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Computer-Aided Design AND APPLICATIONS

Application of Emotion Recognition Algorithm in Brand Design Feedback System and its Influence on User Experience

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Abstract. With the continuous development of emotion recognition application technology, the rapid development of brand recognition human-computer interaction has been greatly improved. Using this technology can create a unique brand feedback technology system. This article captures in detail the emotional brand feedback value of users. A framework for releasing brand emotional value through user experience was constructed through tangible feedback on brand design. At the same time, combining the real-time user emotional value of brand feedback, the brand efficacy experience was carried out on the user experience. By evaluating the user expectations of the brand, a deep-level interactive experience was conducted on user satisfaction and loyalty. With the help of computer emotion recognition, users have enhanced their sense of participation. At the same time, they have had a deep interactive experience with the market competitiveness of brand image. In addition, this article explores the user experience of the algorithm feedback system for emotion recognition. This human-computer interaction brand recognition provides a new perspective on user experience.

Keywords: Emotion Recognition Algorithm; Brand Design; Feedback System; User Experience; Man-Machine Interaction; Computer-Aided Design
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1 INTRODUCTION

In the context of the information age, with the rapid development of the Internet, multimedia, and information technology, the environment of information transmission has changed because of the media and information technology. The dynamic development of brand visual identity design has put forward new requirements for us [1]. In the information-diversified new media environment, what new ideas and design methods should be proposed for brand visual identity design? This is the most critical issue discussed in this article. By sorting out the development of the media environment and its characteristics in information dissemination, the new media environment is defined [2]. The brand communication in the traditional printing media environment is subject to certain limitations [3]. Simple two-dimensional static visual recognition design cannot quickly and effectively convey diverse information, and can no longer meet the market competition of brands and the needs of mass communication. Compared to the information dissemination characteristics of traditional printing media, summarize the characteristics of information dissemination in the new media environment [4]. There are three types of brand visual identity design, mainly based on multi-form logos, dynamic videos, and interactive logos, combined with relevant theories such as communication studies, design psychology, and brand visual identity design. Analyze and compare excellent brand visual identity design cases generated in the new media environment, and classify them from the perspectives of their forms of expression, brand promotion, audience needs, and user experience [5]. By analyzing the event-based case - the visual image system of the Hanover World Expo in Germany - as a starting point, new requirements for brand visual identity design in the new media environment are proposed. Based on a review of relevant cases and research status both domestically and internationally, the definition of brand visual identity design is first provided. Finally, extract its reference significance and dynamic trend research for the development of brand identity design, hoping to bring new thinking to brand visual identity design [6]. Afterward, the design ideas and methods for brand visual identity design in the new media environment will be sorted, summarized, and studied. In this way, users can easily access, analyze, and process cultural relic image data through an intuitive human-computer interaction interface, providing strong support for cultural relic protection and restoration work. In addition, our approach also focuses on providing a protection recovery model aimed at generating useful graphic documents that can be used for design and statistical purposes in a short time. Through human-computer interaction technology, it is possible to more accurately capture and analyze key information in cultural relic images [7].

The birth of design art has always been accompanied by the development of technology and manufacturing techniques. Since the Bauhaus period, the level of design to a certain extent reflects the level of scientific and technological development at that time. The concept and form of modern brand visual identity design have gradually broken our traditional understanding of a single logo effect. In the context of the information age, with the rapid development of the Internet, multimedia and information technology, the traditional two-dimensional static logo has been unable to meet the market competition of brands and the needs of mass communication. At the same time, science and technology and process technology also directly affect the development trend of design, and the two interact with each other [8]. The systematic dissemination of brand visual image recognition requires increased interaction with the audience and sensory experience, in order to strengthen the brand's extended application and dissemination in the new media environment. Designers should not stay at the level of racking their brains for a simple individual graphic but should consider using various forms, means, and forms to express the entire system of brand visual identity [9]. In this situation, how to effectively and quickly disseminate brand identification information has become a new topic. Unlike actively receiving information in traditional printing media, in the environment of information dissemination through new media, we are often forced to receive massive amounts of information. In the era of rapid progress in digital technology and widespread dissemination of information through new media, we are bombarded with a large amount of information every day. However, the research on the dynamic trend of brand image recognition design is still in the initial stage, and the research in this field is not long. Studying its design ideas, methods, and development trends can provide a new carrier for information dissemination [10].

