Development of the ColorEmoNet Dataset and of a Machine Learning Approach for Emotion Recognition Using Color Theory

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ABSTRACT

Color theory is a way of understanding how colors influence human perception and emotions. Color theory and Machine Learning (ML) can be combined to deeply understand the psychological impact of colors on human emotion. This study aims to expand our understanding of the color-emotion relationships. To establish a relationship, ML algorithms, such as Support Vector Machines (SVM), Convolutional Neural Network (CNN), and Recurrent Neural Network (RNN), were employed to classify the emotional feedback induced by colors in images using the ColorEmoNet dataset. The proposed approach achieved an accuracy of 76% using SVM, 86.49% using CNN, and 68% using RNN, demonstrating the effectiveness of color-based features for emotion recognition. The results of this study can contribute to developing innovative emotion recognition systems that enhance emotional understanding in practical applications.

Keywords-ColorEmoNet; color theory; emotion recognition; machine learning; deep learning

I. INTRODUCTION

In [1], emotion was defined as a short-term physiological response that adapts to a changing environment. Different industries use colors to attract people's attention. For example, in architecture and interior design, colors can brighten up a dark room or make a space appear larger or smaller [2]. Color is associated with emotions, but these associations can vary between cultures, genders, and age groups. Understanding the connection between colors and emotions is difficult because it is influenced by individual experiences, cultural background, and age [3]. Detecting emotions from colors is important for understanding art or paintings, monitoring the mental health of patients, and improving human-computer interaction. Although the impact of color combinations has not been extensively examined, colors are a key element in identifying the emotions evoked by abstract artworks. State-of-the-art computer vision techniques help to understand how colors and two-color combinations evoke positive or negative emotions [4].

Previous studies explored emotion detection using facial features, audio, videos, and text/documents with various Deep Learning (DL) and Machine Learning (ML) algorithms. Combining feature-based, holistic-based, and hybrid approaches provides a way to create facial emotion recognition systems [5]. Face detection is also important, and expressions can appear in images at different sizes and angles, requiring preprocessing [6]. Both static images and videos can be used to detect facial expressions. In [7], a neuro-fuzzy approach achieved good results in detecting emotions, including happiness, fear, sadness, anger, disgust, and surprise. The Facial Emotion Recognition using Convolutional Neural Networks (FERC) [8] was based on a two-part CNN: one to remove backgrounds, while the other extracts facial features. Using an Expressive Vector (EV) of 24 values, FERC achieved the highest accuracy in identifying five facial expressions from a dataset of 10,000 images. ML models can improve accuracy by utilizing features extracted from CNNs [9].

Deep Neural Networks (DNNs) resemble the human brain, allowing for capturing emotion-color associations [10]. DL techniques can solve the problem of emotion detection from images. In this approach, feature engineering is not necessary, as image processing improves accuracy and reduces noise in the data [11]. The Extended Cohn-Kanade (CK+) dataset is a valuable resource for studying human facial expression classification. In [12], K-Nearest Neighbors (KNN), SVM, and neural networks were used to detect eight basic facial expressions, and Principal Component Analysis (PCA) was used to reduce the dimensionality of features. Among these three algorithms, SVM provided the best results.

The most popular method of human-computer interaction in the Web 2.0 era is text-based input, where semantic approaches can be used to improve detection capabilities [13]. Detecting emotions in text can determine and analyze the type of feeling associated with it. In [14], an LSTM+CNN-based approach built a robust classifier that opens ways to create innovative applications in different fields. In emotion detection using speech, specific features can differentiate different emotional states. In [15], the KNN, Decision Tree (DT), and Extra Tree (ET) classifiers were used to classify emotions, but only KNN and ET were very effective.

The application of the Luscher color test, in conjunction with advanced image processing techniques, characterizes an important phase in the progress of quantification of emotional responses to visual art. In the standard version of the test, eight color cards are arranged according to the subject's preference. The basic colors represent good personality features, while the auxiliary colors demonstrate less good personality [16]. In [17], human emotions were recognized using a defined 2D emotional model and ML for facial expression analysis. This system modifies the colors of input images based on emotional associations from an emotional color wheel, focusing solely on color information. The integration of color psychology, fuzzy logic, and the use of an α-cut to refine the classification process improves the effectiveness of emotion classification [18]. Fuzzy sets allow for degrees of membership rather than binary classifications, aligning closely with the nuances of human emotional experiences. Adopting a fuzzy set and logic approach is advantageous due to its consistency with human perception [19].

