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Research Article

Application of Traditional Culture in Intelligent Advertising Design System in the Internet Era

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This paper focuses on the application of traditional culture in the intelligent advertising design system in the internet era. The existence form of traditional culture is abstract and vivid. It is extremely charming when used in advertising design. It is unique and subtle and has the beauty of holding a pipa half-covered. The classic colors reveal the splendor of history, which is fascinating, and it seems to want people to integrate into it and appreciate its beauty. This paper, firstly, introduces the background of traditional culture and intelligent advertising design and discusses its significance and innovation. Combined with the research methods and experiments put forward by the related work, the advertising system model is, firstly, proposed. The process of ad request processing, system hardware topology, and ad real-time bidding process are introduced. It will talk about the feature association algorithm in advertising design, explain the linear logistic regression and nonlinear algorithms, and describe the GBDT feature processing process. It combines stochastic gradient descent, decision trees, etc., to calculate ad click-through rates. It also explained the allocation algorithm of traffic and quality and market competition in advertising design. It is guided by a probabilistic filtering mechanism that tests ad spend, bidding, and market competition. Finally, the effect evaluation experiment of intelligent advertising system based on traditional culture fusion is carried out. It displays the application of traditional culture, such as Dunhuang Feitian and blue and white porcelain, Huizhou architecture, and Miao embroidery. It uses pictures to show its beauty, and it compares the advertising situation in the perspective of traditional culture and modern fashion. It is concluded that the introduction of traditional culture into advertisements is more attractive. Through the establishment of an outdoor advertising evaluation system based on face gesture recognition to calculate the pedestrian parking viewing rate, it is concluded that the system has a very high accuracy rate and a very small error, only 3.76%, which can be effectively applied to actual scenarios.

1. Introduction

The traditional culture seal engraves the history in human thought. Even in today's environment, where various cultures are bursting out, traditional culture is unique in the world by virtue of its wide range of subjects, long history, and profound connotations. Because of this, the international communication and influence of traditional culture has become more far-reaching. In the form of cultural pluralism and cultural globalization, the phenomenon of the integration of traditional culture and advertising is a natural occurrence. The combination of advertising and traditional culture makes it more characteristic and disseminated. The combination of the two not only allows advertising to play its own promotional role but also can spread and promote traditional culture and its value. In addition to expressing the phenomenon of the combination of advertising and traditional culture, traditional culture is not limited to tradition. The reason why it can be so active and full of vitality in modern society is inseparable from its variability and inclusiveness. The progress of the times and society has also promoted the transformation and innovation of traditional culture. Therefore, in modern society, traditional culture has more possibilities and more tenacious vitality [1]. In the process of combining advertising and traditional culture, various questions will be encountered. Advertising, as a commercial culture, cannot be separated from the heritage of the nation and country. The injection of traditional culture makes each component of the advertisement more attractive. Concise and meaningful advertising words, culturally rich copywriting, etc., make advertising out of the original limited structure and expression. The rhythm of ancient poetry in traditional culture has brought far-reaching influence to advertising. Under the smudge of traditional culture, the mode of communication and the form of expression are more worthy of appreciation. Advertising and traditional culture are integrated with each other and influence each other. The addition of traditional culture makes advertising more oriental and more oriental.

The innovation of this paper is to substitute random forest into the advertising design system so that it has more accurate testing ability and can reduce errors. For imbalanced datasets, random forest can balance the error. When there is a classification imbalance, random forest can provide an effective method to balance the error of the dataset. The traditional culture is integrated into the advertisement, and the product is promoted in a more subtle and tactful way of expression so that it has a unique temperament and an endless aftertaste. The designed system is used to test the interest of pedestrians in advertisements, which can better design and adjust advertisements, which is of great practical significance.