In brand design, fine-grained changes such as mirror materials and lighting effects have a significant impact on conveying brand concepts and emotions. Before actual design, we can use this information to simulate different design schemes in a physically correct way and determine the optimal visual presentation parameters through user feedback and data analysis [11]. Some scholars have introduced an innovative approach that combines the precision of semantic segmentation with the powerful representation ability of deep learning, aiming to capture prominent visual elements in brand design. The core of this method lies in a unique segmentation network that utilizes a multipath network structure and integrates multiple information-rich views to capture the multidimensional characteristics of brand design [12]. The method not only helps designers more accurately identify prominent elements in the design but also helps users better understand and experience the brand by simulating brand displays from different perspectives and scenarios. The system is not limited to static brand display. In the initial stage, our system can predict and simulate the brand's 3-DoF (three degrees of freedom) posture in different scenarios based on data-driven methods. To train our network, we assume that all design component information, including error tolerance, is obtainable during the brand design process. The method also achieves precise alignment with precise semantic masks, which means that designers can precisely control the position, size, and colour attributes of various elements in brand design, thereby achieving a more refined brand design. Through our approach, designers can choose the most prominent viewpoints to more accurately capture these detailed changes and integrate them into brand design. The purpose of this study is to explore the application mode, effect and potential of emotion recognition algorithms in brand design feedback systems. By constructing a brand design feedback system based on an emotion recognition algorithm, this study will analyze the specific role and influence of the system in the process of brand design, and provide more scientific and reasonable guidance for brand design. At the same time, this article will also pay attention to the influence of this system on UX. By collecting and analyzing the feedback data of users in the process of using the system, this study will discuss how the system can improve UX, strengthen the emotional connection between users and brands, and how to further optimize the system to improve UX. This study focuses on the application of emotion recognition algorithms in brand design feedback systems. The specific contents include: building a brand design feedback system based on an emotion recognition algorithm, analyzing the specific function and influence of the system in the process of brand design, discussing the influence of the system on UX, and putting forward optimization suggestions.

The article is carried out in the order of introduction, related theory review, system construction and implementation, experimental design and data analysis, results discussion and suggestion, and conclusion and prospect. Each chapter carries out an in-depth analysis of different research contents to ensure the systematicness and integrity of the research.

The innovation of this study is mainly reflected in the following aspects: ⊖ This study applies the emotion recognition algorithm to the brand design feedback system, which provides a new perspective and method for brand design; ⊜ This study focuses on the influence of emotion recognition algorithm on UX, and discusses how to optimize the system to improve UX; (3) This study combined with specific cases for in-depth analysis, providing a useful reference for brand design practice.

2 RESEARCH STATUS

With the rapid development of technology, we have witnessed the rise of an increasingly super-interconnected world. In the context of super interconnection, brands are no longer sole proprietorships of a single owner but are gradually transitioning towards co-ownership. Swaminathan et al. [13] used human-computer interaction technology to gain a deeper understanding of consumer needs, preferences, and feedback, thereby more accurately positioning the brand's core values and target audience. With the progress of society and the rapid development of Internet technology, people no longer passively receive information through traditional offline media but more and more actively share information through more convenient and fast social media software. Social media marketing has become an indispensable marketing method for enterprises. The brand is a traditional and mature silver jewelry brand, and in the fierce market competition, the brand has also engaged in social media marketing. Taking the brand as the research object, based on the research of domestic and foreign scholars, the social media marketing theory and user consumption behaviour SICAS model are comprehensively applied. However, its marketing methods are relatively traditional and have poor results. How to improve and optimize social media marketing strategies to enhance marketing effectiveness is an urgent problem that M brand needs to solve. On this basis, targeted optimization suggestions for brand social media marketing strategies are proposed to solve existing social media marketing problems and achieve M brand social media marketing goals. The conclusion drawn from the research is that social media marketing is a development trend, and brands and enterprises need to pay attention to user consumption behaviour and carry out social media marketing on time. To study and analyze the current status of brand social media marketing through a questionnaire survey, using the SICAS model of user consumption behaviour as the analytical framework. Nowadays, people's material living standards are constantly improving, and the demand for jewellery is also increasing. High-quality and affordable silver jewellery is more likely to be favoured by consumers. Enterprises and brands should actively use high-tech for marketing, closely integrate social media marketing with new technologies such as big data and cloud computing, continuously meet consumer needs, and improve marketing effectiveness. Enterprises and brands should fully utilize the participatory and two-way characteristics of social media marketing when conducting marketing, to stimulate consumer interest. Combining the current status of brand marketing with the five dimensions of mutual perception, interest interaction, communication, purchasing behaviour, and social sharing in this model, we will deeply analyze the problems that brands face in social media marketing and the reasons for these problems. Brand design human-computer interaction can promote collaborative creation by providing an open, interactive, and innovative platform, encouraging consumers, designers, and other stakeholders to jointly participate in the creation of brand value. Meanwhile, brand design human-computer interaction can also promote emotional connections between brands and consumers, enhancing the emotional value and loyalty of brands. Brand design human-computer interaction can help brand managers better understand and respond to consumer needs and changes. In summary, most of the existing research on social media marketing has focused on types, differences from traditional marketing methods, and influencing factors. Therefore, Weihua et al. [14] studied brands in the silver jewellery industry based on the SICAS model of user consumption behaviour. Although some scholars have focused on the research of social media marketing methods and strategies, most of them have studied a single strategy, and have not paid enough attention to the combination strategy of social media marketing, resulting in a lack of unified and accurate conclusions. It has certain practical guidance significance for brand social media marketing and has great research space and value for the marketing of the silver industry. In addition, there is still a lack of research on the SICAS model that combines consumer behaviour, and it needs to be expanded and supplemented. There is even less research on social media marketing in the silver jewelry industry.

