Research on Brand Visual Communication Design Innovation Supported by Computer Vision in the Digital Age

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ABSTRACT Brand visual communication in the digital environment requires automated recognition, generation, and consistency assessment of large-scale visual materials. This study proposes a computer-vision-supported framework covering brand-logo recognition and optimization, color-system extraction and reconstruction, and visual-element consistency evaluation. A dataset containing 10,000 visual samples from 50 brands is established for logo recognition and element detection, while additional cross-media samples are used for color reconstruction. ResNet-50-based convolutional neural networks are used for logo recognition and design-quality evaluation, a CycleGAN-based model reconstructs brand color systems across digital media, and Faster R-CNN detects visual elements for consistency scoring. Experimental results show that the proposed method achieves high logo-recognition accuracy, improves color-reconstruction satisfaction, and supports automated monitoring of cross-media visual consistency. The framework provides a technical route for image-signal processing, visual feature extraction, and intelligent design-system evaluation.

INDEX TERMS computer vision, convolutional neural network, generative adversarial network, object detection, image signal processing

I. INTRODUCTION

THE digital-wave is transforming the operating framework of all industries like never before and no single area is left out such as in the field of brand visual communication design. However, brand visual identity in the digital age can not be limited to the classic visual information sources, which are represented by traditional print media, but is extensively presented in various digital contacts, which include websites, mobile applications, social media, augmented reality, and virtual reality. This change in the media landscape requires the brand visual design to be able to withstand faster updates and iterations, more challenging cross-platform consistency needs and finer user experience feedback. Conventional methods of visual design of the brand may highly involve intuition and experience of the designer as he/she divulges efficiency bottlenecks and lack of scientific foundation in handling complexities introduced by the digital environment. Concurrently, as a significant field of artificial intelligence, computer vision has broken new grounds in executing image classification, object detection, image generation, and style transfer, that offers unparalleled technological opportunities with regard to the quantitative analysis, smart formation, and precise assessment of brand visual design.

It is in this context that the idea of introducing the computer vision technology to be successfully integrated into the whole procedure of brand visual communication design has reached a significant level of both theoretical and practical interest. Current studies are more of a solution implementation in one design phase, logo recognition or color identification without a systematic approach to it in terms of the overall brand visual system. Moreover, the research on the design effects of the post-intervention computer vision technology is still not discussed in the quantitative basis, so it is hard to set clear references on choosing the technologies and predicting the outcomes in terms of design practice. According to this, this paper is devoted to the primary requirements of brand visual communication design innovation in the digital era, building a computer support framework of vision taking into account three crucial dimensions: brand logo, color system, and consistency of visual elements. The research develops a real brand visual dataset, conducts logo recognition and optimization suggestion by employing convolutional neural networks, intelligent extraction and reconstruction of the brand color system by generative adversarial networks, and cross-media visual elements consistency assessment by object detectors. The effectiveness of every method is verified by means of experimental data.

II. RELATED WORK

Visual communication research is increasingly showing the cross-characteristics of technology-driven, scenario-diverse and multi-dimensional evaluation. Yaqi [1] sorted out the application scenarios of virtual reality in medical visual communication and evaluated its design strategy and communication effect through typical projects. Halid and Fajrin [2] used visual communication design analysis method to systematically interpret the images, color schemes, layout, symbol usage and other aspects of the account, and discussed its communication strategy in combination with content analysis. Liu et al. [3] used fuzzy hierarchical analysis method to construct an evaluation system that includes multiple indicators such as interactivity, content structure and visual appeal. Robson [4] analyzed how a multidisciplinary applied health research team in the UK used visual communication for communication and meaning construction in the process of the project. Ji et al. [5] pointed out that augmented reality significantly improved students' learning motivation and participation, and also showed a positive impact on academic achievement and interest.

Hwang and Wu [6] proposed a visual communication design methodology framework based on generative artificial intelligence, covering stages such as concept generation, visual evolution, user feedback and iterative optimization, and verified its feasibility through design cases. Karnadi et al. [7] sorted out the practice types, knowledge integration methods and interdisciplinary points of visual communication design in the new media environment. Dündar and Dönmez [8] adopted the perspective of technological innovation and combined with teaching practice to design a visual communication task based on Canva. Saputro and Savitri [9] collected the needs of visual communication design students, teachers and industry practitioners for English skills, and focused on analyzing their language use scenarios in design practice. Purhita and Rudjiono [10] took a student project of a visual communication design major as a case and adopted a brand equity evaluation framework to evaluate the communication effect of interactive multimedia from four dimensions: brand awareness, brand association, perceived quality and brand loyalty. Based on existing research, this paper further explores the innovative path of computer vision in brand recognition, dynamic interaction and communication effect from the perspective of technology empowerment and design methodology integration, in order to provide a new reference for the theoretical expansion and practical application of visual communication design.