Color, a fundamental aspect of human experience, has a profound influence on emotions. Although previous research has explored emotion recognition from different sources, such as facial expressions, vocal tone, and textual content, the role of color in the evocation of emotions remains relatively unexplored. This study focuses on closing the gap by examining the association between color and emotion and developing an innovative method for color-based emotion identification. Specifically, this study aimed to:

- Explore the psychological underpinnings of color-emotion associations.
- Develop a robust color feature extraction technique.
- Analyze how well different ML algorithms perform in classifying emotions
- Create a comprehensive dataset of images labeled with emotional categories.

Related work on this topic includes studies on abstract images [20], Iranian-Islamic paintings [16], the collection of images for exploration [21], the creation of an emotional movie database, the psychophysiological evaluation of evoked emotions [22], and the quantitative analysis of changes in human emotion over time [23]. In [24], SVM, Random Forest (RF), and CNN were used for sentiment detection and classification on six sentiment tags (fury, revulsion, fear, happiness, sorrow, and shock). Experiments were conducted on two datasets (Ekman-6 and VideoEmotion-8), yielding average recognition rates of 59.51% and 52.85% for the two fusion methods. It is well-established that DNNs outperform conventional classification algorithms on large datasets. In [25], DNN and CNN methods for EEG-based emotion detection achieved classification accuracies of 75.58% and 73.28%, respectively, under valence and stimulation conditions. In [26], a method was based on the S-transform and CNN to predict human emotions. Using the S-transform, EEG signals were converted into a Time-Order Representation (TOR), and features extracted using TOR were provided as input to the CNN. In [27], emotional states were classified with 94.58% accuracy.

In addition to the use of color in movies, the interaction of multiple audiovisual aids, such as hue, text, and audio, plays a vital role in shaping audience emotions. Product-color design influences consumer decisions and should align with users' emotional color perceptions [28]. Traditional methods, relying on color harmony or single-user input, fail to capture diverse and complex consumer preferences. Recent approaches use intelligent algorithms (e.g., SVM, ANN, genetic algorithms, swarm intelligence), but face issues such as instability, premature convergence, and slow search. In [28], hybrid ML methods were used with multi-user color image data to improve accuracy, overcome algorithm limitations, and address distribution problems in product-color decisions. In [29], a CNN-based approach was used to enhance the accuracy of facial emotion identification systems. By employing transfer learning and data augmentation techniques, the model demonstrated improved generalizability on several standard datasets, such as FER-2013, CK+, and JAFFE. The results show that this CNN-based method is highly effective in accurately recognizing facial emotions, showcasing its potential for practical applications.

In [30], a base lexicon of color and emotion was established, linking precise signs to human sentiments. Using the Trailers12k dataset, this study demonstrated notable associations between color forms and viewer emotional responses. The results emphasize the influence of color on emotional insight, highlighting potential applications in digital content creation and marketing, and representing a notable advancement in understanding color psychology in multimedia. In [31], emotions were predicted based on colors in images and video excerpts through three main phases. Initially, various ML algorithms were tested for classifying emotions based on color, utilizing three different color extraction methods: clustering into a predefined palette, applying the RYB model, and generating color histograms. Preliminary results from these approaches were obtained in various parameter configurations and training sets. An online survey was used to validate the algorithm's results by comparing them with the participants' responses. A discussion of the results summarized the findings and suggested further directions for improving the algorithm's performance.

In [32], the concept of emotional distractions was introduced to examine the extent to which color data can affect the duration of attentional bias in the early visual cortex. Visual Event-Related Potentials (ERPs) elicited by neutral and disagreeable background images were measured. The findings demonstrated that the distraction effect persisted longer with colored and unpleasant distractor images and was more pronounced with color than with grayscale images. Findings from ERP analyses show that emotional scenes presented in color elicit stronger early negativities (N1–EPN) compared to neutral scenes, indicating a heightened neural response. Moreover, the unpleasant clips in color were rated as more emotionally undesirable and arousing than those in grayscale. These results suggest that color plays a crucial modulatory role in emotional perception, enhancing the withdrawal of emotional information and influencing the duration of attentional bias toward affective stimuli in early visual processing areas.