Brand visual logo design is not a simple exception; it is an event-oriented logo design that brings new thinking to the design industry. It is precisely because of this that Wu [15] has realized the feasibility of dynamic expression in brand design and its enormous value and has actively and effectively explored design concepts and visual images. The movement relationship assisted by images, text, and graphic elements has gained tremendous power by stimulating human emotions and capturing attention. Smooth and moving visual symbols and standardized systems are increasingly becoming a demand for consumers. Whether in terms of the impact of its case or the timing of its launch, Hanover's design is far greater than that of other projects, which makes the design of the Hanover World Expo so eye-catching. More importantly, it is to explore the possibility of information transmission and audience acceptance brought about by design, breaking the constraints of traditional laws. This makes the brand visual image of enterprises or products stand out in the complex information, becoming a new issue of concern for enterprises and brands. The changes of the times have made it so fast that people can no longer rely on tradition or replicate previous successes. The brand's visual image has brought us new thinking. Xu et al. [16] are no longer limited to a particular programmatic design. The dynamic mechanism, open spirit, and innovative potential are the characteristics that integrate the needs of enterprises or brands with the market. In the new media environment of information explosion, changing design ideas and utilizing technology and media for visual communication of brand recognition can effectively and quickly convey information.

Xu and Zheng [17] constructed a complex neural network model that can automatically adjust the layout, colour, and content of brand visual pages to provide more personalized services by recognizing user voice emotions. Although the application of emotion recognition algorithm in the field of HCI has achieved certain results, its application in the field of brand design is still in its infancy. At present, only a few researchers have begun to try to apply emotion recognition algorithms to brand design feedback systems, and the related research is not deep and comprehensive enough. Therefore, this study has important theoretical significance and practical value.

3 EMOTION RECOGNITION ALGORITHM AND BRAND DESIGN FEEDBACK SYSTEM

3.1 Principle and Technology of Emotion Recognition Algorithm

The core of the emotion recognition algorithm is to understand and simulate the generation and expression process of human emotions. Based on the theoretical basis of psychology, neuroscience, and computer science, it can identify and understand the emotional state of human beings through the analysis and processing of human facial expressions, voice intonation, text content, and other information. The basic principle of the algorithm is to find and extract features related to emotional expression, and then use machine learning or deep learning technology to model and classify these features, and finally realize automatic recognition of emotions.

Commonly used emotion recognition techniques and methods are shown in Table 1.

Emotion recognition technology and method.	*Method description*
Emotion recognition is based on facial expressions.	Through image processing technology, we capture and analyze the changes of human facial expressions, such as the dynamic changes of eyes, eyebrows, mouth, and other parts, to identify the emotional state.
Emotion recognition based on speech.	By analyzing the acoustic characteristics of speech such as tone, volume and speech speed, as well as the linguistic characteristics such as vocabulary and grammar in speech, the emotional state of the speaker can be recognized.
Emotion recognition based on text.	Through the analysis of the text content, the characteristics of emotional words, emotional phrases, and emotional sentences in the text are extracted, and then these characteristics are modelled and classified by a machine learning algorithm to realize the recognition of text emotions.
Emotion recognition is based on physiological signals.	Physiological signals such as human heart rate and skin electrical response are captured by physiological signal monitoring equipment, and the emotional state is identified by analyzing the changes in these signals.
Multi-modal emotion recognition technology.	Combining various information sources (such as facial expression, voice, text, physiological signals, etc.) to identify emotion, in order to improve the accuracy and reliability of emotion recognition.