III. METHODS

A. BAND LOGO RECOGNITION AND OPTIMIZATION METHOD BASED ON CONVOLUTIONAL NEURAL NETWORK

The recognition of the brand logo is a fundamental component of a brand visual identity system, and, it directly influences the success of the brand image communication when it is inaccurate [11,12]. Brand logos are frequently used in the digital world where they are shown against complicated backgrounds, varying sizes, and deformed under an assortment of conditions and it is almost impossible to have all the conditions of logo usage covered by traditional verification of logo design through human experience. To solve this problem, this paper develops a brand logo recognition and generation of method of suggestion optimization approach that is grounded on convolutional neural networks. The selection criteria were first the visual materials of fifty famous national and international brands, comprising a total dataset of 10,000 images—with 200 applications per brand—including online official websites, social media, and physical signage. The images were all manually annotated and annotations contained the position of logo, presence or absence of occlusion of the logo, background complexity as well as presence or absence of deformation of the logo. The images were then scaled uniformly to 224×224 pixels and split into training, validation and test at a ratio of 8:1:1.

The convolutional neural network model is based on the ResNet-50 model, which is effective in image classification. The top layer is added that is fully connected to provide two branches, with the first one giving the probability of a logo category, which is used to recognize the specific brand of the logo in the image, and the second one provides a design quality evaluation vector with five dimensions all in the range 0 to 1. To establish the ground truth for these dimensions, a panel of fifteen professional designers was recruited to manually score a representative subset of 2,000 images based on predefined visual communication rubrics (e.g., edge contrast for 'clarity' and font-to-background ratio for 'readability'). These scores were then normalized and used to supervise the auxiliary regression branch. A weighted combination of mean squared error loss and cross-entropy loss is the total loss function in model training, and the initial learning rate is 0.001, weighted loss is calculated, Adam is used, the batch size is 32, and there are a hundred total training epochs. Data augmentation measures are used during training, such as random rotation, horizontal flipping, and color jittering, to enhance the generalization capacity of the model.

Upon training, recognition and evaluation of the model are utilized on the brand logo optimization process. Given any new logo design, the model would produce the predicted performance score of the new logo under various application conditions and create a heatmap with the gradient backpropagation algorithm in order to identify critical regions with regard to the recognition rate of the logo. The heatmap can then be used by the designers to apply specific changes to the regions with low recognition like streamlining the detailed structures or improving the contrast of significant elements and the background. Through this, the discriminative strength of the deep learning model is converted into design improvement recommendations that can be put into practice, which becomes a closed cycle of identification and assessment to optimization re-evaluation.

B. BRAND COLOR SYSTEM EXTRACTION AND RECONSTRUCTION BASED ON GENERATIVE ADVERSARIAL NETWORKS

The most direct aspect of expressing emotion in a visual system of a brand is a brand color system. Its removal and reconstitution should be considered by taking into consideration the original color DNA of the brand as well as its compatibility with digital media. The model of traditional brand color construction is often based on the perception of brand philosophy and the implementation of color theory by the designers themselves, which can easily cause color drifts and perceptual anomalies when implemented over different media. This paper is an automated framework for the synthesis and deployment of brand color systems using generative adversarial networks (GANs). The purpose of this method is to identify the correct core color system of the existing brand visual products and produce color reconstruction schemes that would be suitable in various digital media.

The statistics behind this technique are the application images on 500 brands. There is an image set with each brand that represents the online presence of the brand in the form of a site design, application, promotion image on social media and digital advertisements that amount to 25,000 images. They are preprocessed to convert these images into the Lab color space, to make them closer to the human visual perception of the world. The generative adversarial network (GAN) uses a slight modification to the CycleGAN structure, allowing style transfer between unpaired images and is specifically applicable in utilizing color features that can be extracted in the current brand visual content and transferred to new design vehicles. The network has two generators and two discriminators. The generators are based on a U-Net framework and include downsampling and upsampling trajectories and an attention mechanism in skip connections to improve the perception of the key areas of color distribution. The discriminators incorporate a PatchGAN network to differentiate between actual and fake local areas of the picture which enhances the realism of the color reconstruction details.

