Emotion Assessment of YouTube Videos using Color Theory

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Abstract

In the realm of digital media, the subtle interplay of colors in video content holds the key to unlocking viewer emotions. Our innovative study delves into this fascinating domain, leveraging the rich tapestry of colors in YouTube videos to decipher the emotional undertones they convey. By constructing a robust Color-Emotion Baseline Dictionary, we mapped specific colors to a spectrum of human emotions, uncovering the intricate ways in which visual hues influence viewer sentiment. Our methodology involved generating nuanced tints and shades, transcending conventional color-emotion models, and employing sophisticated barcode generation techniques for YouTube videos. This approach allowed for an unprecedented analysis of color psychology in digital media.

In an innovative experiment using the Trailers12k dataset, we demonstrated the efficacy of our model, revealing significant correlations between color patterns and emotional responses. Our findings not only validate the profound impact of colors on emotional perception but also pave the way for novel applications in areas like digital marketing and content creation. Our work stands out as a unique contribution to the field, offering a fresh perspective on the emotional power of colors in multimedia content and setting a new benchmark for future research in this intriguing area.

CCS Concepts: • **Information systems → Multimedia content creation**; • **Human-centered computing** → *Human computer interaction (HCI).*

Keywords: Color Theory, Emotion Analysis, Multimedia Content, Emotive Color Mapping, Color Barcode

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1 Introduction

The intricate relationship between human emotions and the colors in our environment is a fascinating subject, especially when viewed through the lens of images, photography, and movies. Understanding emotion is complex, with definitions varying across different fields. This variability presents challenges in studying, modeling, and quantifying emotions [1]. Recently, in the evolving field of digital media analysis, the concept of emotion extraction from the colors of video barcodes represents a cutting-edge intersection of technology, psychology, and visual arts. Video barcodes, a unique representation of a video's color palette compressed into a single image, offer a novel way to understand and interpret the emotional impact of visual content [2].

Human emotions, however, extend beyond the traditional five senses of sight, smell, touch, taste, and hearing, to include secondary senses like nociception—the sensory system related to pain. This research recognizes the significant influence of elements like color on emotional states. One of the key challenges lies in identifying emotional triggers and determining appropriate methods for labeling and evaluating these emotional states. The foundation of this research lies in the psychological theory that colors have a profound effect on human emotions. Different colors and their combinations can evoke a range of feelings, from tranquility to excitement. By analyzing video barcodes, which condense the essence of a video's visual journey into a compact, color-coded format, we aim to unlock new insights into how colors influence viewer emotions over the course of a video [3, 4].

This study dives into the fascinating world of color psychology in movies and other visual media, aiming to better understand how colors influence our emotions. We blend time-honored theories of color, recent insights from psychology, and modern methods of analyzing media to uncover new ways of predicting and understanding emotional impacts in digital content. The main challenge lies in deciphering the complex ties between colors and emotions. This task is complicated by the fact that people from different cultures and backgrounds can perceive colors and emotions in vastly different ways. Our approach is comprehensive and detailed, incorporating a broad spectrum of literature that encompasses various emotional perspectives, helping us to grasp the full range of human emotions and the diverse interpretations of colors. This comprehensive view is crucial for understanding how colors affect us emotionally in the context of movies and other visual content.

2 Related Work

This section explores research on color, emotion, and their applications in various fields, from color theory to emotion mapping.

2.1 Color Theory

Color theory history in the late 19th and early 20th centuries, marked by James Clerk Maxwell's 1860 work, includes groundbreaking developments. He established the color-matching functions of the human eye, demonstrating how mixing three primary colors in various proportions could perceptually match any color in the spectrum. This finding, represented by the R, G, and B curves, fundamentally changed our understanding of color perception and representation [5]. During the same period, color theory evolved in the realms of statistics, science, and data visualization, linking color perception with the human visual system. Studies focused on quantifying color perception, notably through the Munsell System, which views color as a combination of hue, chroma, and value, and the International Commission on Illumination (CIE) models, which provide numerical values for color perception. These theories also considered the physiological and cultural context of color perception and application, blending art and science for a deeper understanding of color interactions and harmonies [6].