Table 1: Commonly used emotion recognition techniques and methods.

3.2 Construction of Brand Design Feedback System

The construction of a brand design feedback system aims to provide scientific and reasonable guidance for brand design by collecting and analyzing user feedback data. The system design shall follow the principles in Table 2:

Principle classification	*Specific content*

User-centered	System design should give full consideration to users' needs and experiences to ensure that the system can obtain users' feedback information accurately and timely.
Data-driven	The system should analyze and make decisions based on a large number of real user data to ensure the accuracy and effectiveness of feedback.
Real-time	The system should be able to monitor users' feedback in real-time and make timely responses and adjustments.
Expandability	The system should have good scalability and can be flexibly adjusted and optimized with the change in brand design requirements.

Table 2: Construction principle table of the brand design feedback system.

In this article, the brand design feedback system mainly includes the following functional modules:

User feedback collection module: This module is responsible for collecting user feedback data, including text, pictures, videos, and other forms.

Feedback processing and optimization module: according to the feedback results of users, optimize and adjust the brand design to improve the pertinence and effectiveness of the design.

The brand recognition model based on customer emotional value is shown in Figure 1.

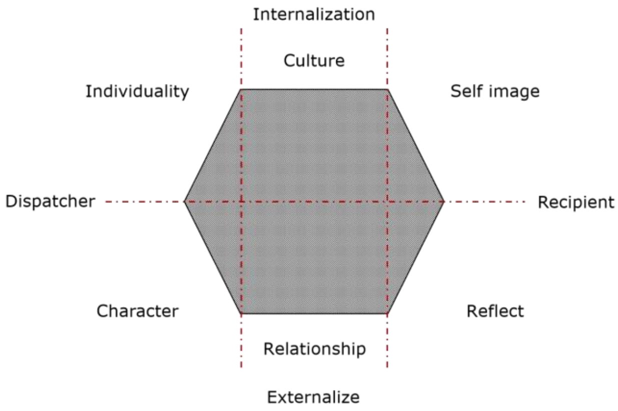

Figure 1: Brand recognition model based on customer emotional value.

The implementation of the system encompasses various crucial technologies, such as emotion recognition algorithms, data processing methods, and user interface design. Specifically, the emotion recognition algorithm stands as a pivotal component for achieving the system's core functionalities, as it dictates the system's ability to precisely detect users' emotional states. Furthermore, efficient data processing technology plays a significant role in ensuring the smooth operation of the system by handling and analyzing a vast amount of user data to extract valuable insights. Lastly, the design of the user interface is crucial in determining the system's usability and overall user experience; it must be clean, intuitive, and user-friendly.

3.3 Application of Emotion Recognition Algorithm

In the feedback system of brand design, emotional data is usually collected in many ways, such as user questionnaires, user evaluations, social media comments and so on.

$$h_t = RNN\ h_{t-1}, x_t \tag{1}$$

$$r_t = \sigma\ W_h h_{t-1} + W_x x_t + b_r \tag{2}$$

$$\hat{h}_t = \mathrm{Tanh}\ W_h h_{t-1} + W_x x_t + b_h \tag{3}$$

Where r_t is the result of forgetting the gate, $\hat{h}_t$ is the candidate hidden state, σ is the sigmoid function, Tanh is the hyperbolic tangent function, and W_h, W_x and b_r, b_h are the weights and offsets from the hidden layer to hidden layer and input to hidden layer respectively.

In the standard RNN, the hidden state h_t usually directly uses the candidate hidden state $\hat{h}_t$:

$$h_t = r_t \circ h_{t-1} + \ 1 - r_t \ \circ \hat{h}_t \tag{4}$$

Where $\circ$ stands for multiplication at the element level. This formula shows that the forgetting gate r_t determines the information to be forgotten in the previous hidden state h_{t-1} while $1 - r_t \ \circ \hat{h}_t$ determining the contribution of the new input x_t to the hidden state.

To address the issue of long-term dependency in text, this article opts to utilize a variant of RNN, namely LSTM (Long-term and Short-term Memory Network). This variant incorporates a gating mechanism or memory unit, enabling RNN to more effectively handle dependencies in long sequence data. Refer to Figure 2 for the detailed model structure.

