as follows:
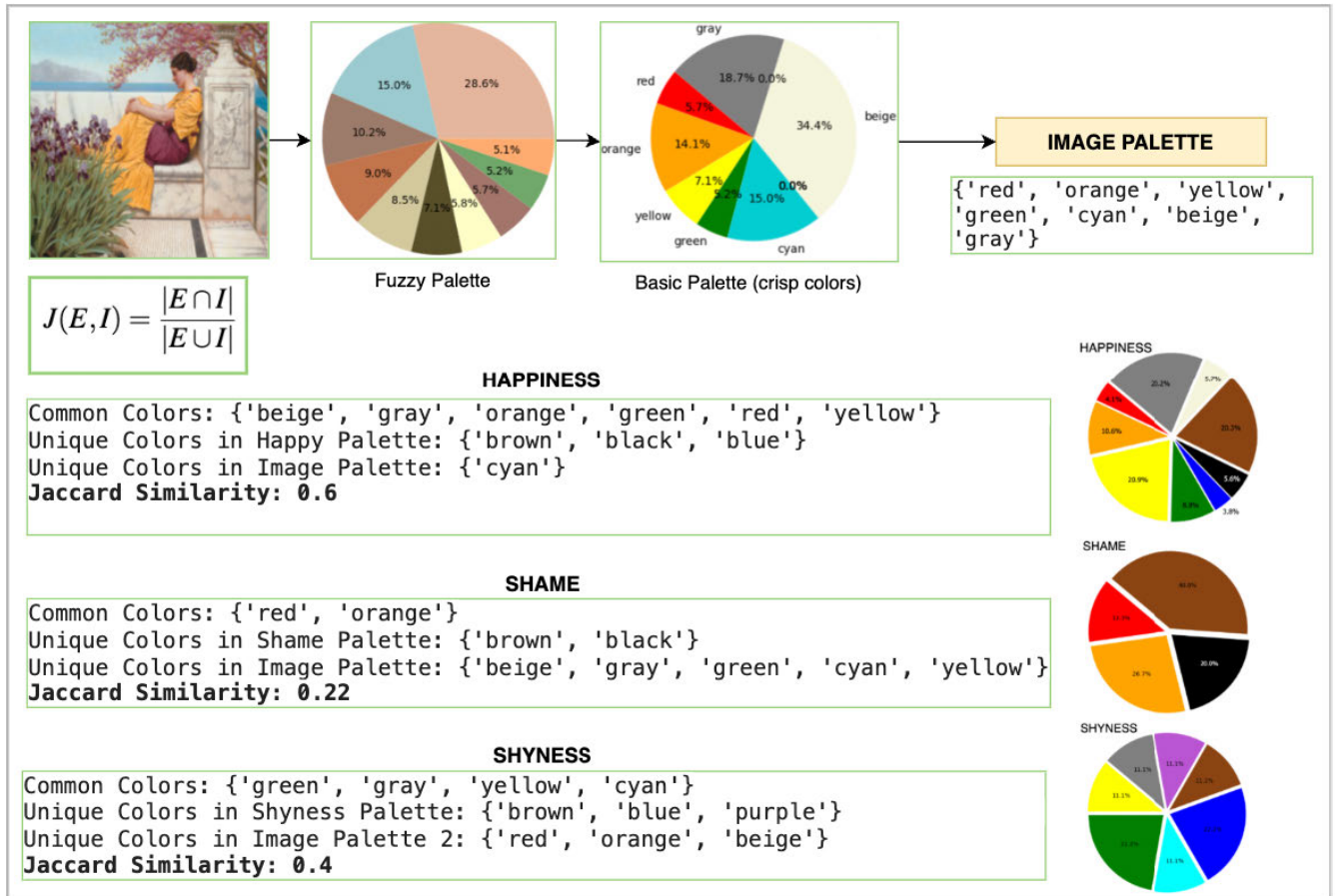
$$J(E, I) = \frac{|E \cap I|}{|E \cup I|} \qquad (5)$$

where $|E \cap I|$ is the size of the set of common colors that appear in both image and emotion palettes I and E, $|E \cup I|$ is the total number of unique colors in image and emotion palettes I and E.