Today, color theory bridges historical legacy and modern innovation, extending beyond traditional boundaries to integrate into all aspects of visual culture. Modern technology allows for digital color manipulation, expanding the range of possibilities beyond the traditional color wheel. The field now encompasses the psychological and cultural dimensions of color, exploring how colors affect emotion, perception, and communication, making color theory a dynamic and evolving discipline that reflects the diversity of human experience and creativity [7–9].

2.2 Color and Human Psychology

The concept of color and its impact on human psychology has been a subject of interest for centuries. Early theoretical work can be traced back to Johann Wolfgang von Goethe, who in his 1810 work 'Theory of Colors,' speculated on the influence of color perception on emotional experience. Goethe categorized colors as either 'plus' or 'minus,' with the former inducing positive feelings and the latter negative ones. This intuition-based speculation laid the groundwork for later explorations in the 20th century, notably by Kurt Goldstein, who integrated Goethe's ideas with his clinical observations, proposing that color perception produces physiological reactions manifesting in emotions, cognitive focus, and motor behavior [10–12].

Recent advances in color psychology have explored the biological basis of human responses to color, with a focus on red and its effects in various contexts, such as sports and personality traits. Methodological challenges have been addressed using precise color calibration tools like Photoshop and the Munsell system. Studies have shown that red influences sports outcomes, cognitive performance, and perceptions of attractiveness [11]. Further research links color preferences, particularly red, to personality traits like interpersonal hostility, suggesting a deeper psychological association between color and personality. Cultural considerations in psychology emphasize the need for an inclusive approach, recognizing the unique experiences and strengths of people of color, and the impact of cultural values and adversities on optimal human functioning. Lastly, the color-in-context model reveals that the psychological impact of color, especially red, varies significantly with context, affecting behaviors differently in romantic and achievement settings [13, 14]

2.3 Color and Emotion in Multimedia

The field of color, emotion, and technology in movies and movie trailers is rapidly growing, contributing significantly to our understanding of cinematic storytelling and human perception. Key studies have highlighted Hollywood's common use of specific colors in movie trailers enhancing genre identity [15]. In addition to the use of color in movies, the interplay of various multimedia elements, including color, text, and audio, plays a crucial role in shaping audience emotions, as explored in the study [16].

Research in this area has also introduced advanced methods for visualizing and predicting emotions in movies, utilizing tools like Russel's VA circumplex for emotional representation. These techniques aid in personalized movie selection and have been instrumental in bridging the affective gap in movie trailers through mid-level concept features [17, 18]. Additionally, integrating AI with human creativity, particularly in horror movie trailers, exemplifies the potential of technology in filmmaking [19].

In social media contexts, the importance of individual differences in color perception and its relation to emotional and psychological states is highlighted, as illustrated by studies exploring YouTube's recommendation algorithm's impact on emotional content distribution [20, 21] and how such algorithms can influence viewers' feelings and beliefs in morally complex topics [22]. Studies have shown that personal emotional responses to images on platforms like Flickr can be predicted by considering factors such as visual content and social context [23]. Similarly, research analyzing Instagram photos reveals connections between users' personality traits and their photo color choices, indicating the potential of using color analysis in social media [24].

Furthermore, practical applications in webpage design have been explored. Studies focusing on color combinations and geometric shapes in webpage design demonstrate preferences for certain color pairs and shapes, providing valuable insights for webpage designers about the emotional impact of color and shape in multimedia [25].

2.4 Color Emotion Mapping

In everyday life, people often associate colors with emotions, sometimes unconsciously. Common sayings like 'black thoughts,' 'seeing through rose-colored glasses,' and 'acting like a red rag to a bull' are examples of such associations, indicating that colors like black, pink, and red are linked to emotions of sadness, happiness, and anger, respectively. Emoticons also use color to convey emotions, with red often symbolizing aggression and green disgust. Researchers like Takei and Imaizumi have explored how color-emotion associations affect perception, discovering that matching background colors (like yellow for happiness and red for anger) can facilitate the recognition of facial expressions, but only when presented simultaneously with the facial stimuli [26]. Another study by Bleicher examined the influence of colors in the Holtzman Inkblot Technique on different groups, including healthy individuals and those with various mental disorders [27]. This technique uses color to evoke emotional responses, revealing that people with schizophrenia responded differently to colored versus black-and-white cards, unlike other groups.

