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Research On Multi-Dimensional Image Processing In Intelligent Design Based On Perceptual Feature Quantification

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Abstract. *This paper centers on exploring the utilization of artificial intelligence in the realm of graphic design, with a particular emphasis on the construction of methodological models. Graphic design, as a discipline that amalgamates art and communication, encompasses numerous facets, including visual communication, layout, color theory, and graphic design. In the perpetually evolving technological milieu and burgeoning visual demands, its pivotal role in various domains becomes increasingly conspicuous. Specifically, this article investigates a multidimensional image processing technique rooted in perceptual features. Primarily, texture and color characteristics were extracted via convolutional neural networks (CNN). Subsequently, attention-based fusion convolution was introduced to augment feature performance. Ultimately, by synthesizing multi-tiered features, intelligent classification of image emotions predicated on perceptual feature vectors was accomplished. The experimental findings evince that the proposed fusion of multi-tiered features for sentiment classification attains an average recognition rate of 85.5% for positive, negative, and neutral emotions. In comparison to single features, fused convolutional features exhibit superior recognition accuracy. Furthermore, the framework advanced in this article presents a novel feature fusion approach within domains such as image sentiment classification processing, as opposed to prevailing methodologies, thereby providing robust underpinning for prospective endeavors in intelligent graphic design and image sentiment classification.*
Keywords: Perceptual features; Graphic Design; feature fusion; image processing; CNN

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1. **Introduction.** As an artistic discipline, graphic design aims to convey information and evoke a visual impact through the skillful utilization of typography, illustration, and

color. It places a strong emphasis on both the aesthetics and functionality of visual presentations while considering the requirements and psychological responses of the target audience. The history of graphic design can be traced back to the advent of printing techniques, and today it has expanded its scope to encompass digital media, brand design, advertising, and user interfaces [1]. With the continuous advancement of technology, graphic designers encounter new challenges and opportunities, necessitating the exploration of innovative methodologies to enhance visual impact and user experience.

The rapid evolution of artificial intelligence technology has brought forth a multitude of possibilities for graphic design. By harnessing algorithms and technologies in domains such as machine learning, computer vision, and natural language processing, AI aids designers in automating tasks, enhancing efficiency, and fostering more captivating design creations [2]. For example, image recognition and classification algorithms enable designers to quickly sift through extensive materials to select appropriate image components. Moreover, generative adversarial networks (GANs) and deep learning models empower the creation of artwork, the generation of unique visual effects, and the provision of personalized design recommendations. The integration of artificial intelligence equips graphic designers with powerful tools and technologies, propelling the innovation and advancement of design [3].

The integration of AI into graphic design encompasses the utilization of perceptual features. By comprehending human perception and emotional responses, designers can craft designs that are more accessible and captivating. Emotion analysis algorithms assist designers in evaluating and understanding audience emotions and responses to design works, facilitating adjustments to design elements and effects as needed [4]. Additionally, natural language processing techniques analyze and grasp user semantics and context, thereby providing designers with guidance on text typesetting and content presentation. Sound and audio processing algorithms can also be employed to create sound logos or sound effects, introducing dynamism and variety to design compositions. The incorporation of perceptual features bestows graphic design with intricacy and personalization, addressing the diverse needs and emotional experiences of various audiences [5].

In conclusion, the integration of AI into graphic design and the multidimensional processing of images based on perceptual features hold immense significance and value. By merging the realms of artificial intelligence technology and graphic design, designers can efficiently produce imaginative, captivating, and personalized design works. The intelligent algorithms and tools offered by AI provide designers with expanded choices and creative latitude to rapidly generate, assess, and refine design creations [6]. This not only enhances design efficiency but also elevates the quality and allure of design works. Therefore, this paper delves into multidimensional image processing and feature perception within the domain of intelligent graphic design. The specific contributions are outlined as follows:

(1) The adoption of CNN for the extraction of texture and color features from images.

(2) The achievement of deep fusion between texture features and color features using a convolutional network that incorporates an attention mechanism.

(3) The execution of image emotion recognition and classification using multi-level convolution features, resulting in an overall recognition accuracy of 85.5%.

The remainder of this paper unfolds as follows: Section 2 introduces related works concerning intelligent design and image analysis. In Section 3, the establishment of the model for emotion recognition using images is presented. The experimental results and analysis are conducted in Section 4. The discussion is provided in Section 5, and the conclusion is drawn at the culmination of the research.