2) TWO-ALTERNATIVE FORCED CHOICE
The procedure for the 2AFC experiment was designed to evaluate the effectiveness of our proposed fuzzy approach in classifying emotions in art as perceived by humans. The experiment consists of the following steps:

- **Analysis of the selected paintings using our fuzzy color-emotion classification model.** This analysis involved extracting fuzzy dominant colors from each painting, converting them to basic crisp colors, and then predicting the associated emotions based on our developed knowledge base of color-emotion associations and the Jaccard similarity coefficient.
- **Human Evaluation.** Then we compared the predictions with the responses from 177 participants, each evaluating five randomly selected images per session. This five-image selection was intentional to limit the session to ten manageable comparisons. We utilized a subset of Wiki Art Dataset paintings covering various artistic styles and periods. Each participant was asked to choose between pairs of images, resulting in ten choices per session. They were asked to select the one they felt more strongly represented a given emotion. This step was crucial for understanding human perception of

$$J(E,I) = \frac{|E \cap I|}{|E \cup I|}$$

HAPPINESS
```
Common Colors: {'beige', 'gray', 'orange', 'green', 'red', 'yellow'}
Unique Colors in Happy Palette: {'brown', 'black', 'blue'}
Unique Colors in Image Palette: {'cyan'}
Jaccard Similarity: 0.6
```

SHAME
```
Common Colors: {'red', 'orange'}
Unique Colors in Shame Palette: {'brown', 'black'}
Unique Colors in Image Palette: {'beige', 'gray', 'green', 'cyan', 'yellow'}
Jaccard Similarity: 0.22
```

SHYNESS
```
Common Colors: {'green', 'gray', 'yellow', 'cyan'}
Unique Colors in Shyness Palette: {'brown', 'blue', 'purple'}
Unique Colors in Image Palette 2: {'red', 'orange', 'beige'}
Jaccard Similarity: 0.4
```

FIGURE 17. Examples of Jaccard similarity calculation using happy, shy, shame emotion palettes and the John William Godward painting - *Under the Blossom that Hangs on the Bough, 1917..*

emotions in art and for comparing it against our model's predictions.

- **Comparison and Analysis**. Finally, we compared the participants' responses with our model's predictions. The comparison aimed to quantify the alignment between human perception and our method's capability to classify emotions based on color usage in paintings.

a: MOTIVATION

The use of the 2AFC method in our emotion detection study is not only appropriate due to its alignment with the subjective nature of emotional perception, but its prevalent use in similar studies also validates it focused on emotion and perception detection. Specifically, it was used to evaluate the performance in the Computer Expression Recognition Toolbox (CERT), which automatically recognizes facial expressions in real-time [66], in predictive modeling of emotions expressed in music [67], detection of person's emotion using contextual information [68], detection of the presence of multiple facial actions [69], automatic recognition of asymmetric facial action units [70].

b: METHOD DESCRIPTION

The experiment involved a total of 177 subjects, bachelor and master students of Kazakh-British Technical University. All subjects who provided answers passed the Ichihara color test. Two students' results were excluded because they did not prove to have normal vision. The experiment utilized a well-known behavioral measure - Two-alternative forced choice (2AFC) [71], [72]. The primary idea is to compare individuals' real emotion choices based on their evaluations to predicted emotions.