The perception of colors and the emotions they evoke are not uniform across individuals; they vary depending on personal and cultural factors. A person's mental state, personality, and cultural background can significantly influence how they perceive and emotionally respond to colors [28]. For example, black signifies mourning in European culture but represents happiness in China, exemplifying the wide cultural variances in color perception [29]. The Lüscher Psychological Color Test also underscores the individualized nature of color-emotion perception [30]. It involves selecting colors that evoke positive reactions in the respondent and interpreting these choices to reveal various aspects of the individual's current state and personality traits. Similarly, Liu and Pei developed a method using a convolutional neural network and color transfer to colorize images based on user-defined emotions [31]. This method considers the hue distribution and texture features, demonstrating a significant correspondence between emotions and colors and highlighting the role of image segmentation in extracting main colors. This diverse range of studies and methods illustrates the complex and subjective nature of color-emotion associations, emphasizing the need for nuanced approaches to understand these relationships in various context [32, 33].

The literature reviewed reveals extensive research on the impact of colors on emotions, yet several limitations are evident. Studies often used attributes like colorfulness and harmony to infer personality traits but did not employ pure colors directly linked to emotions. This approach overlooks the nuanced emotional responses elicited by specific visual elements. Furthermore, some research was constrained to a narrow selection of colors and emotions, limiting the breadth of the color-emotion spectrum explored. Another notable limitation is the over-reliance on specific participant groups, such as patients, which may introduce bias. Additionally, a few studies focused primarily on cultural interpretations of color-emotion relationships, potentially neglecting other influential factors like psychological or situational contexts. Some research was confined to a physiological perspective, overlooking the broader context influencing emotional responses. In terms of methodology, certain models aimed to transfer colors between images based on selected emotion keywords, but this does not necessarily capture the overall emotional tone. Lastly, challenges in dataset and labeling were apparent, particularly in video analysis, where the rapid succession of frames complicates emotion identification and data processing, raising concerns about both accuracy and efficiency.

In our work, we aim to address these limitations by focusing on the complex interplay of colors, emotions, and contexts. We plan to explore a wider range of colors and emotions and incorporate insights from many different works or literature, thereby reducing the overall bias and advancing a more comprehensive understanding of the color-emotion relationship in multimedia.

3 Methodology for Color-Emotion Mapping

This section explores the complex link between color and emotion. It outlines a systematic approach, including creating a Color-Emotion Baseline Dictionary and applying advanced color analysis techniques in various visual contexts.

3.1 Color-Emotion Baseline Dictionary

The representation of colors and the emotions they evoke is highly contextual. It can vary based on personal experiences, cultural backgrounds, and specific circumstances. Relying on biased representation can lead to inconsistent or skewed results. Hence, in our work, we aim to create a structural and systematic manner for interaction between color and emotion. Using widely accepted diverse sources, we work toward providing uniform reference points by constructing a Color-Emotion Baseline Dictionary. This unity of different sources assists in mitigating the biases that were previously mentioned and ensures a more objective and comprehensive overview of the color-emotion relationship.

To achieve this result, we focused on emotion wheels, tools that show a wide range of human emotions and their interconnections. Emotion wheels offer a structured way to understand, categorize, and communicate emotions, and their recognition is well-established in the field of color psychology. These emotion wheels serve as the foundational core of our dictionary. In this work, we have used color-emotion representations from [10, 34–37], which offer a rich, intricate relationship between color and emotion to create the dictionary.

In constructing our Color-Emotion Baseline Dictionary, we employed a meticulous, multi-step process. Initially, to ensure clarity and consistency, and to avoid redundancy in creating the baseline dictionary, we normalized the emotional terms in the emotion wheels that we had selected since different literature uses slightly different terms for the same emotional statements. For example, 'happiness' and 'happy' are considered as 'happiness', 'depressed' and 'depressive' are considered as 'depressive', and so forth.

Moving forward, to have a clear understanding of the dominant emotions that each color evokes, we quantified the emotional responses associated with primary colors by counting the occurrence of emotions for each primary color, ensuring the capture of the core emotional resonance of every color. We assigned a half count to mixed colors like yellow-red and purple-blue, based on their primary color components This process ensured a balanced emotional profile, preventing dominance by any single primary color emotion.