Many studies have investigated the area of color theory and emotion detection. Color can predict emotional responses that are not universal but depend on the individual's cultural background or personal experience. Colors have also been shown to have a great impact on emotional perception. Using SVM, emotions can be reliably classified based on color information. SVMs are used in many disciplines, such as marketing, healthcare, Human-Machine Interaction (HMI) systems, and advanced emotion recognition technologies [33]. In addition, the literature shows the importance of facial expressions along with color in emotional expression. Six primary emotions are identified, and the SVM algorithm has proved that it can fuse color features and facial cues for emotion classification. Combining color theory with facial expression analysis may enable the extraction of more information about emotional responses for emotion detection. SVM has been used to classify emotions in a wide variety of contexts, showing that it can be applied to emotion applications in general [34].

Sound therapy can also be used to heal negative emotions and induce positive emotions. Using SVM for emotion recognition, positive emotions were found to increase significantly after sound therapy-based sessions [35]. This further strengthens the motivation for using sound therapy for mental health applications of color theory, as it becomes possible to quantify the impact on the emotional state. The development of image process technology, in which a two-stage CNN is used for color transfer [36], has also expanded research on the emotional response to color. Through feature extraction and emotional color, the applications of these models are also assumed in art restoration and medical images. [37-39]. However, the availability of comprehensive databases for studying human emotional responses to colors is limited. The Two-Color Affective Response (TCAR) database comprises diversified simple and patterned two-color images to analyze the impact of color parameters on emotion [40].

The literature review on emotion detection shows that SVM, colors, and emotions are closely related. For emotion recognition, SVM is integrated with color features, based on facial expressions, to provide better performance for accurate emotion recognition. Its potential can be used for many applications in marketing, healthcare, etc. [41-43]. Previous research has demonstrated significant advances in emotion detection using modalities such as facial expressions, speech, video, and text. Several studies have also highlighted the intricate relationship between color and human emotions. Building on these insights, this study presents a new method of emotion recognition that uses color theory and DL techniques to improve the understanding of emotional responses.

II. PROPOSED METHOD

This study follows a structured methodology that combines color theory and ML techniques to create an emotion detection system. Emotional detection in this context means identifying, analyzing, and modeling emotions based on the feelings evoked by the dominant colors in the visual content. This study aims to establish a color-based emotion detection framework and design a system capable of accurately predicting emotions. Figure 1 shows the detailed phases of this study. Each step plays a crucial role in the dataset creation objective. The method starts by clearly identifying the main purpose of creating a dataset using color theory and choosing a suitable color model, such as RGB or HSV, depending on the purpose. Image data was collected, where the colors were prominent and meaningful. It was ensured that the data reflected real-world use cases and aligned with the objective, along with considering ethical guidelines.

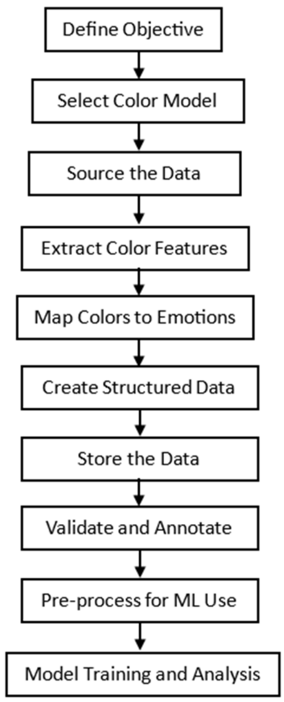

Fig. 1. Procedure overview.

Using image processing tools, features such as dominant color, average hue, saturation, or color histograms were extracted. These features are measurable inputs that can later be linked to emotional or perceptual labels. Principles from color theory were applied to associate specific colors with emotional states, e.g., red with anger or passion, blue with affection, etc. This mapping may be predefined based on psychological research or adapted based on empirical observation. The extracted color and emotion data were organized into a structured format, with each entry including fields such as image ID, color values, extracted features, and the associated emotion. The data was securely stored and well-organized for easy access during preprocessing or modeling. Then, the data was labeled by ten annotators and refined. This process involved manual annotation, cross-validation by multiple raters, and automatic checks to ensure that emotional labels and color mappings are consistent and accurate, reducing bias in the dataset. Color and emotion data were converted into machine-readable formats. Numeric values (such as hue/saturation) were normalized, categorical features (such as emotion) were encoded, and any missing or noisy data were handled to prepare for input into ML models. The structured and cleaned dataset was used to train and evaluate ML models.