2. Related Work.

2.1. Application of artificial intelligence in design.

In the era of big data, knowledge engineering has garnered significant attention, as the extraction of meaningful insights from vast databases remains paramount for data analysis. Artificial intelligence technology has found widespread application across various design disciplines, with landscape architecture serving as a noteworthy example for theoretical research in this context. For instance, Deng et al. employed deep neural networks and particle swarm algorithms to optimize non-linear parametric models for landscape design objectives [7]. Zhang et al. developed a landscape ecological framework, training LSTM (long-short term memory) and natural language processing (NLP) models to extract environmental parameters and evaluate landscape design cases based on them [8]. Jahani et al. conducted spatiotemporal analysis and mapping of forest ecosystems, designing a decision support system for assessing landscape visual quality using artificial neural networks, yielding remarkable results [9].

In the realm of Chinese research, traditional landscape design concepts serve as the foundation. Shan et al. explored urban and rural development and ecological civilization construction in China, employing convolutional neural networks and genetic algorithms to predict and evaluate the rationality of landscape plant species selection in northeast town parks [10]. Xie et al. utilized the BPNN algorithm model and CSiXRevit software tool to optimize interactive strategies for street landscape planning and design, showcasing the effectiveness and rationality of machine learning in urban landscape design [11].

In the field of graphic design, researchers have also undertaken various data analyses. For example, Li and colleagues introduced a layoutGAN network, which models geometric relationships among different types of 2D elements to synthesize and arrange images, focusing on the stacking relationship of graphic elements and generating relevant layouts [12]. Zhang and fellow researchers presented an automatic banner layout design system that primarily revolves around the adjustment of multi-size style parameters and the arrangement of banner elements [13].

When engaging in graphic design, some tools lack modification suggestions, which can be less user-friendly for novice designers. Addressing this issue, O'Donovan et al. [14] conducted a study on a system capable of providing interactive layout suggestions throughout the design process. The system has been developed with both a prompt interface and an adaptive interface, wherein layout suggestions are provided and refined by adjusting elements within the adaptive interface.

In the realm of web design, for the purpose of guiding users' attention more effectively and conveying information with greater precision, Pang et al. [15] utilized users' gaze data to construct a user attention model. This model facilitates innovative design interactions, enabling users to direct their gaze based on the visual flow created by the designer, thus obtaining a specific sequence of information. Meanwhile, Yang et al. [16] investigated a system comprising layout templates and computational frameworks designed to automatically generate visually appealing layouts.

2.2. Analysis and application of image emotion perception.

With the rapid progression of mobile devices, the Internet, and social media, an increasing multitude of individuals are inclined to divulge their lives and convey their emotions through imagery. Consequently, the scrutiny of emotional content within images has garnered substantial attention from scholars both domestically and internationally. Unlike textual emotion analysis, which boasts a well-established framework, the analysis of emotions within images, being an interdisciplinary field encompassing artificial intelligence, computer vision, psychology, and aesthetics, represents a relatively nascent domain that demands continuous exploration [14]. As early as 2010, Siersdorfer et al. [17] unearthed a robust correlation between emotional nuances in images and their associated metadata, such as titles, descriptions, or labels. They extracted characteristics such as color and SIFT features from images, deploying machine learning techniques, including support vector machines, to categorize images based on positive and negative emotions. Li et al. [18] contend that emotional content within images is not solely contingent on global attributes but is also influenced by localized information and their intricate interplay. In response to this, they proffered a network model founded on a two-layer sparse representation (Bilayer Sparse Representation, BSR) to separately extract global and local features, while establishing interactive connections between the two for image emotion classification. Rao et al. devised a multi-tiered CNN network for the extraction of low-level visual characteristics, mid-level image aesthetic attributes, and high-level deep semantic features, incorporating a total of 11 convolutional and fully connected layers for fusion-based classification [19]. Building upon Rao's research, Zhu et al. [20] delved deeper into the fusion methodology across varying levels of features, advancing a two-way gating cycle unit to integrate them based on their mutual dependencies, thereby augmenting the effectiveness of classification.