In one trial of a standard 2AFC experiment, participants indicate which of two visual choices displayed simultaneously they find more appealing or appropriate for a certain category. In our case, it means that for each pair of art images, observers must select which image more accurately represents a specific emotion (e.g., between images a and b, which better conveys happiness). For every pair that could exist, this process is repeated. Therefore, $\frac{n(n-1)}{2}$ trials are needed for 2AFC to measure choices for n stimuli. When a participant is presented with only two mutually exclusive stimuli, it makes the decision job easier for them. We use The Spearman-Karber method to calculate 2afc measures [71].
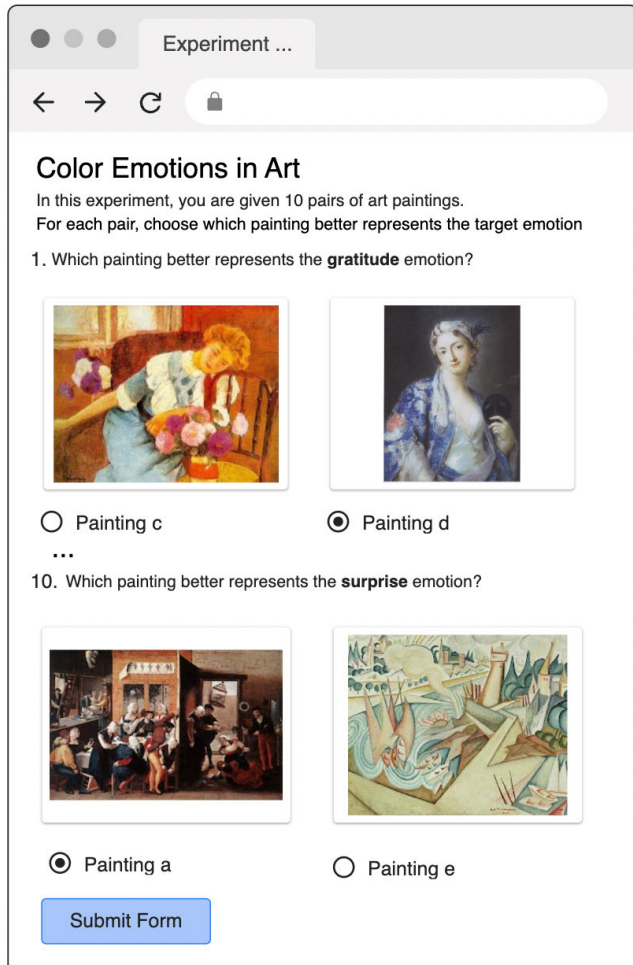
FIGURE 18. 2AFC Experiment on perceptual emotion categorization of art paintings. *Art images in the figure: Interior (Lorica), Luchian's last painting; Lady in a Turkish Costume, Felicita Sartori); Brothel scene, Brunswick Monogrammist; Landscape,Amadeo de Souza-Cardoso..*

c: PROCEDURE

The experiment corresponds to the filtering mechanism of the theory of visual attention [40], choosing an item $x \in S$ for a target category i.

Each subject has one session with 10 questions corresponding to categorization tasks. According to Bundesen's theory of visual attention, perceptual categorization takes the form of ''x belongs to i'' (represented as E(x, i), where E(x, i) is a value between 0 and 1). In this context, x refers to a perceptual unit and i refers to a perceptual category. The collection of all units is denoted as S, while the collection of all categories is denoted as R. Each question has one perceptual category (e.g., *happy*) and two perceptual units (art paintings).S contains 5 randomly chosen images. For each predicted emotion, values were calculated. R corresponds to emotions *{angry, shyness, happy, sadness, gratitude, shame, fear, trust, love, surprise}*

On each trial, responders choose an art piece that corresponds more to the target emotion. The stimulus pairs

differ in predicted emotion intensity. Observers are only allowed to select one item only. After collecting the data, we can compare it to predicted preferences, calculate the ''Hits'' percentage, and conduct further analyses. A ''Hit'' occurs when the observer's choice aligns with the stimulus that our model predicts as having higher emotion intensity.

d: DATA INTERPRETATION

Equaltion 6 gives the mean of the psychometric function cite2afc:

$$\mu_{2\hat{A}FC} = \frac{1}{2} \sum_{i=1}^{k+1} (\hat{p}_i - \hat{p_{i-1}})(x_i + x_{i-1}) \quad (6)$$

where $x_1 < x_2 \ldots < x_k$ are k monotonically increasing stimulus values, and $\hat{p}_i (i = 1, \ldots, k)$ are the observed response probabilities, associated with each stimulus value. To calculate $\mu_{2\hat{A}FC}$, we choose values for x_0 and x_{k+1} such that we can assume $p_0 = 0$ and $p_{k+1} = 1$. Note that x_0 and x_{k+1} are not part of the experimental design and are only used for the calculation of $\mu_{2\hat{A}FC}$. In our experiment, calculated $\mu_{2\hat{A}FC} \approx 0.183$.