2. Related Work

Advertising design has always been an object of great enthusiasm for new media. Ding et al. designed and implemented a blockchain-based digital advertising media system (B2DAM) with Hyperledger as the implementation platform. The B2DAM system integrates distributed ledgers, multichain, smart contracts, and consensus mechanisms to ensure the decentralization and multiparty maintenance of immutable data [2]. Dong et al. proposed an efficient random forest-based detector for metric learning, called the random forest metric learning (RFML) algorithm. It combines semimultiple metrics with random forests to better separate the desired target and background. Experimental results show that the proposed method outperforms state-of-the-art object detection algorithms and other classical metric learning methods [3]. Xia et al. proposed a new ensemble method called rotation random forest by kernel principal component analysis (RoRF-KPCA). Specifically, the original feature space is, firstly, randomly split into several subsets, and KPCA is performed on each subset to extract high-order statistics [4]. Papathomas proved that assigning a g-prior (or mixture of g-prior) to the parameters of some log-linear model specifies the g-prior (or mixture of g-prior) of the parameters of the corresponding logistic regression. By deriving asymptotic results and numerical descriptions, this correspondence extends to the posterior distribution of model parameters when g-prior is employed [5]. HudaS uses multiple linear regression and p-values for each individual API feature to select the least relevant and most important features. It reduces the dimensionality of large malware data and ensures that there is no multicollinearity. Then, a stepwise logistic regression method is employed to test the importance of individual malware features against the corresponding Wald statistic, and a binary decision model is constructed [6]. Baneshi et al. constructed a tree-based model using the Gini index as a homogeneity criterion and also applied a complementary discrimination analysis. The variables that helped build the tree were stressful life events, mental disorders, family support, and religious beliefs [7]. Although these studies have certain guiding significance, there are insufficient demonstrations, which can be further improved.

3. Advertising System Model and Related Algorithms

3.1. Advertising System Model. Before designing the advertising publishing system, it is necessary to comprehensively consider many requirements, such as users' needs for business updates and related services [8]. Only by adding these important requirements into the design of the system in advance can we finally provide users with a stable, efficient, practical, and reliable advertising publishing system [9]. In terms of humanization, it is necessary to add support in many aspects, such as system scalability, security, etc. Under the ever-changing situation of advertising in the future, the system can expand different functions with different advertising needs. At the same time, it is necessary to take adequate protection in terms of data security to effectively prevent data leakage [10]. The business processing flow of each subsystem in the advertising publishing system is shown in Figure 1.

On the premise of the nonfunctional requirements of the system, the hardware topology is defined according to the relevant functional definitions of the subsystems of the system [11]. Its system topology is shown in Figure 2.

The structure of the server-side subsystem is shown in the figure. It is not difficult to see that the advertisement management system, the advertisement delivery system, the advertisement display system, and the data analysis system have corresponding servers. A server and a server node constitute the database server [12]. In the above-mentioned corresponding servers, both the ad delivery server and the ad display server are composed of one server to achieve a balanced load [13]. The advertisement management background is generally deployed on a separate server node. Because the function of the background is single, this deployment can improve reliability and security. At the same time, it can improve the efficiency of advertisement display and delivery, reduce the impact on advertisements as much as possible, and further reduce the risk of overall system downtime [14]. The responsibility of the statistical analysis server is to be responsible for the statistics and calculation of a large amount of data.

The data management platform can summarize and process the user's information. The main purpose is to process the collected user data and make it available for use in advertising systems and markets. The data management platform usually collects users' browsing records, identifies users' preferences, and reasonably categorizes different users. These obtained data are sold to DSP, etc., who can orient the data more precisely [15]. DSP is a system and an online advertising platform. It can make it easier and more