You et al. [21] examined the influence of localized image regions on visual emotion analysis. They employed a visual attribute detector, image attribute descriptions, and a network for extracting visual features. They incorporated an attention module to acquire the relationship between specific emotional regions in images and attribute labels, resulting in a weighted aggregation of local visual features for training the emotion classifier. In recent years, researchers have increasingly directed their attention towards cross-modal emotion analysis utilizing deep learning techniques. Yu et al. [22] employed two distinct CNN models to autonomously extract features from textual and visual content. Subsequently, they applied late fusion and logistic regression for emotion prediction. Chen et al. [23] amalgamated the extracted modal information within a pooling layer, subsequently channeled into a fully connected layer for emotion analysis. You et al. [24] initially fine-tuned a CNN model using an image emotion dataset and derived the penultimate layer as image features. They also utilized unsupervised learning for training a word2vec model to extract distributed documents or sentences. Additionally, they delved into characteristic-level fusion and decision-level fusion methods, resulting in superior outcomes compared to single-mode approaches [25].

From the previously cited research, it becomes apparent that the swift advancement of artificial intelligence and deep learning, coupled with the growing abundance of data, has streamlined the application of this data in the realm of intelligent graphic design. Pictures, serving as a medium for emotional expression, quantitatively encapsulate people's emotions during the design process, assuming a pivotal role as perceptual attributes within intricate graphic design endeavors. Hence, considering the demands of graphic design and the present level of sophistication in picture emotion and cross-modal emotion analysis technology, this paper seeks to conduct emotion analysis grounded in the perceptual attributes of images. In doing so, it aims to facilitate precise and efficient realization of subsequent intelligent graphic design initiatives.

3. **Establishment of image emotion analysis model based on multi-level convolution of perceptual quantified features.** Upon concluding the investigation into the status of perception vectors and their associated principles, along with image design founded upon artificial intelligence methodologies, this section will delineate the overarching approach to emotional feature recognition. Primarily, this encompasses three key facets:

(1) Extraction of texture and color attributes via the Gray Level Co-occurrence Matrix.

(2) Comprehensive feature extraction achieved through the amalgamation of convolutional neural networks with attention mechanisms.

(3) The utilization of multidimensional perceptual attributes in the emotional analysis process.

3.1. **Quantification of texture features and color characteristics.** In the domain of graphic design, the significance of texture attributes and color characteristics cannot be overstated, as they assume a pivotal role in the perception and expression of design compositions. Texture features are instrumental in depicting the surface intricacies and structural elements of visual entities, encompassing attributes such as roughness, smoothness, fineness, irregularity, among others. Within the realm of graphic design, texture features find application in elevating the overall tactile quality of a work, generating visually captivating effects, or eliciting specific emotional responses. Diverse methods are available for the quantification of texture features, one of which entails the utilization of the Gray-level Co-occurrence Matrix (GLCM). The GLCM quantifies texture attributes by scrutinizing the interrelationships among pixel gray levels within an image.

The calculation formula for the GLCM is demonstrated in Equation (1):

$$P(i,j) = \frac{1}{N}\sum_{x=1}^{N}\sum_{y=1}^{N}\delta(i - I(x,y))\delta(j - J(x,y)) \tag{1}$$

where N represents the number of gray levels in the image, δ is the Kronecker Delta function, and $I(x,y)$ and $J(x,y)$ are the gray levels at the (x,y) pixels in the image. In addition, energy and contrast are also more common characteristics, and the calculation formula of energy is shown in (2):

$$\text{Energy} = \sum_{i=1}^{N}\sum_{j=1}^{N} P(i,j)^2 \tag{2}$$

where *Energy* indicates the uniformity and clarity of the texture. The greater the energy, the more clear the texture is. The calculation formula for contrast is shown in Equation (3):

$$\text{Contrast} = \sum_{i=1}^{N}\sum_{j=1}^{N}(i-j)^2 P(i,j) \tag{3}$$

The contrast reflects the degree of difference between the different gray levels in the texture, and the greater the contrast, the more obvious the change in the texture. Color represents one of the most conspicuous and prominent visual attributes in the realm of graphic design. Its significance lies in its capacity to convey emotions, evoke resonance, and establish a visual impact. Color features are harnessed to articulate brand identity, evoke specific emotional responses, and create visual depth. The quantification of color features typically involves the selection of a color space and the computation of color histograms. Key formulations encompass those pertaining to the RGB color space, the HSV color space, color histograms, and color moments.