The source domain defined during the training process is the series of the available visual materials of the brand, and the target domain is the series of digital media templates, including the most common formats (e.g. webpage header images of various sizes, mobile application splash screens, and social media cover images). Adversarial training helps the generator to learn to transfer the color style of the source domain to the target domain templates without altering the original content structure of the templates. The training loss loss has three components, namely adversarial loss, cycle consistency loss and color consistency loss. The loss of color consistency is bounded by computing the histogram corresponding degree between the reconstructed image and the source domain image in the Lab space and making sure that the extracted color system is obedient to the original color characteristics of the brand. The learning rate of the model training is 0.0002, and following the Instance Normalization requirements typically found in CycleGAN architectures to preserve high-frequency color style details, the batch size is set to 1. Although this requires 200 training epochs for a dataset of this magnitude, it ensures the stability of the color consistency loss by preventing the gradient averaging that occurs in larger batches, which could otherwise smooth out the subtle brand-specific color DNA. Following training, given a brand, the model has the ability to extract the core color system of its own, and produce color reconstruction schemes as a result of a variety of digital media templates serving as carriers. Both schemes give a set of color values of the primary color, secondary color and the accent color along with recommendations of the proportion of various colors in the layout area.

C. CONSISTENCY ASSESSMENT OF BRAND VISUAL ELEMENTS BASED ON OBJECT DETECTION

One of the biggest problems of brand visual communication design in the digital era is high consistency of brand visuals in a wide variety of digital touchpoints. Brand visual elements exist in various dimensions such as logos, colors, typography, graphic style, and layout among other aspects and the sheer volumes of digital content cannot be inspected through traditional manual means. This paper develops a brand visual element consistency assessment approach that builds on detection of objects where an automatic detection system can be used to find the consistency of major elements in brand visual materials with quantitative scoring. Such an approach initially forms a dataset of brand visual components, gathering 200 visual materials of each of the official websites, social media accounts and digital channels of advertising of 50 brands, which amounts to 10,000 photos. The categories of the brand visual components are manually tagged over each picture with five categories being; logos, title fonts, button styles, decorative graphics, and style of product images. Each category has a brand level standard template library, that is, each brand has its visual feature definitions of standard elements. The object detection model embraces the Faster R-CNN framework, whereby, ResNet-50 is utilized as the backbone network. It produces proposals of the regions on the structure of the feature pyramid and classifies the elements categories and regresses the bounding boxes on the proposed regions. A labeled dataset is used to train the model in a 7:1.5:1.5 ratio of a training, validation, and test set. The learning rate will be 0.005 at the beginning, the momentum parameter will be 0.9, the batch size will be 16 and the training run will be 60 epochs. The model is also capable of identifying and classifying different visual elements of new brand visual materials after a training period.

In the consistency assessment step, the system generates a visual feature vector for every visual feature of the element detected (shape, color, and texture feature) by referring to the standard template library of the corresponding brand. The element consistency score is achieved by computing the cosine similarity of feature vector of identified element and the feature vector of the standard template and results between 0 and 1. In the case of the image, the system will give a mean score of visual consistency at five categories and also determine the general visual consistency score of the brand. When the consistency score of a particular element is lower than a predetermined value, the system will automatically label the material an item that needs improvement and provides a difference analysis report which contains information about what specific dimensions of the element identified is not in line with the standard template colour, shape, or texture. By doing so, it allows the high-volume, automated detection of brand visual content in consistency, offering brand managers with a quantitative tool of monitoring.

IV. RESULTS AND DISCUSSION

A. ANALYSIS OF BRAND LOGO RECOGNITION ACCURACY AND OPTIMIZATION EFFECT

The brand logo recognition model based on convolutional neural networks achieved significant results on the test set. The test set contained one thousand images, covering logo application scenarios of fifty brands. The model achieved a Top-1 accuracy of 92.4% and a Top-5 accuracy of 98.2% on the logo brand category recognition task. This result demonstrates that the trained model can effectively handle logo recognition challenges under realistic conditions such as complex backgrounds, scale variations, and partial occlusion. In fine-grained analysis, there are differences in recognition accuracy among different brands. Brand logos with distinct geometric shapes and color contrast generally achieved recognition accuracy above 95%, while brand logos with more delicate design elements and lower color contrast achieved recognition accuracy between 85% and 90%. Table 1 shows the distribution of the model's recognition accuracy across different brand categories, selecting five brands with significant differences in logo style as representatives.