Lastly, to have a standardized and consistent comparison between colors, we normalized the occurrences of emotions to weights. They are scaled down between 0 to 1 for each color that they are included. Through this approach, the dictionary we build effectively captures the interplay between colors and emotions. The Color-Emotion Baseline Dictionary is exhibited in Figure 1.

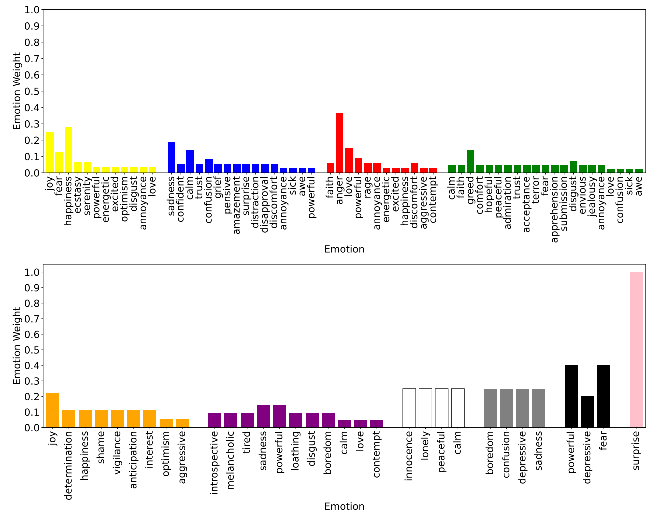

Figure 1. Color Emotion Dictionary

3.2 Generating Tints and Shades for the Dictionary Colors

The initial approach in our study involved directly mapping the colors identified in videos to the single RGB representations within our established Color-Emotion Dictionary. However, we soon realized that relying solely on one color representation brought about a generalization that proved inadequate. This limitation often resulted in inaccurate mappings, primarily because single RGB representations lack the complexity and range to accommodate all the color variations present in real-world imagery.

To address this, we turned our focus toward generating tints and shades of the dictionary colors, aiming to enhance the specificity and accuracy of color-emotion mapping in videos. In our first attempt, we manipulated the RGB values of a given color based on specified percentages in the RGB space. Positive percentages were used to create tints (lighter variants) and negative percentages for shades (darker variants). Despite this method's logic, it quickly became apparent that the RGB color space does not align perfectly with human color perception, leading to inconsistent visual experiences.

This inconsistency is mainly due to the RGB color space's lack of perceptual uniformity, where equal steps in RGB values do not correspond to equal perceptual changes. To counteract this, we transitioned to using the CIELAB color space [38], known for its alignment with human vision. The Lab space considers lightness (L*) and color-opponent dimensions (a* and b*), offering a more nuanced and perceptually uniform scale for creating tints and shades by simply adjusting the L* value.

Implementing this strategy, we generated shades and tints in the Lab space, ensuring perceptual differences that were more consistent and predictable. This was crucial in our study, where the precise visual appearance was paramount for accurate emotion-color interpretation. Additionally, we recognized the inherent uniqueness of each color, particularly in terms of their initial brightness, which naturally led to the necessity for customized L* adjustments for each. This individualized approach accounted for the specific perceptual properties of every color, thus enhancing the reliability of our color-emotion mappings. Furthermore, considering the extremes of black and white, we exclusively generated tints for black and shades for white, acknowledging their positions at the ends of the lightness spectrum.

In the end, for each primary color, we created 10 tints and shades, resulting in 21 distinct variations. To verify the effectiveness and discernibility of our generated shades and tints, we utilized a barcode-like visualization as shown in Figure 2, allowing for an at-a-glance assessment of color variations and their perceptual differences. This refined approach of generating tints and shades significantly enhanced our color-emotion mapping's accuracy, capturing the finer nuances of human emotion associated with subtle color variations observed in everyday visuals.

Figure 2. Color shades and tints

3.3 Barcode Generation

In our study, we adopted the method of barcode generation for YouTube videos, as outlined in the research [39]. This method, inspired by the Movie barcode concept, compresses the entire visual content of a video into a single barcode image. By focusing on the color theory, this approach extracts the essence of a video through its color palette. These barcodes capture not only the dominant colors in each frame but also the overall mood and thematic elements of the video through its color transitions.