In the RGB color space, color is comprised of three channels: red (R), green (G), and blue (B). A common quantification approach entails the calculation of histograms for each individual color channel, representing the distribution of colors across varying intensity values. The HSV color space, on the other hand, comprises three components: hue, signifying the fundamental color; saturation, denoting purity and concentration; and value, relating to brightness. A prevalent quantification method involves computing histograms for each of these components and deriving the average hue, saturation, and value of the color.

The color histogram is a technique employed to illustrate the distribution of colors. It subdivides the color space into discrete regions and tabulates the pixel count within each region. Color histograms can be computed in various color spaces, including RGB, HSV, and others. Color moments encompass statistical measures that characterize color distribution attributes. Common color moments include mean, standard deviation, and skewness. These statistical measures aid in delineating the brightness, contrast, and shape of the color distribution [26].

3.2. **Generation of convolution features based on attention mechanism fusion.** The attention mechanism stands as a frequently employed technology in the domains of machine learning and deep learning. It emulates the attention mechanism observed in the human visual system, enabling the model to discerningly concentrate on particular segments of the input, consequently enhancing the model's performance and efficacy. The fundamental concept underlying the attention mechanism involves the allocation of distinct attention weights to various portions of the input, with the aim of affording greater emphasis to crucial information during the processing phase [27]. This allocation of attention weights can be conceived as a weighted summation process, wherein the weight assigned to each input segment signifies its relative significance [28].

The color attention matrix was generated from feature cell matching with feature representation C and feature representation X. The formula for calculating the column feature matrix A_r is as follows:

$$A_{rw,d} = f(|X_{h,w,d}, C_{h,w,d}| \cdot \mathrm{sign}(X_{h,w,d}, C_{h,w,d})) \tag{4}$$

Moreover, the output of the color attention operation obtained from the row feature matrix and the column feature matrix. The formula is defined as follows:

$$H_{ch,w,i} = (A_{ch,1,i} \times A_{c1,w,i}) \cdot C_{h,w,i} \tag{5}$$

For the texture features, the feature convolution method is similar to the color features. The attention mechanism calculation of the texture features is shown in Equation (6):

$$A_{h,w} = f(|X_{h,w,d}, T_{h,w,d}| \cdot \mathrm{sign}(X_{h,w,d}, T_{h,w,d})) \tag{6}$$

Among them, the calculation of f and $|\cdot|$ are similar to that in Equation (4), which is different from the calculation of color attention features based on the axis of depth. The calculated value output for the texture features is shown in Equation (7):

$$H_t = A_{h,w} \times T_i \tag{7}$$

Among them, $i \in d$, the formula indicates that each element in the attention feature and the input texture feature performs the matrix multiplication operation, and then the resulting attention feature weight and the input feature are point-multiplied to obtain the output H_t of the texture attention operation.

3.3. **Emotional perception based on multi-level convolution features.** Following the fusion of features facilitated by the attention mechanism, these amalgamated features are employed to execute subsequent identification and classification tasks. The phase loss function selected is shown in (8), where $F(x_i, x_j)$ represents the output from the last model, $\hat{l}_k$ is the amplified factor, and L_c is the loss result from the whole image.

$$L_c = \sum_{(x_i,x_j,y)\in\mathbf{b}} \sum_{k}^{K} -\hat{l}_k \times \log(F_k(x_i, x_j)) \tag{8}$$

After completing the network construction, the flowchart of the image fusion perception method using multi-level convolutional features is shown in Figure 1.

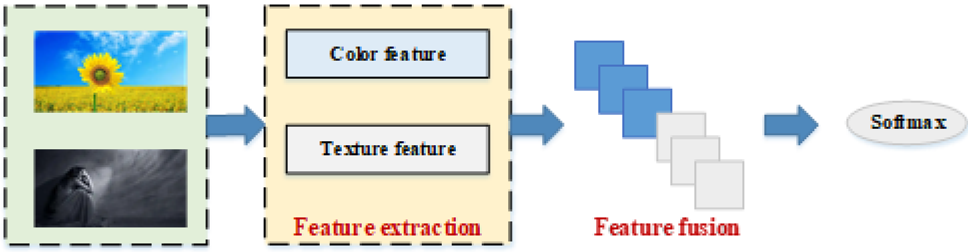

Figure 1. The framework for the picture emotion recognition using perceptual features

In Figure 1, we take images containing emotional elements in graphic design as input and subsequently extract their color and texture features through a deep neural network. Following the extraction of these two types of features, another neural network is employed to combine these features, thereby accomplishing multidimensional feature perception. These extracted features are then input into the softmax function to finalize the classification process, categorizing them into three distinct emotional types.