A. *Preparation of the Dataset*

The goal of this dataset is to provide a way to build ML models to detect sentiment by implementing color theory from visual inputs. This dataset includes various images that represent nine emotions, namely Angry, Sad, Surprise, Happy, Hope, Calm, Excitement, Affection, and Fear, using color theory. The dataset was compiled from online sources, namely Pixabay, Unsplash, Pexels, and Shutterstock, which provide high-quality images that are freely available to use. These sites allow researchers to collect data without any cost or legal constraints. Only images that were based on color theory and contain nature or humans that are suitable for expressing emotions in different ways were selected. Each image depicts scenes, subjects, or situations that align with the emotional association of the respective colors.

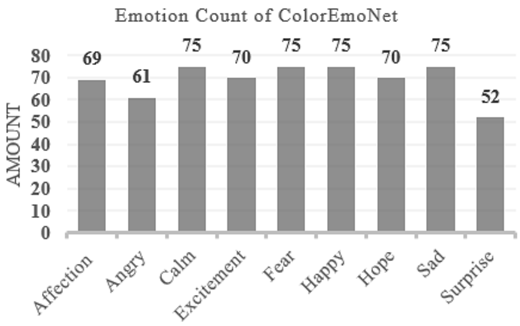

Fig. 2. Count of emotions in the ColorEmoNet dataset.

A Python script was used to detect emotions from images using a predefined color mapping. Using libraries such as Pandas, PIL, and NumPy, the script processes the image file and gives output in a CSV file with corresponding emotions. The script calculates the Euclidean distance between colors to identify the closest color to the average of each image. The script takes RGB values from each pixel and an average of them, representing a specific single color. This allows for detecting emotion from color. Figure 2 shows the distribution of the ColorEmoNet dataset [44], and Figure 3 illustrates sample images.

Fig. 3. Sample images from the ColorEmoNet dataset.

B. *Color-Emotion Mapping*

Color emotion mapping is a technique that explores the psychological associations between colors and emotions [45]. Different colors can evoke various emotional responses, influencing moods and behaviors. In this study, before image labeling, specific colors were assigned to specific emotions based on previous studies. The yellow color is assigned to happiness, the green color is assigned to calmness, the red color is assigned to anger, and the gray color is assigned to sadness [45-47]. Table I shows the color-emotion mapping used.

TABLE I. COLOR-EMOTION MAPPING

	Emotion	**Color mapping**
1	Anger	Red
2	Happy	Yellow
3	Sad	Grey
4	Surprise	White
5	Calm	Green
6	Fear	Black
7	Affection	Pink
8	Hope	Blue
9	Excitement	Orange

In this study, the process of mapping images, emotions, and color is rooted in the analysis of the background color composition of an image, rather than human figures. The central idea is to determine the emotional tone of an image by examining its dominant colors, since colors are strongly associated with specific emotions according to psychological studies. The workflow begins by inputting an image, which is then processed to extract dominant color values using unsupervised techniques on the image pixels. These RGB color values are then mapped to the closest known color names using color distance algorithms or color libraries. Once identified, each color is associated with a corresponding emotion. This color-to-emotion mapping enables the system to interpret the mood or emotional message conveyed by the visual content, even in the absence of human expressions. By treating color as the emotional carrier within an image, the framework supports applications in visual mood classification, emotionally adaptive design, and content-based emotion labeling for images and multimedia. Figure 4 shows the basic steps used in the color-emotion mapping.

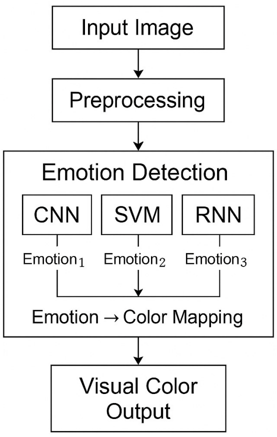

Fig. 4. Process of color-emotion mapping.