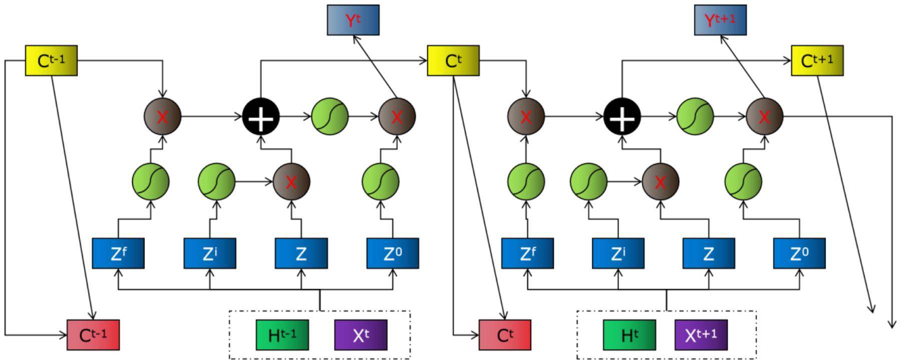

Figure 2: Structure diagram of LSTM model.

LSTM manages the flow of information through the implementation of three gates: the forgetting gate, the input gate, and the output gate. The formula for the forgetting gate is as follows:

$$f_t = \sigma\ W_f h_{t-1} + U_f x_t + b_f \tag{5}$$

The formula for the input door is:

$$i_t = \sigma\ W_i h_{t-1} + U_i x_t + b_i \tag{6}$$

$$\hat{c}_t = \mathrm{Tanh}\ W_c h_{t-1} + U_c x_t + b_c \tag{7}$$

Where c_t is the current cell state, $\hat{c}_t$ is the candidate cell state, and $W_f, W_i, W_c, U_f, U_i, U_c$ and b_f, b_i, b_c are the corresponding weights and offsets, respectively. The formula of the output gate is:

$$o_t = \sigma\ W_o h_{t-1} + U_o x_t + b_o \tag{8}$$

$$h_t = o_t \circ \mathrm{Tanh}\ c_t \tag{9}$$

Where o_t determines the information to be output in the current hidden state h_t .

Finally, in the output layer, this article uses the fully connected layer to deal with the final hidden state of the loop layer and outputs the probability distribution of each emotion category through the

Softmax activation function. In this way, a complete RNN model is constructed, which can receive text data as input and output the corresponding probability distribution of emotion categories.

When training the RNN model for emotion recognition, it is very important to choose the appropriate loss function. Cross entropy loss function is a common choice because it can effectively measure the difference between emotional tags predicted by the model and real tags.

For a multi-classification problem with N categories, suppose that the model outputs a probability distribution $P(y|x)$, where y is the real label and x is the input data. A probability distribution $P(y|x)$ is usually calculated by the softmax function. The cross-entropy loss function is defined as:

$$L(y,P(y|x)) = -\sum_{i=1}^{N} y_i \log(P(y_i|x)) \tag{10}$$

Where y_i is the indication of the i class in the real tag, and $P(y_i|x)$ is the probability of predicting the i class when the model gives the input x.

In certain scenarios, to enhance training efficiency and stability, a simplified version of the cross entropy loss function is employed. This involves computing losses individually for each category and then summing them up:

$$L(y^*,P(y|x)) = -\sum_{i} onehot(y^*)_i \log(softmax(z)_i) \tag{11}$$

$softmax(z)_i$ here is the value of i position z after softmax transformation.

RNN deeply analyzes and identifies the preprocessed data, extracts emotional features and judges emotional categories. This process involves several subtasks, including emotion classification (judging whether the emotional tendency of a text is positive, negative or neutral), emotion intensity evaluation (evaluating the intensity or degree of emotion in a text) and emotion attribution (determining which entity or event caused emotion). Through the processing of these subtasks, the algorithm can generate accurate emotion recognition results.

The emotion recognition algorithm displays the recognition results to users or designers in a visual form, forming emotional feedback. This feedback can include users' overall evaluation of brand design, their preference for a certain design element, and suggestions for improvement of the design scheme. Based on user feedback, designers can refine and adjust brand designs to enhance their relevance and effectiveness. Additionally, the system has the capability to produce visual outputs, such as analysis reports or statistical charts, utilizing user feedback data, thereby offering more comprehensive and insightful guidance for brand design.

4 EXPERIMENTAL DESIGN AND DATA ANALYSIS

4.1 Experimental Design

To ensure the credibility of the experimental results, this article carefully chose participants representing a wide range of ages, genders, occupations, and cultural backgrounds. This diversity aims to mimic the variety of users encountered in the real world (refer to Table 3). Additionally, to minimize experimental interference, all participants were briefed on the basics of the brand design feedback system before the experiment while ensuring they had no prior extensive experience with similar systems.