4. **4. Experiment result and analysis.** This section performs practical testing utilizing the emotion recognition framework predicated on image perception features, as depicted in Figure 1. Throughout the testing procedure, the image data undergoes initial standardization and cropping. Seventy percent of the data is allocated for the training set, with the remaining 30% reserved for the testing set. The dataset is compiled from a combination of publicly available datasets and self-generated datasets.

In the classification of experimental outcomes, the images employed in the experiment are categorized into three groups: positive, negative, and neutral. The relevant data is employed for both training and testing, with subsequent result validation. The specific results are as follows:

4.1. **Data features and model training.** In this paper, the texture features and color attributes are analyzed based on the chosen images, with a selection of 10 representative pictures for computation. The problematic features and color characteristics are depicted in Figure 2 and Figure 3:

In Figure 2, we primarily focus on key features, which include contrast, energy, and entropy. It is evident from the characteristic distributions in Figure 2 and Figure 3 that distinct images exhibit more pronounced variations in their feature distributions. Additionally, the texture characteristic distribution appears more dispersed. Hence, the fusion of these characteristics demonstrates certain advantages in emotional recognition.

Following the feature extraction phase, we conducted an analysis of the model. The overall training loss function and accuracy are illustrated in Figure 4:

In Figure 4, it is evident that as the number of training iterations increases, the trends in loss and accuracy remain relatively stable, indicating a well-balanced overall model. The final identification accuracy of the model consistently hovers around 0.85. Specific identification results are depicted in Figure 5:

In Figure 5, it is evident that the proposed model exhibits a high recognition rate for all three categories of emotions. Notably, the negative class attains the highest recognition rate in terms of precision, while the neutral class registers the lowest recognition rate, just slightly above 80%. This disparity can be attributed to the challenge of distinguishing

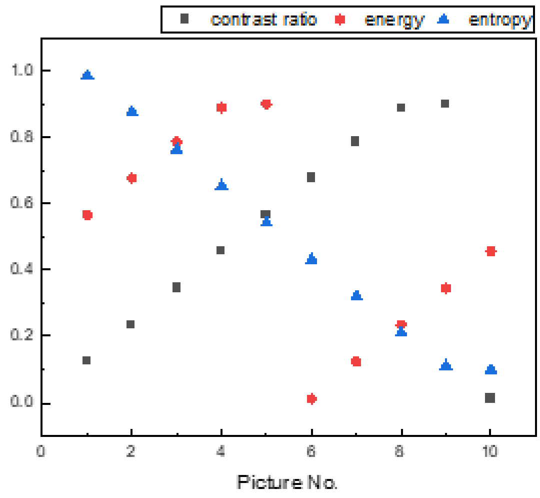

Figure 2. The texture feature of the typical picture in the dataset

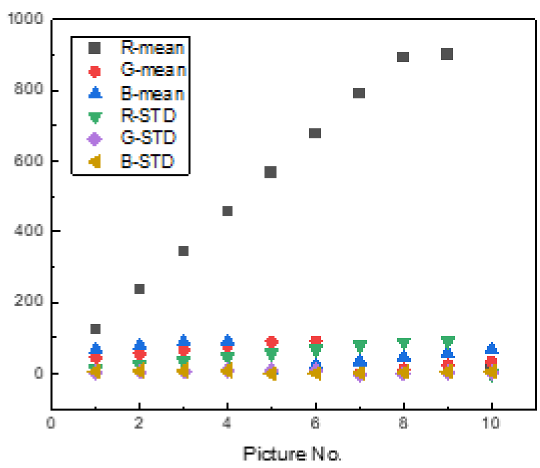

Figure 3. The color feature of the typical picture in the dataset

emotions in real-world usage of the model. During the data partitioning process, neutral emotions are often grouped due to their difficulty in differentiation, resulting in some misclassification into positive and negative categories during model calculations.