The process involves calculating the mean RGB values for each frame of the video. These values are then condensed into layers within the barcode, each representing the dominant color of a particular frame. These layers are arranged in sequence to reflect the video's timeline, creating a barcode that encapsulates the video's dominant color narrative.

This innovative approach allows us to categorize and understand videos based on their color patterns without actually watching them. This is particularly useful in our research, where we aim to map colors to emotions. By examining the prominent colors in these barcodes, we can deduce the emotions they are likely to evoke. This provides us with a novel and efficient way to interpret the emotional content of YouTube videos, using color as a primary indicator.

3.4 Finding the Closest Color and Emotion

In our approach to identifying the predominant emotions within YouTube videos, a critical step involved pinpointing the closest match between the colors extracted from video barcodes and those cataloged in our color-emotion dictionary, a process that can be optimized for efficiency through innovative methods such as parallel processing [40].

Instead of the conventional RGB space and Euclidean distance method, which can be inadequate due to the non-linear nature of color perception in RGB space, we employed the CIEDE2000 color difference formula [41]. The CIEDE2000 formula is a sophisticated color-difference model, accounting for human perceptual differences between colors in a manner more aligned with how the human eye perceives color variations. This makes it especially suitable for tasks requiring precise color differentiation.

The process commenced with each color layer in a video's barcode, which symbolizes the dominant color for a specific frame. We then determined the nearest color from our dictionary using the CIEDE2000 distance method. By calculating the minimum color difference, we accurately mapped the video's color to the closest shade, tint, or primary color in our dictionary.

In cases where the minimum distances were equivalent for multiple colors, we implemented an average distance calculation. This involved computing the mean distance for all related shades and tints of each potentially closest color, compared to the target color. The color bearing the least average distance was deemed the closest match, ensuring a meticulous assignment of colors.

Upon establishing the closest color for each layer, we proceeded to map these to corresponding emotions using our previously constructed dictionary. This facilitated an analysis grounded in a solid empirical foundation, allowing us to quantify the emotional content of YouTube videos. We concluded by normalizing the emotion percentages derived from the count of each emotion, presenting a clear illustration of the emotional landscape portrayed in the videos.

3.5 Generalizing Emotional Keywords through Similarity

Understanding and interpreting emotions is complex. While the detailed representation of emotions can provide deep and subtle insight, there is also a strong case for simplifying them for easier comprehension and broader perspective, especially for users unfamiliar with the complications of emotional analysis.

Up to this point, emotions were presented in a detailed manner, capturing a wide range of sentiments extracted from literature. However, to enhance the user experience and simplify the interpretation of results, we needed to present emotions in a more generalized form. Simplifying emotions to a more generalized form would not only decrease output complexity but also provide a holistic view of emotion distribution, thus aiding in a comprehensive understanding of data.

Our initial tendency was towards Global Vectors for Word Representation (GloVe) [42] primarily due to its expertise in capturing semantic meanings across a broad word spectrum. Although GloVe effectively recognized that emotion keywords were inherently related, it struggled to differentiate subtle distinctions between them. This can be attributed to GloVe's broad and generalized word representations, which often overlook the unique variances among emotions.

BERT [43], with its deep layers and vast training, seemed promising. Its strength lies in understanding context, capturing on small differences in meaning from nearby words. However, our task was context-independent, and we were dealing with isolated emotion keywords without accompanying text. Introducing artificial contexts would not only complicate matters but could also skew results based on the subjectivity of sentence creation.

Our task led us to the NRC Word-Emotion Association Lexicon, a valuable resource [44, 45]. This lexicon finely maps English words to eight primary emotions: anger, fear, anticipation, trust, surprise, sadness, joy, and disgust. It also includes sentiments (negative and positive), with each word represented by 1s and 0s, denoting strong or absent emotional associations. This crowd-sourced lexicon, based on real individuals, is crucial for studying emotions linked to human experience.

Employing the NRC Lexicon, our methodology evolved into a more systematic approach. Each emotion, once identified, was cross-referenced within the lexicon. We used cosine similarity to measure its closeness to core emotional categories. In scenarios where the NRC Lexicon presented vectors with all-zero values, effectively lacking any defined emotional association, we pivoted to the Euclidean distance method since cosine similarity becomes undefined with all-zero vectors.