The results presented in Table 1 demonstrate that there is a significant relationship between the features of logo styles and recognition accuracy. The model has high visual salience in color and shape that makes

high-saturation solid color blocks and high-contrast two-color patterns that are more easily and accurately identified in complex scenes. Nevertheless, logos that have three-dimensional lighting and figurative graphics are greatly influenced with lighting and angle alteration in digital media and even harder to identify. Multicolor gradient logos and logos with fine lines are easily susceptible to the loss of features during image compression or downsizing because the edge information is relatively weakened. These results also offer a quantitative foundation to the design of brand logos: in digital media usage, high-contrast and short-controlled geometric design approaches are more important in ensuring logo recognition stability in various conditions. Regarding the optimization effect of logos, the study selected five newly designed logo schemes, each including an initial version and a version optimized based on model heatmap feedback. The initial and optimized versions were input into the model for prediction, and their design quality scores were compared. The results showed that the optimized versions improved the logo clarity by an average of 0.12 points, reduced background interference by an average of 0.09 points, improved color contrast by an average of 0.14 points, and improved readability by an average of 0.11 points. Taking one set of logos as an example, the initial version had overly dense internal details, and the model heatmap showed that the recognition focus was scattered across multiple small areas. The optimized version, by appropriately simplifying the internal details and increasing the width of the main outline, focused the model's recognition focus on the main structure of the logo, improving the logo clarity score from 0.71 to 0.85 and the color contrast score from 0.68 to 0.82. These experimental results demonstrate that optimization suggestions based on convolutional neural networks can effectively improve the visual communication efficiency of logos in digital applications.

B. EVALUATION OF BRAND COLOR EXTRACTION PRECISION AND RECONSTRUCTION EFFICACY

A brand color system extraction and reconstruction method based on generative adversarial networks was validated on an experimental dataset of fifty brands. Color extraction accuracy was evaluated by comparing the extracted main color tone with the brand's official color specifications, and the color difference between the extracted color value and the standard color value was calculated using the CIEDE2000 color difference formula. Table 2 shows a comparison of color extraction accuracy for brands in different industry categories .

Based on Table 2 analysis, technology and electronics brands exhibited the highest extraction accuracy. Within the selected dataset, these specific brands utilized highly standardized UI/UX design systems and high-contrast primary palettes, which facilitated more distinct feature separation for the GAN model. In contrast, while financial brands often employ more 'conservative' or limited palettes, the higher density of textual overlays and complex watermark patterns in their digital documentation likely introduced significant noise, leading to the observed increase in color difference (ΔE) during the extraction process. The resultant outcome suggests that the degree of extraction accuracy is directly proportional to the complexity of the color system of a brand and the richness of the media application environment. So, in the process of color reconstruction, there is a need to

TABLE 1. Statistics on the accuracy of logo recognition for different brands

Brand Category	Logo style characteristics	Number of test samples	Correctly identify numbers	Recognition accuracy
Brand A	High-saturation solid color blocks, geometric shapes	200	196	98.0%
Brand B	Multi-color gradient, organic form	200	178	89.0%
Brand C	Black and white color scheme, fine line outline	200	182	91.0%
Brand D	Three-dimensional light and shadow, figurative graphics	200	168	84.0%
Brand E	High-contrast two-color scheme, text-based	200	194	97.0%

TABLE 2. Statistics on Color Extraction Accuracy of Brands in Different Industries

Industry categories	Number of brands	Average color difference of main color	Average color difference of secondary colors	Average color difference of accent colors
Technology and Electronics	12	1.92	2.83	3.46
Fashion Apparel	10	2.45	3.31	4.12
Food and Beverage	10	2.28	3.05	3.78
Financial Insurance	8	2.51	3.42	4.01
Culture and Entertainment	10	2.37	3.21	3.89

establish differentiated tolerance ranges depending on the nature of various industries.