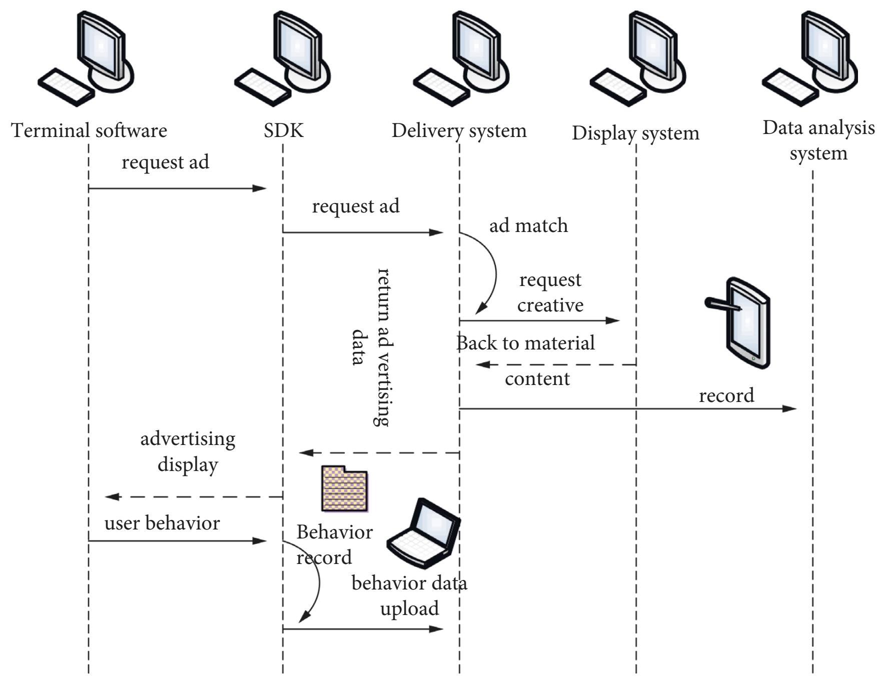


Figure 1: Ad request processing flow.

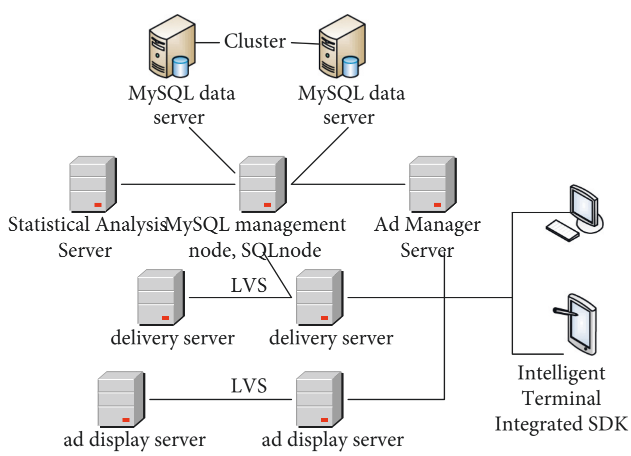


Figure 2: Topology.

convenient for advertisers to follow a unified bidding and feedback method. It purchases high-quality ad inventory in real time at reasonable prices for online ads located on multiple ad exchanges. These data have a decisive influence on the level of quotations in the real-time bidding process. The advertising real-time bidding process is shown in Figure 3.

3.2. Feature Association Algorithm in Advertising Design. Linear logistic regression has a relatively simple learning ability when learning attribute features. It can only learn a single feature or a single attribute. For example, it can only learn the type of advertisement that can get more click-through rate or the type of product advertisement that is more popular with consumers [16]. In the collected data, each component can be regarded as a characteristic data. Each feature corresponds to at least one unknown parameter, thus forming a linear model function. However, linear logistic regression cannot learn effectively when multiple features or multiple attributes are interleaved, for example, which sports enthusiasts prefer between health products and sports equipment, and which type of product advertisement has higher attention than the advertisement of the same product. These situations are not faced by linear logistic regression [17]. In simple terms, it is actually a combination of multiple features or multiple attributes to get more features or attributes. At the same time, it can also analyze the impact of more aspects or dimensions. Essentially, it is a case of polynomial regression. The maximum depth is set in advance, each branch is probed with a step-by-step strategy, and the entire process is processed continuously. It is transformed into a binary discrete attribute, and at the same time, it learns and trains the relationship between each feature or attribute so that the output can obtain appropriate enhanced attributes [18]. Considering the base attribute and the enhancement attribute as a feature vector, we can have the advantages of both. Basic attributes are used to obtain basic click trends, and enhancement attributes are used to improve the accuracy of final click prediction [19]. Figure 4 shows the GBDT feature processing.