After determining the similarity measures, we proceeded to refine our emotion mapping. By identifying the most similar emotions using the maximum similarity scores, we integrated them with our previously calculated weights. Given that these prior weights had undergone normalization, there was no need for an additional normalization step, ensuring that our new results retained values between 0 and 1. This systematic approach allowed us not only to calculate the emotional distribution for each individual video but also to derive a holistic view of the entire dataset's emotion distribution.

This comprehensive insight was crucial in understanding the broad emotional themes present within our collection of videos. Having both detailed and generalized results provided a multifaceted perspective on our dataset. Each type of result, whether detailed or general, had its own benefits in understanding the emotions and main ideas of our videos.

4 Experiment

This section outlines an experimental study that analyzes the relationship between color and emotion in movie trailers, using the Trailers12k dataset. It details the methods used for mapping colors to emotions, validating these findings against movie genres, and employing statistical measures to assess the accuracy of the model.

4.1 Dataset

The core of our experimental analysis was based on the Trailers12k dataset [46], a rich repository of movie trailers. Our decision to use this specific dataset was driven by several key factors.

Firstly, the use of colors by producers in movie trailers is a deliberate and expressive tool to evoke specific emotions and set the mood for the scenes. This aligns perfectly with our research goal of exploring the relationship between color and emotion. Trailers, by their nature, are concise yet comprehensive, offering a distilled essence of the entire movie. This quality makes them ideal for our study, as they provide a snapshot of the overall emotional tone of a movie without the need for an exhaustive analysis of full-length films.

Furthermore, the Trailers12k dataset is not just abundant in content but also diverse in its range. It encompasses a wide array of genres, adding another layer of depth to our analysis. The availability of genre information allowed us to cross-validate our emotion mapping results.

The dataset's popularity and the diversity it offers are also noteworthy. It includes a broad spectrum of movie types, reflecting a realistic cross-section of contemporary cinema. The top 10 genre distribution within the dataset is shown in Figure 3. This distribution not only underlines the dataset's comprehensiveness but also its relevance for a study aiming to generalize across various film categories.

In summary, the Trailers12k dataset provided us with fertile ground for our investigation into color-emotion correlations in movie trailers. Its rich content, genre diversity, and concise representation of movies make it an invaluable resource for our experimental needs.

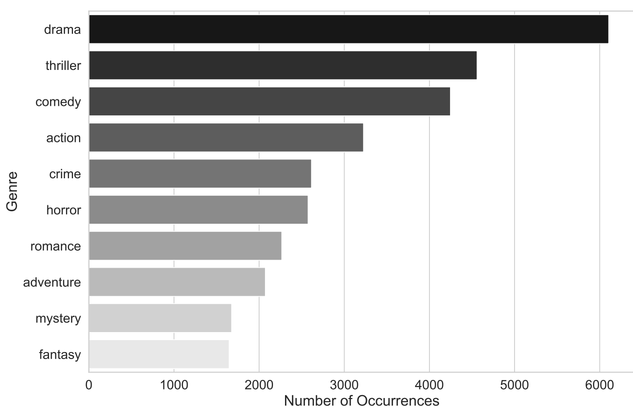

Figure 3. Top 10 Genre Distribution

4.2 Results

In our analysis, we focused on eight general emotions included in the NRC lexicon, aligning our findings with these broader emotional categories to facilitate later validation with the movie genres.

Utilizing the YouTube video IDs from the Trailers12k dataset, we generated barcodes that captured the dominant colors in each frame as shown in Figure 4. These colors were then mapped to the closest matches in our color dictionary, enabling us to identify the range of emotions these colors were likely to evoke, based on established emotion wheels and other resources.

Figure 4. An Example Barcode of the Movie Trailer Texst(Text) with corresponding YouTube.

The initial results provided a detailed, non-generalized distribution of emotions. To make these findings more accessible and comparable, we mapped these detailed emotions to the eight general emotions from the NRC lexicon. This step was crucial for correlating our color-emotion analysis with the broader, established emotional categories and for validating our results against the genres of the movie trailers.