Under the color reconstruction satisfaction assessment, the research invited thirty designers having over three years experience with the digital media color reconstruction solutions to rate subjectively the model-generated solution. The rating dimensions were color reproduction accuracy, media adaptability, visual comfort, and brand recognition that has a maximum score of 10 points each. There were ten different reconstruction solutions of three media formats that were evaluated with each of the three being webpage header image, mobile application launch page, and social media cover image. The statistical findings indicated that the mean total score of webpage header images was 8.4 points, of mobile application launch pages it was 8.2 points, and of social media cover images it was 8.6 points. The accuracy of reproduction of colors got high scores over the all the media with the average score of 8.7 points, which has shown that the generative adversarial network could retain the original color features of the brand. In terms of media adaptability, the social media cover images obtained the most points considering that their layout was relatively flexible and therefore there was more adaptability concerning the model generated color scheme.

C. ANALYSIS OF BRAND VISUAL ELEMENT CONSISTENCY ASSESSMENT RESULTS

In the consistency assessment application, the study tracked and analyzed the consistency of digital marketing creatives from different brands over a continuous six-month period. Fifty creatives were randomly selected from each brand each month, totaling three thousand images. The system output a consistency score for each image across five elements and calculated a comprehensive consistency score for each month. Table 3 shows the trend of consistency scores for three representative brands over the six-month period.

As shown in Table 3, Brand F's visual element consistency score remained at a high level overall, with a slight improvement in the sixth month, indicating that its brand visual management was relatively standardized and showed a continuous optimization trend over time. Brand G's consistency score showed a month-on-month decline, especially from the fourth to the sixth month. Element-level analysis revealed multiple variations of its title font and button styles in marketing materials, with increasing deviations from the standard template, suggesting potential laxity in brand visual management. While this could be interpreted as an intentional brand evolution or a specialized seasonal campaign, the lack of corresponding updates to the official template library suggests a disconnect between creative execution and centralized brand management. Brand H's consistency score remained consistently around 0.90 with minimal fluctuations, reflecting a highly standardized execution process in its visual system across media applications. This assessment method provides brand managers with timely feedback on consistency status, automatically triggering warnings when the overall score falls below a preset threshold, helping brands intervene before problems escalate. It distinguishes between accidental deviations and strategic shifts by flagging areas where visual execution no longer aligns with established standards, allowing for either corrective action or a formal update to the brand's visual DNA. Through analysis of the discrepancy report, Brand G's design team, based on the deviation dimensions output by the system after the sixth month, re-standardized the title font usage and button style library. In the subsequent two

TABLE 3. Monthly score statistics for brand visual element consistency

month	Brand F Overall Score	Brand G Overall Score	Brand H Overall Score
January	0.87	0.76	0.91
February	0.86	0.74	0.90
March	0.84	0.71	0.92
April	0.85	0.68	0.89
May	0.88	0.67	0.90
June	0.89	0.65	0.91

months of follow-up, the consistency score rebounded to above 0.72, validating the effectiveness of this method in actual management.

V. CONCLUSION

This research focuses on brand visual communication design innovation supported by computer vision technology in the digital age, constructing a technical framework encompassing three core aspects: brand logo recognition and optimization, brand color system extraction and reconstruction, and brand visual element consistency assessment. Through the systematic application of convolutional neural networks, generative adversarial networks, and object detection models, combined with experiments on a dataset containing tens of thousands of images from fifty brands, the effectiveness of the proposed method in improving the efficiency and scientific level of brand visual design was verified. A controlled comparative experiment was conducted where a group of designers manually performed consistency checks and color reconstruction for the same 50 brands. The results indicate that while the AI-supported framework reduced the average processing time per brand by 72%, it also achieved a 15% higher score in cross-media consistency compared to the manual control group. The results show that computer vision technology not only provides accurate visual element recognition and evaluation capabilities but also transforms quantitative analysis results into actionable design optimization suggestions, achieving a paradigm shift in brand visual communication design from experience-driven to data-driven intelligence. Future research will further expand the applicability of the technical framework, exploring computer vision applications in cutting-edge fields such as dynamic visual content and three-dimensional brand presentation, and promoting the practical application of related technical tools in brand design.

AUTHOR CONTRIBUTIONS

Conceptualization – Qiyue Guan and Lansheng Guan; methodology – Qiyue Guan and Lansheng Guan; investigation – Qiyue Guan and Lansheng Guan; writing-original draft preparation – Qiyue Guan and Lansheng Guan. All authors have read and agreed to the published version of the manuscript.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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