The proportion of positive samples in the original dataset has a great impact on the learning of the model. In the ad network, there are a huge number of ad requests every day, and these ad requests make the number of learning samples increase accordingly. In the offline state, training the model consumes more resources. At the same time, the data used needs to be updated continuously. Hence, the feasibility of this training method is very low [20]. Therefore, according to the actual needs, the proportion of positive samples is adjusted, and the negative samples are used by sampling. In

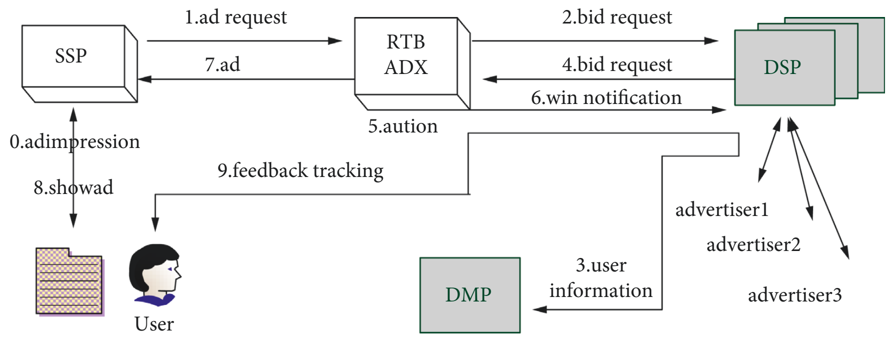


Figure 3: Ad real-time bidding process.

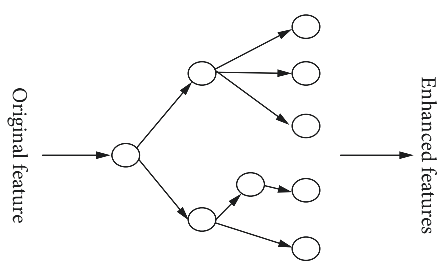


Figure 4: GBDT feature processing.

this environment, the model can perform more training and learning on positive samples, thereby reducing the overall computational cost [21]. There are far fewer positive examples than negative examples, and the original data has a serious class imbalance problem. There is a huge challenge for training to learn useful patterns. Hence, the data is negatively sampled.

CTR prediction models are generally divided into two types: linear and nonlinear. Among them, logistic regression is one of the most commonly used linear CTR prediction models. When the raw data is processed, it is modeled and solved. The linear logistic regression model regards the information in each request as a feature vector m, and the function click rate $\phi(m)$ of the feature vector m can be expressed as follows:

$$\phi(m) = \text{sigmoid}(f(m)). \tag{1}$$

The linear sum of the features can be expressed as follows:

$$f(m) = \mu_0 + \sum_{k=1}^{N} \mu_k m_k. \tag{2}$$

Then, the logistic function and the s-type function are as follows:

$$\text{sigmoid}(s) = \frac{1}{1 + e^{-s}}. \tag{3}$$

$f(m)$ is the linearly weighted sum of the eigenvectors that wraps them to [0, 1] via the sigmoid function. At this time, when the weighted sum wireless approaches infinity, $\phi(m)$ approaches 1 infinitely. When the weighted sum infinitely approaches negative infinity, $\phi(m)$ infinitely approaches 0. At this time, upon combining the probability density of a, m and the predicted value of $\phi(m)$, the likelihood function of the data sample with the amount of data as x is solved. The class label and feature vector of the k sample instance are represented by $a^{(k)}$ and $m^{(k)}$, and the logarithmic result is as follows:

$$\text{Log}W(\mu) = \sum_{k=1}^{x} \left\{ a^{(k)} \log \phi\left(m^{(k)}\right) + \left(1 - a^{(k)}\right) \log\left(1 - \phi\left(m^{(k)}\right)\right) \right\}. \tag{4}$$