As an example, Table 1 illustrates that the video's genre is drama and thriller, with dominant emotions of fear, surprise, and sadness after color-emotion mapping. The barcode's dark colors, such as black, gray, and blue, correspond to these emotions. Black often signifies fear, while gray can symbolize depression, and other dark colors are linked with sadness. These associations are supported by Table 2's data, aligning with the drama, thriller, crime, and horror genres prevalent in our dataset. These genres typically evoke fear and surprise, as seen in thrillers and horrors, or sadness, as in dramas. This color-emotion connection validates the expected emotional response to movie trailers, offering empirical evidence of the narrative impact of color in cinematic storytelling.

Table 1. Movie Trailer's Genre and Emotion Distribution gauged by Colors from its Barcode.

Video_id	Genre	Emotion	Weight
sNU5Bx7XQ8U	drama, thriller	surprise	0.262520611
		fear	0.341691127
		sadness	0.361941265
		joy	0.014037823
		disgust	0.00538651
		anticipation	0.005577314
		trust	0.00307648
		anger	0.00576887

Table 2. Average Emotion Distribution of the entire Movie Trailer Dataset gauged by the Colors in Barcode.

Emotion	Weight
fear	0.330889213
sadness	0.306470614
surprise	0.280598016
joy	0.043703083
anticipation	0.013179322
disgust	0.011443447
anger	0.007221866
trust	0.006494439

Surprisingly, although comedies formed a substantial part of our dataset, the emotion of joy was not as prevalent in our findings. This implies that comedy trailers may use colors in a more understated way, relying more on dialogue and storylines rather than visual cues to evoke laughter. This contrast suggests that while dramatic, thrilling, and horror genres often use color intensively to enhance or trigger certain emotions, comedies seem to adopt a more subtle approach in their color usage.

This observation underscores the varied role of color in different movie genres. In emotionally intense genres like drama and horror, color appears to play a significant role in evoking and intensifying feelings. In contrast, in genres like comedy, where the emotional drive is often narrative-driven, the role of color may be less pronounced. This finding opens intriguing avenues for further exploration into the genre-specific use of color in movie storytelling.

4.3 Evaluation of the Model

To validate our model, we utilized a comparative approach, aligning the emotions derived from video colors with those inferred from the genres in the dataset. This allowed us to assess the accuracy of our color-emotion mapping against the emotional associations typically linked with specific film genres.

4.3.1 Mapping Genres to Emotions. We followed the same steps as we did earlier in the section about Generalizing Emotional Keywords. First, we matched movie types (genres) with emotions listed in the NRC Lexicon. We only looked at the eight basic emotions and didn't use 'positive' or 'negative' since they're too broad for our purpose. The trailers were assigned to more than one genre. To handle this, we added up the emotion scores for each genre from the lexicon. Then, we adjusted these totals to get a balanced emotion score for each video. This way, we could figure out the likely emotions for each video based on its genre.

4.3.2 Statistical Measurement of the Validation. Our statistical validation of the model comprised three key metrics: Root Mean Squared Error (RMSE), Cosine Similarity, and Jensen-Shannon Divergence. Each of these metrics offers a unique lens through which we can gauge the similarity between the emotion distributions obtained from our model and those based on genre analysis.

In assessing the accuracy of our model, we first considered the Root Mean Squared Error (RMSE). RMSE helps quantify the average squared difference between the predicted emotional distribution (Y) and the actual distribution inferred from genres ($\hat{Y}$), and then takes the square root of this average. In our analysis, the RMSE was calculated using the formula given in Equation 1.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2} \quad (1)$$

To interpret this in a more intuitive context, consider that the maximum possible error in our predictions, on a normalized scale (0 to 1), is 1. When we express this maximum error as 100%, our RMSE of 0.198 can be interpreted as 19.8% of this maximum potential error. This percentage helps visualize the extent of error relative to the worst-case scenario.

While this 19.8% error rate indicates some deviation between our model's predictions and the actual values, it also suggests a reasonable level of accuracy, especially considering the complex nature of emotional analysis.

Another key metric in our evaluation was Cosine Similarity, a measure that calculates the cosine of the angle between the two vectors of emotion distribution (A and B) in a multidimensional space. In the context of our study, these vectors represent the emotion distributions derived from our model and those inferred from genre analysis. The Cosine Similarity score ranges from -1 to 1, where 1 indicates perfect alignment (or similarity), 0 suggests no correlation, and -1 implies complete opposition. The formula of Cosine Similarity is given in Equation 2.

$$cos(\theta) = \frac{\vec{A} \cdot \vec{B}}{||\vec{A}|| ||\vec{B}||} \quad (2)$$

Our model achieved an average Cosine Similarity score of 0.5604. This score, lying closer to 1 than to 0, indicates a moderate-to-strong alignment in the orientation of the emotion vectors derived from both color-emotion mapping and genre-based analysis.