This diagram illustrates a pipeline for emotion detection and color-based visualization from an input image. The process begins with an Input Image, which undergoes Preprocessing to enhance data quality for analysis. The core component is the Emotion Detection block, which utilizes three different ML models, CNN, SVM, and RNN, to independently predict emotions ($Emotion_1$, $Emotion_2$, $Emotion_3$). These predicted emotions are then passed through a Color Mapping mechanism, which translates each detected emotion into a corresponding color based on predefined associations. Finally, the output is presented as a Visual Color Output, providing an intuitive visual representation of the detected emotion.

C. Feature Extraction

Average color extraction is a simple yet effective feature extraction technique used in color-emotion mapping. It involves calculating the mean values of the Red, Green, and Blue (RGB) channels across all pixels in an image to obtain a single representative color. This average color captures the overall visual tone or mood of the image and can be directly associated with specific emotional states. For example, a dominant average blue may indicate calmness, while red may reflect excitement or anger. This method is computationally efficient and provides a strong baseline for linking image color to emotion.

The primary focus of the emotion detection model was on colors. Therefore, color features were extracted from each image, as they have a vital role in the emotion classification task and the relationship between colors and the emotional response. Initially, an empty list of features is initialized to store the feature vectors for each image. Preprocessing extracts color and other image characteristics. These characteristics are appended to the feature list. Once all image features are extracted, the list is transformed into a NumPy array for efficient processing. The information is then reshaped into a 3D array with dimensions *number_of_samples*, *time_steps*, and *number_of_features*, where *time_steps* is set to 1, indicating that each image is treated as a single time step. The reshaped data is passed to the ML algorithm for classification. The model outputs class chances for each image. The SoftMax function retrieves the index of the maximum probability for each prediction, identifying the predicted class for each image. This allows for the continued use of the vector form of the RGB values for each image as the primary input features of the classification model for emotions.

III. EXPERIMENTAL SETUP

SVM, CNN, and RNN models were implemented to identify emotions built on colors in images. This study aimed to explore how different color associations influence emotional recognition and classification. The accuracy in classifying emotions was evaluated based on specific color cues. Finally, it was examined how the training data influenced the ability to generalize emotion detection across unseen samples.

A. Convolutional Neural Network (CNN)

A CNN was developed using Keras to classify the emotions in the images. The CNN consisted of 32, 64, and 128 filters per layer, respectively. Max-pooling layers were useful after each convolutional layer to decrease the dimensionality of the feature map. The final layers include a flattened layer, a fully connected layer with 64 neurons, and a final layer that employs the SoftMax function for classification. The model was trained for 25 epochs using the Adam optimizer, with sparse categorical cross-entropy as the loss function. Data augmentation was employed to improve generalization, and performance was assessed using accuracy and loss metrics. The CNN can be defined as:

$$Output = ReLU(Conv(input) + bias) \quad (1)$$

where $input$ represents the feature map generated by the preceding layer, $Conv$ denotes the convolution operation with a filter (kernel) of size $f \times f$ and stride s, the $ReLU$ activation function applies non-linearity, and a $bias$ term is incorporated into the output. The pooling layer is defined as:

$$Y = max\_pool(X, k) \quad (2)$$

where Y represents the pooled output, X is the input feature map, and k is the pooling window size. The output layer (for multiclass classification) is defined as:

$$Output = softmax(W * input + b) \tag{3}$$

The final fully connected layer produces the output, where W stands for the weight matrix, and b denotes the bias vector. The SoftMax activation function is applied to generate probability distributions across multiple classes. Figure 5 illustrates the architecture of the CNN.

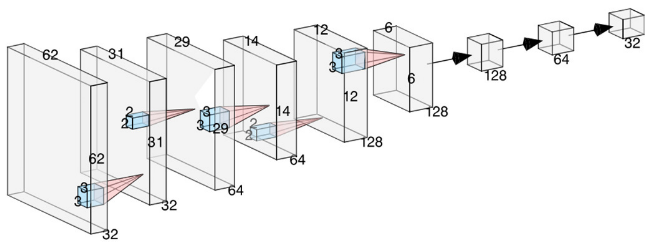

Fig. 5. CNN model architecture.