The mean $\mu_{2\hat{A}FC}$ in 2AFC is also referred to as the point of subjective equality (PSE) [72]. In the context of psychophysics and 2AFC tasks, the PSE represents the stimulus level at which an observer is equally likely to respond ''yes'' or ''no'' (in our case, equally likely to choose the first or second art image for a target emotion). From Fig. 20, we can see that one of the lowest hit rates corresponds to *sadness* and *trust* that have 0.13 and 0.12 stimulus levels, which is less than $PSE \approx 0.183$.

For the Spearman-Karber method, we need transformed probability values [71]. Therefore, the set of observed correct response probabilities $\hat{p}_i (i = 1, \ldots, k)$ in a 2AFC can be transformed into the corresponding probability estimates. (see Eq. (7)).

$$\hat{p}_i = 2 \cdot \hat{g}_i - 1 \quad (7)$$

The experiment's findings are depicted in a psychometric function (Fig. 19), which displays the likelihood of the subject's decision based on the stimulus difference.

For fitting, the logistic function is used. This figure's abscissa illustrates the difference between two expected emotion intensities. The difference is between 0 and 1. The y-axis shows the proportion of correct responses, ranging from 0.5 to 1.0, based on how distinguishable two stimuli are for the user.

The average percentage of accurate answers, or hit rate, can be used to evaluate overall performance (see Fig. 20). The calculated hit rate, or a 2AFC score, is 0.77. The hit rate of 0.77 means that in 77% of cases, predicted emotions matched with human judgments. This high percentage demonstrates a significant correlation between the fuzzy color-emotion associations predicted by our model and human perception of emotions in art. It validates the idea that color plays a pivotal role in evoking emotions.
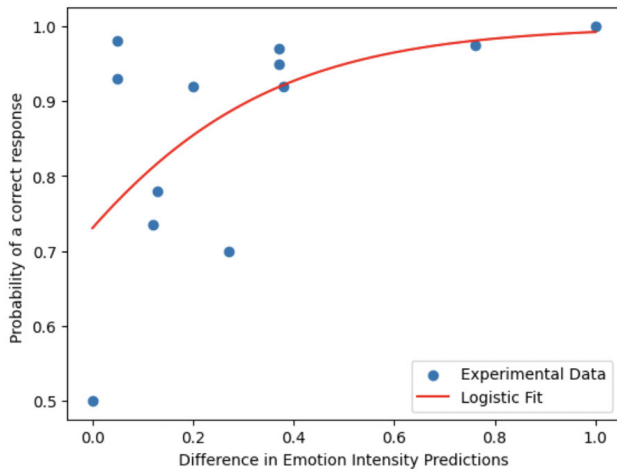
FIGURE 19. Psychometric function in a choice task. $\mu_{2\hat{A}FC} \approx 0.183$, $SE(\mu_{2\hat{A}FC}) \approx 0.013$.

FIGURE 20. Experiment hit rates distribution across emotions.

Next, let us find the standard error, which is also referred to as a "perceptual noise" [71] (see Eq. (8)):

$$SE(\mu_{2\hat{A}FC}) = \sqrt{\sum_{i=1}^{k} \frac{\hat{g}_i \cdot (1 - \hat{g}_i)}{n_i - 1} \cdot (x_{i+1} - x_{i-1})^2} \qquad (8)$$

where n_i represents the number of observations at stimulus level i. The standard error associated with the threshold estimates $\hat{\mu}_{2AFC}$ equals approximately 0.013.