Age bracket	*Gender*	*Occupation type*	*Number of participants*
18-24 years old	Male	Student	20

25-34 years old	Female	New workplace	15
35-44 years old	Male	Middle management	10
45-54 years old	Female	Top management	8
55 years old and above	Male/Female	Retired/freelance	7

Table 3: Diversity table of experimental participants.

In the experiment, we set several variables to test the performance of the brand design feedback system. These variables include the participants' personal information (such as age, gender, occupation, etc.), the characteristics of brand design cases (such as design style, target user groups, etc.), the operation behaviour of the system (such as frequency of use, feedback time, etc.) and the participants' subjective evaluation, etc.

4.2 Data Collection and Processing

A variety of data collection methods and techniques are used in the experiment. Firstly, the built-in function of the brand design feedback system is used to record the participants' operation behaviour and feedback data. These data include buttons clicked by users, filled-in comments, uploaded pictures, etc. Secondly, the subjective evaluation and suggestions of the participants were collected through questionnaires. The questionnaire is designed concisely so that participants can express their views and feelings quickly and accurately. Finally, this article also uses social media and other external channels to collect user feedback data related to brand design to enrich the experimental data set. After collecting the original data, strict data cleaning and pretreatment were carried out.

4.3 Data Analysis and Results

By analyzing experimental data, this article assesses the precision and efficiency of the emotion recognition algorithm. Initially, this section computes the algorithm's accuracy in detecting various emotional states and compares it to the benchmark algorithm. Refer to Figure 3 for the algorithm's accuracy in recognizing diverse emotional states.

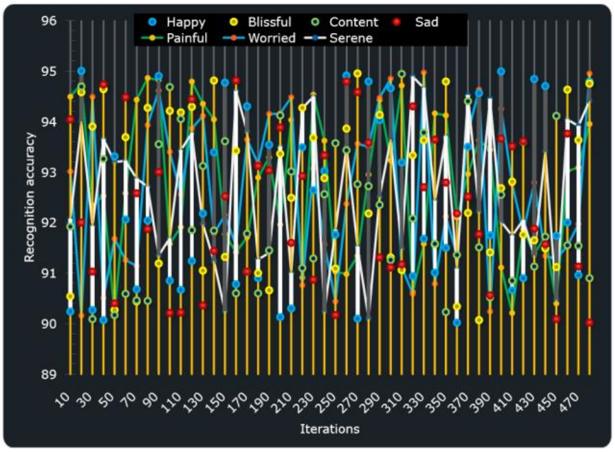

Figure 3: Accuracy of identifying different emotional states.

The comparison result with the benchmark algorithm is shown in Figure 4. The results show that compared with other methods, the emotion recognition algorithm in this article has reached a high level of accuracy, which is about 95%, and it shows good stability and robustness in identifying different emotional States. Secondly, this section also analyzes the running efficiency of the algorithm, including calculation time and memory occupation. The calculation time of the algorithm is shown in Figure 5.

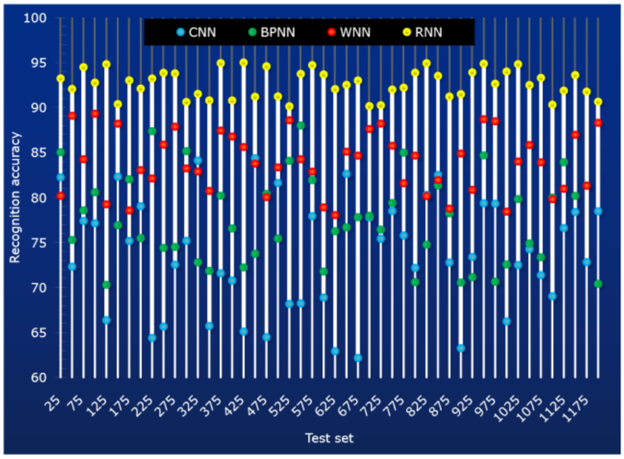

Figure 4: Algorithm comparison results.