4.2. **Identification accuracy under different features.** This section conducts an analysis of the texture and color features present in the selected images. Specifically, 10 representative images have been chosen for a detailed feature analysis. The selected representative images are showcased in Figures 2 and 3:

In Figure 6, it's evident that among the recognition results using different features, the fusion of features yields the highest recognition rate. Among the individual features, texture features exhibit a clear advantage, while the standalone recognition rate is lower than that achieved through the attention convolution-based feature extraction method. The integration of texture and color features in the proposed framework leads to improved recognition rates.

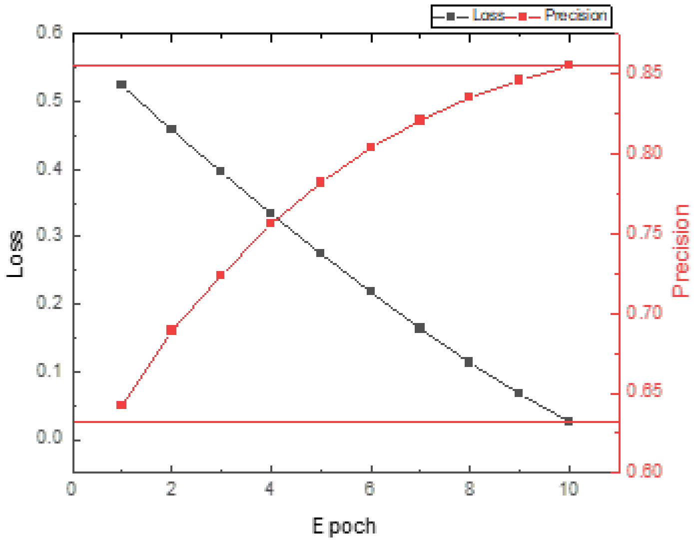

Figure 4. The loss and precision change in the training process

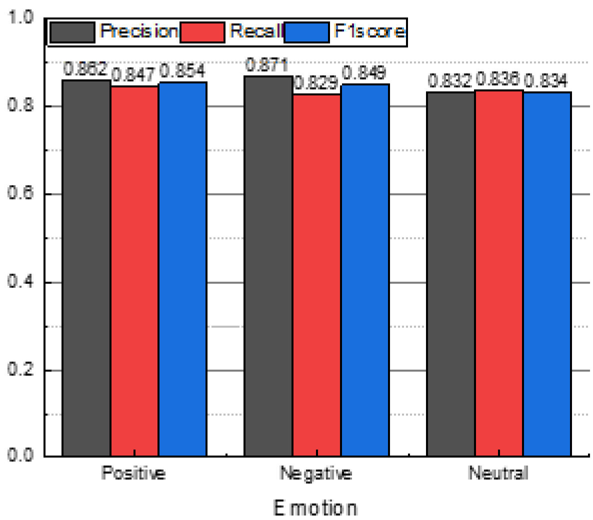

Figure 5. The results of emotion recognition

4.3. **Identification results under different classification methods.** After completing the test experiment of features, we conducted the final emotion classification test according to different networks, and the results are shown in Figure 7:

Throughout the experiment, the data selection and the corresponding partitioning into training and test sets were consistent with the procedures outlined in sections 4.1 and 4.2. In this particular experiment, our focus was solely on comparing the outcomes achieved under different network architectures. Specifically, we conducted a comparative analysis involving widely employed networks, including VGGNet, among others. The results highlight that while most of these networks achieve emotion classification accuracies surpassing 80%, they still fall short in comparison to the performance of the proposed method.