It can be seen that the negative logarithm of the likelihood function can be used as its cross entropy or logarithmic loss function. Then, the iterative rule for calculating the weight is controlled by maximizing the gradient direction and step size of the likelihood function value. At this time, for the i^{th} weight value of the dimension feature vector b, there are,

$$\mu_i \longleftarrow \mu_i + \lambda\left(a^{(k)} - \phi\left(m^{(k)}\right)\right) m_i^{(k)}, \quad i = 1, 2, \ldots, b. \tag{5}$$

Stochastic gradient descent is named because the overall process resembles a random descent route. The stochastic gradient descent method uses only one sample to iterate at a time, and the training speed is very fast. In the whole optimization process, the optimization of this method is not an all-encompassing optimal solution. However, by this method, all the weight values can be updated directly with the error between the obtained predicted value and the actual value. If it is necessary to further shorten the training time and obtain better convergence performance, the Newton-Raphson method can be used. The resulting error is actually a maximum likelihood estimate that fits a Gaussian distribution. Hence, it is equivalent to solving least squares. Because the least squares of linear logistic regression is not a convex function, it is difficult to obtain the global optimal value by stochastic gradient descent. At this time, through the method of logarithmic loss function and the corresponding target formula are established, and the regular term is used to prevent parameter overfitting.

$$\min \sum_{k=1}^{x} \left\{ a^{(k)} \log \phi\left(m^{(k)}\right) + \left(1 - a^{(k)}\right) \log\left(1 - \phi\left(m^{(k)}\right)\right) + \frac{\lambda}{2}\|\mu\|^2 \right\}. \tag{6}$$

In addition to using linear models to predict click-through rates, common click-through rate prediction methods are gradient boosted decision trees. The decision tree construction process is feature selection, decision tree generation, and pruning (reducing the size of the tree structure and alleviating overfitting). Unlike linear models, gradient-boosted decision trees are nonlinear models. Therefore, this method will only leave the best and most powerful features and attributes, and the rest will be discarded. Compared with linear models, decision trees are nonlinear models that can directly use continuous attributes. At the same time, when preprocessing data, its requirements are also lower than linear models. In linear models, the high sparseness of feature vectors is generally caused by the binary encoding in the features. Therefore, using a linear model in the normal flow at this time will adversely affect training. It improves the summation of linear logistic regression by decomposing the model.

$$f(m) = \mu_0 + \sum_{k=1}^{N} \mu_k m_k + \sum_{k=1}^{N} \sum_{i=1}^{N} \langle v_k, v_i \rangle m_k m_i, \tag{7}$$

where $v \in R^{N \times Q}$ and Q are the size of the latent space.

$$\langle v_k, v_i \rangle = \sum_{f=1}^{Q} v_{k,i} \cdot v_{i,f}. \tag{8}$$

This mode can better understand the interaction between the eigenvalues of the sparse vector and improve the shortcomings of the original linear model.