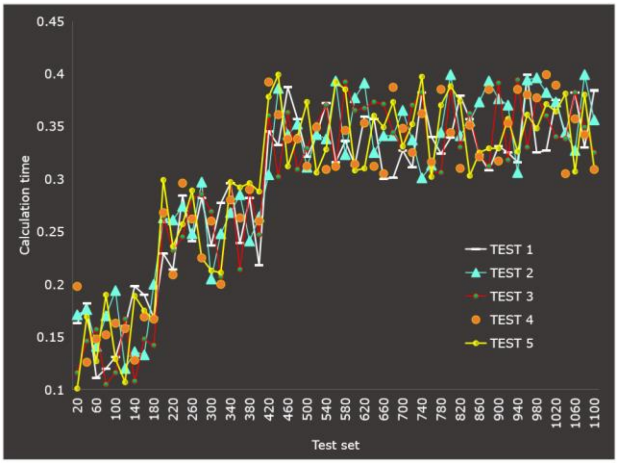

Figure 5: Calculation time of the algorithm.

The memory occupation of the algorithm is shown in Figure 6. The results show that the algorithm performs well in running efficiency and can meet the application scenarios with high real-time requirements. This section further evaluates the effectiveness of the brand design feedback system. The feedback data of the brand design scheme before and after users use the system is shown in Figure 7.

By comparing the brand design scheme and user feedback data before and after using the system, we find that the system can effectively collect and analyze user feedback information and provide scientific and reasonable guidance for brand design. Specifically, the system can accurately identify the user's emotional state and demand preference and generate targeted feedback suggestions based on this information. These suggestions are of great significance for optimizing brand design schemes and improving UX. Finally, this section analyzes the degree of improvement of the brand design feedback system to UX, as shown in Table 4.

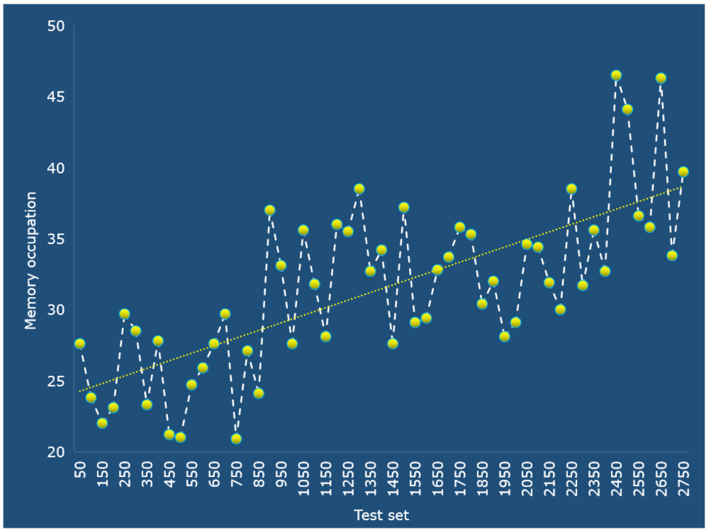

Figure 6: Memory occupation of the algorithm.

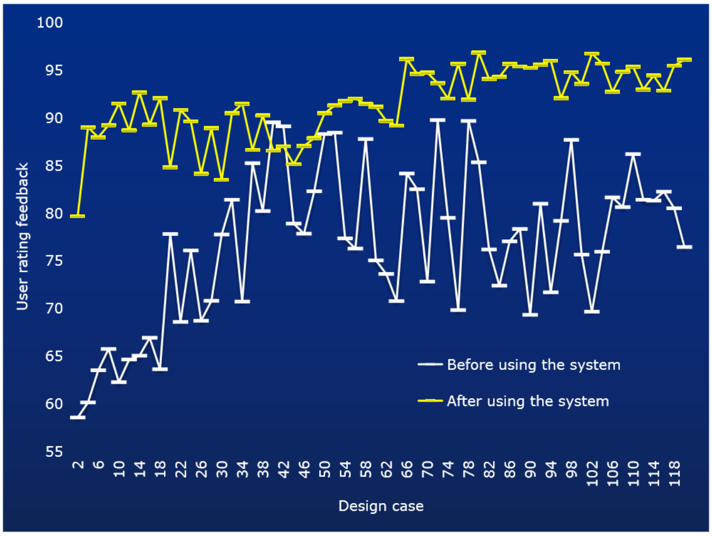

Figure 7: User feedback data.

Index	*Before using the system*	*After using the system*	*Degree of improvement*
Degree of satisfaction	7.5 (out of 10)	9.4 (out of 10)	+1.9
Loyalty	65%	82%	+17%
Feedback response speed	Average 24 hours	Average 4 hours	+20 hours
Solution Effectiveness	60%	89%	+29%
The design style meets users' expectations.	59%	88%	+29%

Design elements are in line with user preferences.	60%	90%	+30%
User experience improvement	Medium	Excellent	Remarkable improvement
Emotional connection enhancement	Weaker	Strong	Significantly enhanced

Table 4: Analysis table of improvement degree of brand design feedback system to UX.