B. Support Vector Machine (SVM)

SVM operates by recognizing an optimum hyperplane that splits information points into different categories. The main idea is to optimize the margin between the support vectors and the hyperplane. By implementing kernel functions, SVMs can manage decision boundaries that map the data into higher-dimensional spaces so that linear separation becomes possible. A linear kernel was used, as it is useful to maximize the margin between two classes while minimizing classification errors. Table II shows the parameters considered.

TABLE II. SVM PARAMETERS

Parameter	Description	Values
C	The regularization parameter controls the balance between model complexity and classification errors.	[0.1, 1, 10, 100]
gamma	Kernel coefficient	['scale', 0.01, 0.001, 0.0001]
Kernel	Kernel type	['rbf']
Degree	Degree of the polynomial kernel function	3 (default)
coef0	Controls trade-off in poly and sigmoid kernels between high/low-order terms	0 (default)
Class weight	Balances class distribution automatically or manually.	None (default)
tol	Tolerance for stopping criteria.	1e-3 (default)
max_iter	Optimization iterations	-1 (no limit, default)

C. Recurrent Neural Network (RNN)

LSTM is a kind of RNN [48]. The output of the first LSTM layer, which has 128 units, is forwarded to the following LSTM. The 64 units in the following layer return the sequence. To mitigate overfitting, dropout layers are incorporated within each LSTM layer. The dense layer is the last and employs the SoftMax activation function. With a batch size of 32, the model is trained across 25 epochs. Table III shows the parameters of the proposed RNN model.

TABLE III. RNN PARAMETERS

Parameter	Value/Details
Model Type	Sequential model
Input Layer	LSTM (128 units)
LSTM layer 1	Input shape: (None, features. shape[1]), return_sequences=True
Dropout layer	Dropout rate: 0.2
LSTM layer 2	LSTM (64 units)
Dropout layer 2	Dropout rate: 0.2
Dense layer	Softmax activation, output size: len(label_encoder.classes_)
Optimizer	Adam
Loss function	Categorical Crossentropy
Metrics	Accuracy
Input data shape	(None, features.shape[1])
Training data shape	(X_train.shape[0], 1, X_train.shape[1])
Testing data shape	(X_test.shape[0], 1, X_test.shape[1])
Epochs	25
Batch_size	32
Validation split	0.2

IV. RESULTS AND DISCUSSION

A series of experiments was conducted using the custom-developed ColorEmoNet dataset to evaluate the effectiveness of different ML algorithms in color-based emotion recognition. The dataset was preprocessed and divided into training and testing subsets using an 80:20 split. Three models, namely CNN, SVM, and RNN, were trained and tested under identical experimental conditions. The models were implemented using Python and TensorFlow, and evaluated using accuracy as the primary performance metric.

Figures 6, 7, and 8 depict the confusion matrices for SVM, CNN, and RNN, respectively, showing visually how often the model correctly or incorrectly predicted each emotion. The rows show the actual emotions, and the columns show the predicted emotions. The numbers in each cell represent how many times each emotion was predicted. The diagonal cells show the correct predictions, where the predicted emotion matches the actual one. The darker the color in the matrix, the more times that emotion was predicted. Figures 9, 10, and 11 depict the Precision, Recall, F1 score, and accuracy of each class for SVM, CNN, and RNN, respectively. High recall demonstrates the model's efficiency in identifying true occurrences of each emotion, minimizing missed classifications. The F1 score provides a stable measure of precision and recall, offering a single metric to assess the model's effectiveness in classifying emotions accurately.

Accuracy is a fundamental performance criterion used in classification tasks to assess the effectiveness of a predictive model, describing the ratio of accurate to total predictions. High precision indicates that the model is successfully identifying the correct class labels for a significant portion of the dataset. The results show that CNN demonstrated superior performance compared to SVM and RNN. The CNN excels at extracting hierarchical features from color-based representations, achieving better accuracy and strength in classifying emotions. Table IV shows a comparison of the results of the proposed method with others.