As seen from Fig. 22, we compared participants' responses regarding the most voted answers and highlighted some outliers. According to categorical data analysis, we consider the respondent an outlier in case of less than 50% responses matching other participants' most selected choice. There are two outliers identified. We also did not analyze the answers of two respondents who did not pass the Ichihara color blindness test (with IDs 107 and 155).

Fig. 20 illustrates the hit rate for each emotion, namely the proportion of participants that could identify an emotion in images representing that particular emotion according to our algorithm.

Table 4 represents two alternative forced choice experiment results analysis. The hit rate refers to the number of participants correctly identifying an emotion in line with

our model's classification. We also calculate their percentage of total respondents. The difference in emotion intensity predictions signifies the numerical variance between the levels of a particular emotion found in two images.

C. SAMPLE APPLICATION (PROOF OF CONCEPT)
The emotion classification method we proposed is simple to adapt for emotion-based retrieval of art paintings. It may be advantageous to retrieve art images from big multimedia archives. The method can be easily adapted for the matching engine that retrieves art objects with similar emotions. For the arbitrary art image, we get the fuzzy color dominant palette (Algorithm 1). Next, we find the relevant emotions to a given art object using the color knowledge base we previously created (See Fig. 21).

Fig. 23 demonstrates the interface of a prototype system for this task. It can potentially use fuzzy natural queries, retrieve emotion labels (e.g., trust) and their desired intensity (e.g., very high), and use fuzzy sets and fuzzy hedges to fetch the corresponding items.

Russell's circumplex model of affect is crucial to analyzing color-emotion connections in art, given its practical applications. This model's valence and arousal dimensions help us categorize emotional responses systematically. We plan to improve art retrieval and recommendation systems by utilizing the emotional interrelations of the model, such as geometrical distances and sector placements in Russell's model. For instance, understanding that happiness is closer to gratitude and trust than shame and fear in Russell's model will aid in providing more accurate recommendations. This deeper use of the model will enable us to refine our data interpretation and improve our future applications.

The proposed approach can be used in various applications, e.g., in the matching engine, that uses emotions similarity measurement to implement retrieval.

Our method manages uncertainty and imprecision in data. Thus, the system has the potential to assist in recognizing emotions in content, suggesting recommendations, and improving user interactions on interactive platforms.

V. DISCUSSION
Several recent studies have explored the emotional effects of art objects on humans [4], [20], [22], [73]. Conceptually similar works were completed by psychologists via surveys and case studies among real people. We identified certain patterns and differences across various emotions by comparing the experimental findings and established psychological studies concerning color-emotion associations.

Yellow emerged as a dominant color associated with *happiness* in both the experimental findings and established psychological studies [62], [63] Several studies [62], [74], [75] matched our results regarding *anger*, identifying it with red and black colors. *Fear* is expressed with gray [74] and shame with red at most researches [63], [75]. Generally, green colors appeared to be associated mostly with positive emotions, and *shyness* in the experiment was displayed
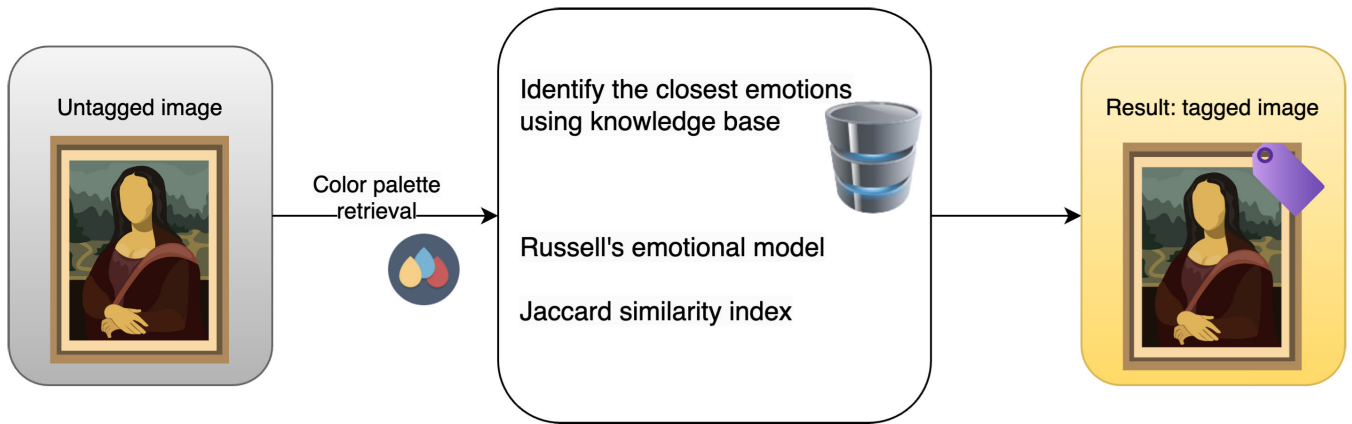
FIGURE 21. Fetching emotions from art image.