3.3. Allocation Algorithm of Traffic, Quality, and Market Competition in Advertising Design. Since the proposed scheme is guided by a probabilistic filtering mechanism, the probabilistic filtering value in it is called the step rate. The step rate can be defined as a function of time s. The reason why advertising campaigns are limited is because different advertising campaigns target different groups. At the same time, its effects under the influence of different factors are also different. Therefore, it is necessary to design its own distribution plan for different types of advertising campaigns, which can be used as a reference for similar advertising campaigns. In general, it is not appropriate to process $w(s)$ as a continuous function, and a more practical method is to process time in segments. It divides the total length of the day into S segments on average. Assuming that the estimated cost in a certain time period is 1, the total budget for the day is $\{q_1, q_2, \ldots, q_S\}$. At the same time, the number of ad requests m from ADX in this time period s is $\{x_1^s, x_2^s, \ldots, x_m^s\}$, and the corresponding function is $req(s)$. After $w(s)$, the ad requests are screened, and the first qualified ad request is $\{c_1^s, c_2^s, \ldots, c_m^s\}, c_n^s \in \{0, 1\}$. 0 means inappropriate, 1 means qualified, and the step rate is as follows:

$$w^{a\ dc}(s) = \frac{\sum_{i=0}^{i=m} c_i^s}{m}. \tag{9}$$

After bidding, the ad request sequence that wins the bid under the calculation of the advertising exchange market is $\{a_1^s, a_2^s, \ldots, a_m^s\}, a_n^s \in \{0, 1\}$, 1 is the chance to win the advertising exhibition, and the probability of winning the bid is as follows:

$$kt^{a\ dc}(s) = \frac{\sum_{i=0}^{i=m} a_i^s}{m}. \tag{10}$$

In the actual RTB environment, the data corresponding to the unqualified ad request is missing. As a result, the data corresponding to the qualified line price is missing, which further affects the optimization of the qualification rate prediction and the establishment of the qualified price prediction model. To effectively improve the prediction accuracy, linear regression and censored regression methods are used to build the model. The final cost sequence for the above ad requests is $\{c_1, c_2, \ldots, c_S\}$, and the cost sequence for ineligible ad requests is 0. Therefore, it can be concluded that in a certain period of time, the smaller the gap between the actual cost and the predicted cost, the better the effect, namely $|q_s - \sum_{i=1}^{m} b_i^s| \leq \varepsilon$. The average impression price during this time period s is as follows:

$$bwn(s) = \frac{\sum_{i=0}^{i=m} b_i^s}{\sum_{i=0}^{i=m} a_i^s}. \tag{11}$$

The quality of ad impressions is affected by many factors, for example, the number of clicks in different time periods, the purchase behavior of consumers in different time periods, etc. The performance of the data of these factors can intuitively show the quality of an advertisement. With this data, it is possible to more accurately increase the budget during the time period when the ad quality is high, thereby increasing the impact of the ad. As much of the budget as possible should be placed in high-quality time periods. The ad display quality metric defined in this article reflects the difference between the display quality and the average quality in a certain period, and it can be expressed as follows:

$$\phi(s) = \frac{iwa(s) - \operatorname{avg}(iwa)}{\operatorname{avg}(iwa)}. \tag{12}$$

$\phi(s)$ is the change of advertisement quality. When its performance is average, the calculated result is 0, and the high quality value is a positive number, otherwise, it is a negative number. It controls the value between 0 and 1 and uses the mapping function to control the quality factor. The mapping function used to control the quality factor at this time may be a logistic function. At this time, the quality factor function is as follows:

$$qf(s) = f^{\phi}(\phi(s)). \tag{13}$$

ϕ controls the speed of change in ad quality and can be set to 1 when its display quality is close to average. On any given day, the numerical changes of the traffic of a certain ad and the number of buyers participating in the bidding are different. At the same time, the winning rate is affected by a variety of factors, such as market trading mechanism, bidding strategy, etc. The change of winning the bid rate is determined by the change of these factors. However, the specific value of the winning rate cannot intuitively show the real situation of the competition level. The difference between the transaction price in a certain period of time and the average transaction price in that day is defined as follows:

$$\lambda(s) = \frac{bwn(s) - \operatorname{avg}(bwn)}{\operatorname{avg}(bwn)}. \tag{14}$$

Then, it takes the mean of the squares of $\phi(s)$ and $\lambda(s)$.