These improvement measures not only improve the user experience but also enhance the emotional connection and loyalty between users and brands.

5 AFFECTION RECOGNITION ALGORITHM ON UX

5.1 Dimension and Evaluation of UX

In the field of brand design, the quality of UX is directly related to users' perception, impression and loyalty to the brand, and then affects the market competitiveness and long-term development of the brand.

In order to accurately evaluate UX, we usually adopt various methods and indicators. Commonly used evaluation methods include questionnaire surveys, interviews, behaviour analysis, eye tracking and so on. These methods can obtain feedback data from users from different angles to fully understand all aspects of UX.

The evaluation indicators include several aspects in Table 5:

Evaluation index	*Index evaluation standard*
Usability	Whether the product or service is easy to use and understand, and whether the user can quickly master the operation method.
Degree of satisfaction	The overall satisfaction of users with products or services, including the evaluation of product functions, design, and performance.
Emotional reaction	Emotional reactions generated by users in the process of using products or services, such as pleasure, disappointment, anger, etc.
Loyalty	Whether users are willing to continue to use or recommend products or services to others.

Table 5: Evaluation index table.

5.2 The Direct Influence of Emotion Recognition Algorithm on UX

The emotion recognition algorithms can analyze users' emotional reactions in real time and provide accurate emotional feedback for brand design. This real-time accuracy enables brand designers to adjust the design scheme in time to meet the emotional needs of users. For example, in website design, an emotion recognition algorithm can monitor users' emotional responses to webpage content in real time. When users are found to be dissatisfied or confused, designers can quickly adjust page layout, colour matching or content presentation mode to improve users' satisfaction and experience (Figure 8). The results of users' satisfaction with various types of design schemes are shown in Figure 9.

It can be seen that the application of an emotion recognition algorithm is helpful for users to perceive and understand brand design. By analyzing users' emotional reactions and feedback data, brand designers can deeply understand users' preferences, needs, and expectations so as to design brand images and products that better meet users' expectations. This design method based on user emotion can enhance the emotional connection and identity between users and brands, and enhance users' loyalty and satisfaction with brands.

Figure 8: Design scheme after using the emotion recognition algorithm.

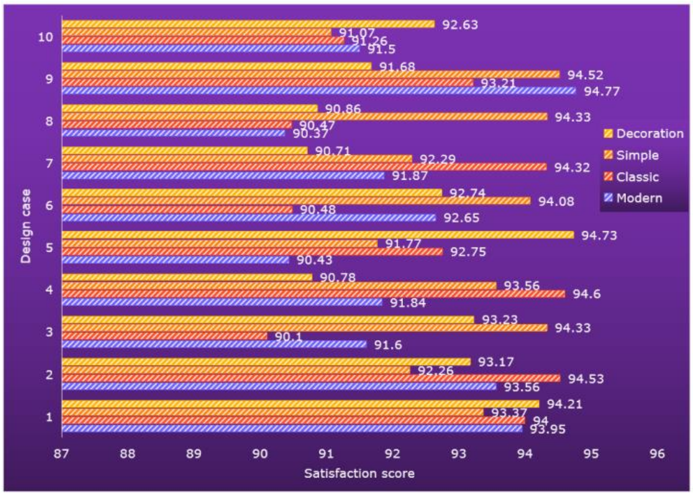

Figure 9: User satisfaction results.

6 CONCLUSIONS

In the field of brand design, a remarkable study has revealed the powerful potential of emotion recognition algorithms in feedback systems. This change not only improves design efficiency but also fundamentally enhances design quality, making the brand more attractive. They are able to more accurately grasp user preferences and needs, thereby making decisions that better meet user expectations in brand image shaping and product design. It is worth mentioning that this design feedback model based on user emotions has brought unprecedented convenience to brand designers.

This study not only demonstrates through in-depth analysis but also through practical validation, how emotion recognition algorithms can capture and deeply analyze user emotional responses in real-time, thereby providing brand designers with accurate and real-time user feedback. Because algorithms can provide real-time feedback on user emotional responses, allowing users to feel that their opinions and feelings are fully valued and respected. This sense of being valued greatly stimulates the enthusiasm and creativity of users, making them more willing to provide valuable suggestions for brand design. In addition, the application of emotion recognition algorithms in brand design feedback systems has also had a profound impact on user experience. Firstly, it significantly enhances the user's sense of participation.

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