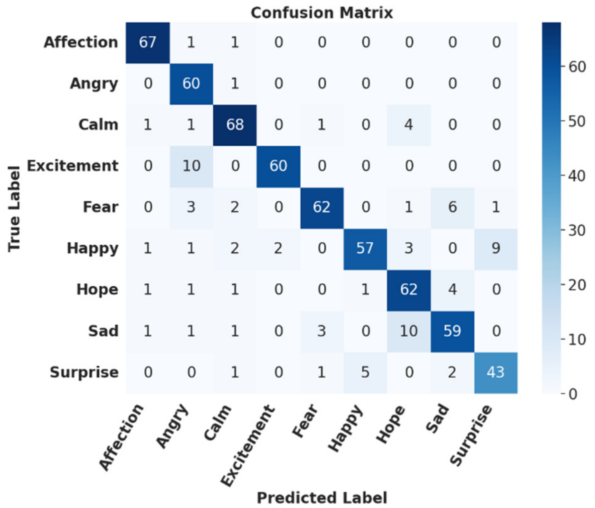

Fig. 6. Confusion Matrix using CNN.

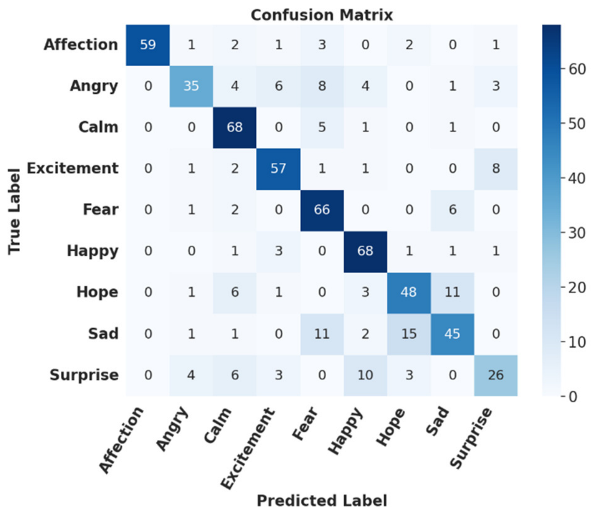

Fig. 7. Confusion Matrix using SVM.

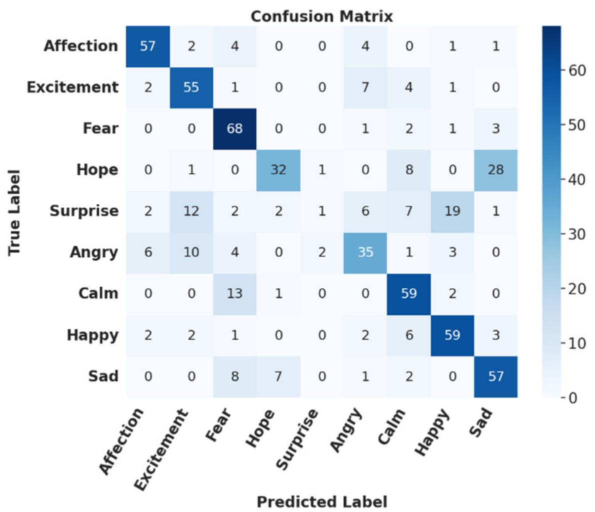

Fig. 8. Confusion Matrix using RNN.

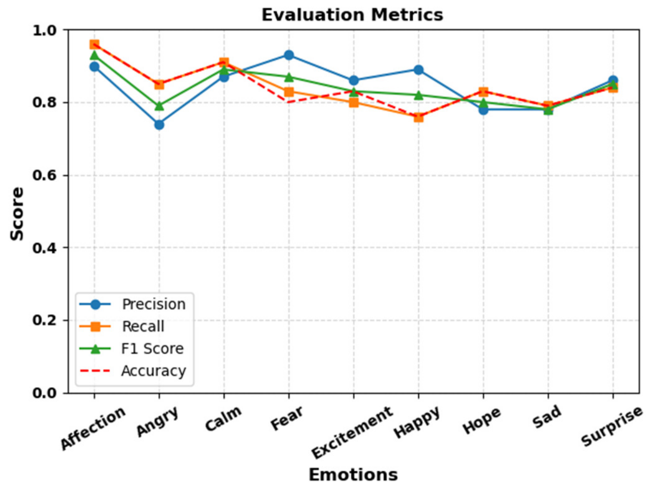

Fig. 9. Accuracy using CNN.