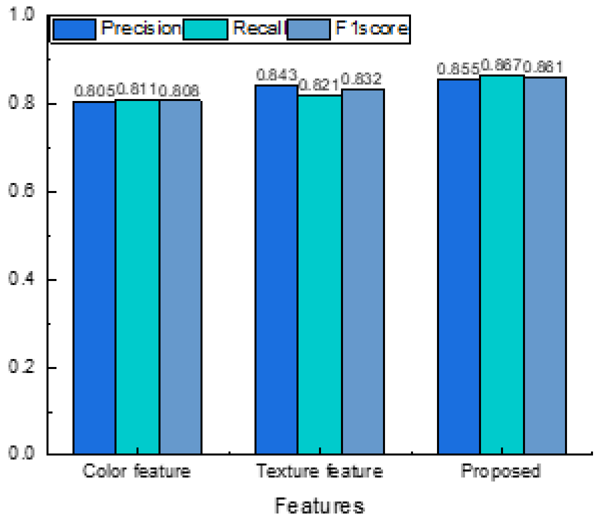

Figure 6. The recognition results using different features

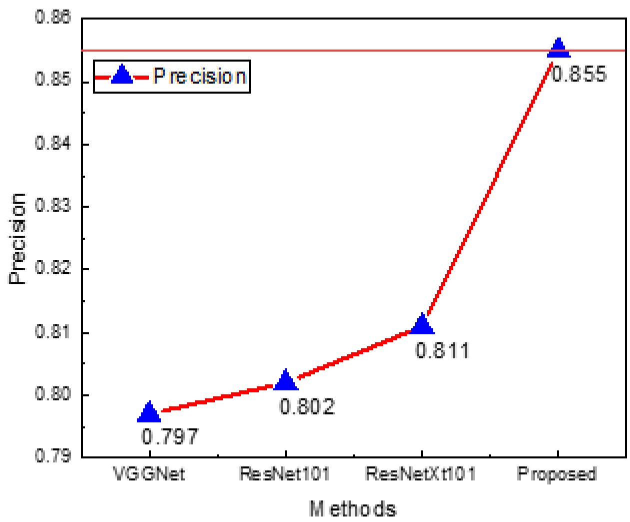

Figure 7. The precision results using different classification methods

5. **Discussion.** Sophisticated graphic design, an outcome of AI advancement, enhances design efficiency. This paper utilizes texture and color attributes for image emotion recognition. Through the classification of these attributes, we attain a more comprehensive representation, thereby enhancing classification. Texture features convey local structures, patterns, and spatial arrangement, capturing variations and pertinent elements. They prove invaluable in distinguishing object categories characterized by distinctive textures. Simultaneously, color attributes elucidate color distribution and information, offering insights into tone, saturation, and brightness. Their analysis facilitates the correlation of colors with categories. The paper employs a convolutional attention network for multi-level deep fusion of these attributes. This approach augments accuracy and robustness

by considering both local and global characteristics. It effectively leverages these attributes through multi-level convolution, successfully identifying three emotional states. In comparison to VGGNet and ResNet, our method achieves superior recognition rates, indicating significant classification enhancement.

Advancements in technology and AI elevate the significance of perceived content in graphic design, encompassing dimensions of emotion, voice, and action. These dimensions enrich design expression through emotion analysis, fostering emotional connections [29]. Thoughtful utilization of color, form, and typography guides emotional experiences. Voice and action perception enable interactive, personalized design through speech recognition and movement interaction. Future prospects entail deep learning and emotion analysis, enabling design adaptation to user emotions, thereby enhancing personalization and engagement. In summary, the integration of perceived content elevates the effectiveness of graphic design and the user experience, evolving towards personalized, emotionally resonant designs.

6. **Conclusion.** In response to the expression of emotional elements within the graphic design process, this article employs deep neural network techniques to analyze the emotional components it seeks to convey. Within this study, the primary emphasis lies in the emotional perception of images during the intelligent graphic design process. Through the amalgamation of texture and color attributes, we achieve intelligent classification of image emotions. To enhance the precision of image sentiment classification, we realize profound fusion of these two feature types through an attention mechanism-based convolution, utilizing multi-level convolutional attributes in the final classification phase. The experimental outcomes reveal that the multi-level feature fusion method, grounded in perceptual features, as introduced in this paper, attains recognition rates of 0.862, 0.871, and 0.832 for the three distinct categories of image emotion classification, respectively. Its recognition accuracy significantly surpasses that of single-feature recognition results in traditional deep learning comparative experiments. This outcome furnishes a more intelligent and high-precision approach for future intelligent graphic design, as well as emotional evaluation and perceptual quantification of design content.

Nevertheless, certain limitations are evident in this paper. Due to constraints in data collection and labeling, some ambiguity may exist in label assignment. Additionally, external interference stemming from subjective judgments by relevant individuals may not have been entirely eradicated. To address these limitations, forthcoming work should concentrate on broadening the data scope and optimizing the model's attributes. In summary, this research provides invaluable insights and lays the groundwork for further advances in quantitative fusion based on perceptual features. Future steps should encompass refining the data collection process, enhancing label precision, and optimizing model features to further enhance the efficacy and resilience of the proposed method.

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