TABLE 4. 2AFC experiment results.

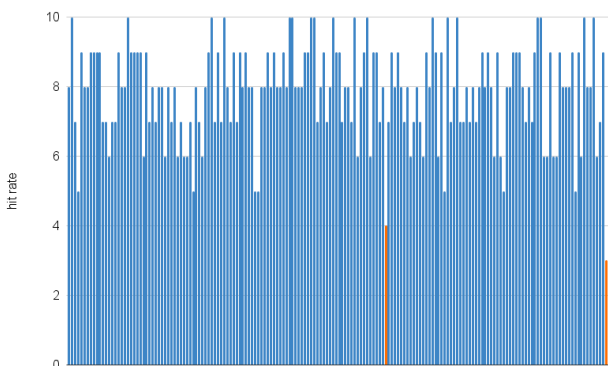|	Anger	Shyness	Happiness	Sadness	Gratitude	Shame	Fear	Trust	Love	Surprise
# hit rates	165	163	148	97	146	146	156	81	166	70
hit rate, %	0,95	0,94	0,86	0,56	0,84	0,84	0,9	0,47	0,96	0,4
Difference in Emotion Predictions	0,76	0,37	0,05	0,13	0,2	0,38	0,37	0,12	0,05	0,27

FIGURE 22. Survey participants hit rates distribution. Outliers are marked with orange color. Their responses were excluded from the analysis.

FIGURE 23. Prototype Art Painting Retrieval System.

with blue and cyan as dominant colors. Moreover, both studies demonstrated a strong correlation between *sadness* and gray and black. The results of [62] also matched our results in associating green with gratitude, although the experimental findings also noted a similarity with brown.

Conversely, our findings did not align with psychological results regarding *love*-associated colors, with no dominant color evident in this emotional context. Also, the *surprise* primarily featured light tones like beige and yellow, deviating from the typical association with black in psychological studies.

Common colors such as gray, brown, and black appeared dominantly in both studies. However, blue did not dominate the experimental findings as it did in psychological studies, highlighting a slight disparity.
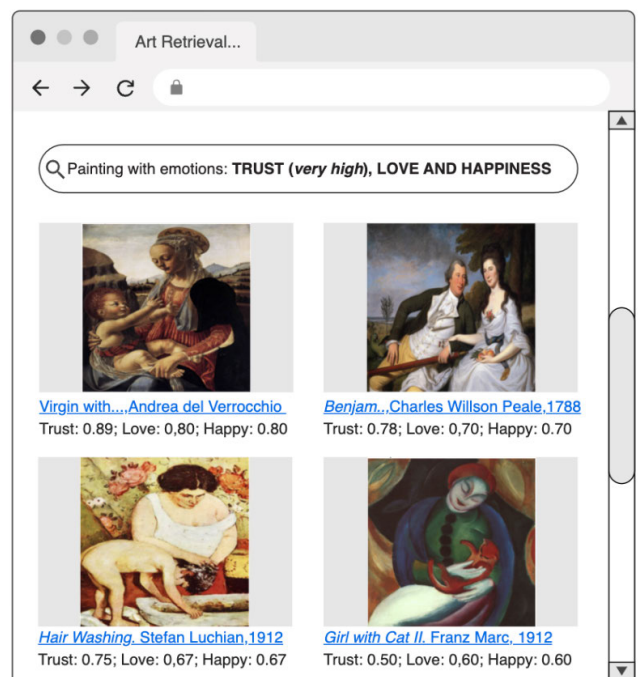
Authors of [4] also used a fuzzy approach to find a relationship between colors and emotion. We can observe universal rules governing certain emotions when comparing our findings with their results. For example, *sadness* is represented mostly with black and brown, and blue is relevant to fear. Similar results were also received in study [20], where the authors proposed a machine learning model. One of the