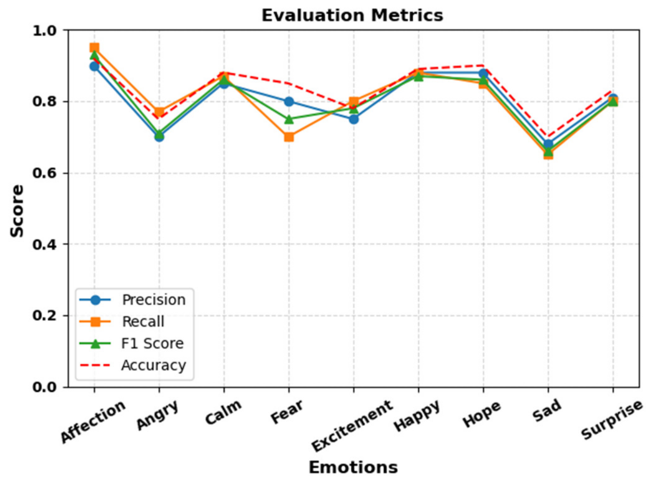

Fig. 10. Accuracy using SVM.

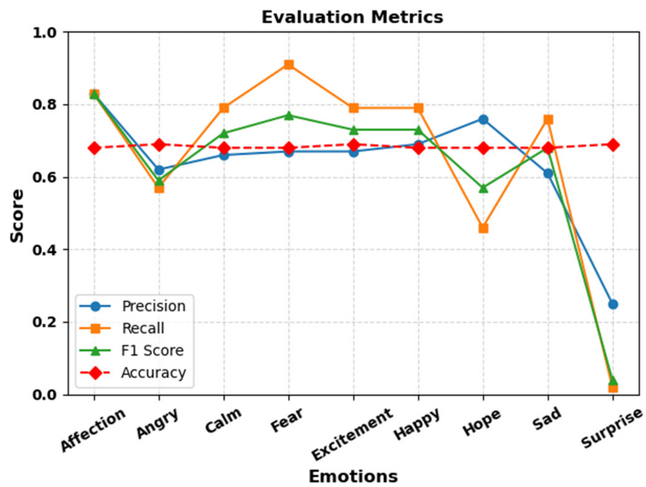

Fig. 11. Accuracy using RNN.

TABLE IV. COMPARATIVE ANALYSIS OF THE PROPOSED METHOD WITH OTHER RESEARCH WORK

Study	Method	Input used	Accuracy %	Color theory implementation	ML use
[2]	API	Image+text (size not mentioned)	-	Yes	No
[10]	LSTM	ImageNet dataset	54	Yes	Yes
[19]	Fuzzy Logic	Wiki Art Dataset of paintings	77	Yes	No
[30]	Root Mean Squared Error (RMSE), Cosine similarity, and Jensen-Shannon divergence.	YouTube Videos	80.2	Yes	No
[49]	Semantic Scale	32 images + form Input	-	Yes	No
This	SVM, CNN, and RNN	ColorEmoNet (own dataset)	SVM: 76, CNN: 86.49, RNN: 68	Yes	Yes

V. CONCLUSION AND FUTURE DIRECTIONS

This study focused on exploring the connection between colors and human emotions using the psychological basis of color-emotion associations. A feature extraction technique was devised to successfully capture the emotional essence contained in colors. A thorough collection of photos with emotional classifications was also devised, which offers a useful resource for further study in this area. Different ML techniques, such as CNN, SVM, and RNN, were used to analyze images and predict emotions based on their colors. The results show that the proposed CNN was very effective in understanding the connection between colors and emotions, achieving an accuracy of 86.49% compared to SVM (76%) and RNN (68%). In the future, the dataset can be expanded to include more diverse images, consider cultural differences in color perception, and combine color information with other cues, such as facial expressions or voice. By examining how well different ML algorithms perform in categorizing emotions based on color cues, the study demonstrates the promise of computational techniques in comprehending and identifying emotions.

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CONFLICT OF INTEREST

The authors declare that they have no conflicts of interest regarding the publication of this paper.

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