However, the score being significantly less than 1 also indicates room for improvement. It implies that, while our model successfully captures a significant portion of the emotional nuances, it doesn't perfectly align with the genre-based emotional expectations. This gap might be attributable to the complex and subjective nature of emotional interpretation and the distinct methods used in deriving these emotion vectors.

The third key metric we used for evaluation was Jensen-Shannon Divergence (JSD). JSD is particularly useful for comparing probability distributions, which in our case are the emotion distributions derived from our color-emotion mapping model and those based on genre analysis. The JSD is mathematically represented in Equation 3.

$$JSD(P||Q) = \frac{1}{2}D(P||M) + \frac{1}{2}D(Q||M) \quad (3)$$

In this formula, P and Q represent the two probability distributions we are comparing, M is the mean of these distributions, and D is the Kullback-Leibler divergence. The range of JSD is from 0 to 1, where 0 indicates identical distributions and 1 signifies maximum divergence.

Our model achieved a JSD value of 0.4710, which translates to a similarity score of approximately 0.529 (since $1 - JSD$ gives the similarity). This score lies in the mid-range of the JSD scale, suggesting a moderate level of similarity between the predicted and genre-based emotion distributions. While the score is not close to 0, which would indicate a perfect match, it is also significantly distanced from 1, implying that our model's predictions are not drastically different from the expectations set by movie genres.

The moderate JSD score reflects the inherent challenges in predicting emotional responses based on color alone, considering the subjective nature of both color perception and emotional interpretation. This balance in the JSD score underlines the potential of our approach while also indicating areas where further refinement could enhance alignment with genre-based emotional distributions.

Our findings point toward a promising direction, indicating that our model, while still subject to refinement, captures a considerable extent of the emotional landscape, as dictated by color usage in movie trailers and their corresponding genres.

5 Conclusion and Future Work

Our study began with the challenging task of linking colors to emotions using YouTube video content, especially focusing on movie trailers. This task involved creating a Color-Emotion Baseline Dictionary. Although this dictionary was detailed, it had some limitations like leaving out certain colors and emotions and possibly missing some information from the literature. These limitations point out areas where our model can be improved in the future and highlight the complexity involved in connecting color to emotional response.

Even with these challenges, our model showed a workable way to figure out emotions from colors. The fair success in our tests, like RMSE, Cosine Similarity, and JSD, shows a hopeful link between our color-emotion mapping and the emotions we expect from different movie genres. However, the process of understanding emotions from colors is detailed and has many aspects, which means there's a lot of room for making it better and for more detailed study.

As we look to the future, our research opens up several exciting opportunities for further exploration and improvement. One key area of interest is in improving the ways we test our model. A more detailed approach, like analyzing viewer reactions frame-by-frame, could reveal deep insights. This might include observing viewers' gestures and facial expressions as they watch different parts of videos, linking their emotional reactions directly to the specific colors used in those parts. Such a method would offer a richer understanding of how video colors affect viewer emotions.

Additionally, there are multiple ways to enhance and expand our work. Enhancing our model with more colors, emotions, and varied sources like crowd-sourced interpretations can improve its accuracy and utility. This comprehensive approach promises to refine our understanding and application of color-emotion relationships in video content.

Another intriguing aspect of future research could focus on the analysis of highly watched segments within videos. By identifying which parts of a video attract the most views or engagement and analyzing the predominant colors used in these segments, we can gain insights into which colors or color combinations are most effective in retaining viewer attention. This could be particularly useful for content creators and marketers aiming to design visually appealing and engaging video content.

In conclusion, the area of linking colors to emotions in digital media content, especially on platforms like YouTube, is ready for more exploration. Our study has set the foundation, and we expect that future research will build on this, leading to more detailed, precise, and insightful analyses. These improvements have the potential to not only deepen academic knowledge but also to provide useful applications in different fields, such as digital marketing, content creation, and psychological studies.

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