most significant findings is that *happiness* is undoubtedly associated with yellow and orange, as indicated in both the model prediction outcomes and psychological studies. Also, in this study, *sadness* was correlated with gray color, which is dominant for our *sadness* result palette too. Generally, *anger* is expressed with red, black, brown, and gray in all the mentioned studies, psychological experiments, and our results.

Our findings and established psychological studies [75] and recent research [29] suggest a blend of universal and context-dependent aspects in color-emotion associations. While some emotions like sadness and happiness show consistent color associations across different domains, variations in others indicate the influence of contextual factors. This highlights the complexity of the relationship between color and emotion, indicating a necessity for further exploration in various contexts.

VI. CONCLUSION

In this study, we introduced a novel approach for emotion retrieval using color-based features and fuzzy sets, providing valuable insights into the intersection of computational methods and human emotional perception in visual art analysis.

The system processed a diverse art dataset to generate color palettes associated with ten distinct emotions. We experimentally validated our approach with the 2AFC experiment and discovered that it has good predictive power for color-emotion associations (average hit rate is 0.77). The result of 0.77 in our experiment signifies that, on average, there was a 77% match between our method's predictions and the participants' responses in the 2AFC experiment. This suggests a substantial alignment between the emotions inferred by the system and those perceived by human observers, validating the system's ability to approximate emotional states accurately.

Adopting the Fuzzy Sets and Logic approach is advantageous due to its consistency with human perception. Our method enhances algorithm interpretability and adaptability in human-like applications. This system could aid in content-based emotion recognition, recommendation systems, and enhancing user experiences in interactive platforms.

Our research contributes to a more comprehensive understanding of color-emotion associations, offering valuable insights for various practical applications besides art, like marketing, design, and psychology

As for the limitations, the system's performance may vary across different art styles, cultural contexts, and individual perceptions. Next, detecting the closest emotion to an image based solely on its presence doesn't account for varying color frequencies. Colors, texture, and composition can evoke emotions [76], creating additional dependencies. We concentrated on color features only, ignoring the objects in the art image, although they also contribute to the overall emotional association. Color can have an impact not only if it

is abundant but also if it contrasts sharply with the main color scheme of the background.

Another limitation of our study is that the emotions in our datasets were not evenly represented. This could have impacted the color-emotion associations that we observed. Emotions with fewer instances in the dataset may have influenced these associations, emphasizing the importance of a more balanced representation of emotions in future research. Doing so will help us to refine our findings.

Future research could focus on expanding the dataset to encompass more diverse artwork, incorporating contextual information, and refining the fuzzy logic model to enhance accuracy. As part of future work, we plan to integrate datasets from platforms such as DeviantArt, which showcases diverse artistic styles and emotional expressions. This could lead to a better understanding of how people perceive emotions associated with color in art, considering human emotional perception's inherent subjectivity and variability. Given the lack of other widely recognized art emotion datasets tagged by humans, other sources should be considered. It could be helpful to examine datasets from platforms like DALL-E, Google, and others to expand the range of emotional expressions in art. However, it's important to remember that the interpretation of emotions in art depends on context, and we should be cautious about how variations in dataset contexts may affect the validity of our findings.

We also see great potential for personalized color-emotion applications. Understanding the emotional nuances of various colors leads to developing personalized color schemes that evoke specific emotional responses tailored to individual preferences or target audiences. We also plan to improve the model with additional dependencies, such as pixel importance.

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