$$\begin{aligned} \overline{\phi} &= \sqrt{\frac{\sum_{s=1}^{S} \phi(s)^2}{S}}, \\ \overline{\lambda} &= \sqrt{\frac{\sum_{s=1}^{S} \lambda(s)^2}{S}}. \end{aligned} \tag{15}$$

$(\overline{\phi}/\overline{\lambda})\lambda(s) - \phi(s)$ is the competition degree of period s, and the competition degree coefficient can be obtained as follows:

$$bf(s) = f^{\lambda}\left(-\frac{\overline{\phi}}{\overline{\lambda}}\lambda(s) + \phi(s)\right). \tag{16}$$

The distribution probability of the campaign in period s is as follows:

$$w^{a\ dc}(s) = b^{a\ dc} \cdot pf(s) \cdot bf(s), \quad w^{a\ dc}(s) \leq 1. \tag{17}$$

The average distribution probability at this time is as follows:

$$\operatorname{avg}\left(w^{a\ dc}\right) = \frac{1}{S}\sum_{s=1}^{S} w^{a\ dc}(s). \tag{18}$$

The relationship between its total budget and each indicator is as follows:

$$BGT^{a\ dc} = \sum_{s=1}^{S} \operatorname{req}(s) \cdot b^{a\ dc} \cdot pf(s) \cdot bf(s) \cdot er^{a\ dc}(s) \cdot bwn(t), \text{s.t.} \sum_{s=1}^{S} \operatorname{req}(s) \geq \frac{BGT^{a\ dc}}{\operatorname{avg}(bwn)}. \tag{19}$$

The adaptive ad distribution strategy proposed in this paper is based on calculated theoretical distribution probabilities. At the same time, the actual distribution probability is continuously adjusted according to the actual situation. In practice, real-time bidding mostly sells the remaining traffic of the media. It is usually difficult for users to have enough favorable impression on it, and the user's click behavior has great randomness. It is not to mention the instability of the predictor effect caused by the sparse click behavior. Assuming that the actual spending budget in a certain time period s is $V^{a\ dc}(s)$, the actual distribution ratio in the next time period should be adjusted to the following:

$$p^{a\ dc}(s+1) = w^{a\ dc}(s+1) \cdot \frac{BGT^{a\ dc} - \sum_{a=1}^{s} v^{a\ dc}(a)}{\sum_{j=s+1}^{S} \operatorname{req}(j) \cdot w^{a\ dc}(j) \cdot er^{a\ dc}(j) \cdot bwn(j)}. \tag{20}$$

Its continuous analogy ensures the progress of budget allocation.

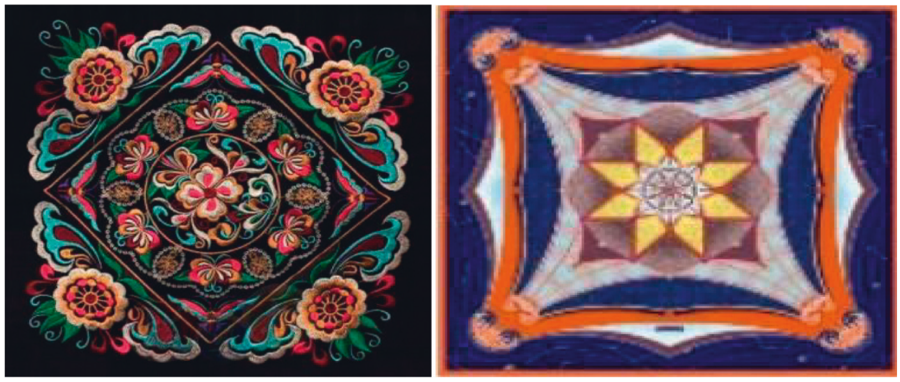
4. The Effect Evaluation Experiment of Intelligent Advertising System Based on the Integration of Traditional Culture

4.1. Application of Traditional Culture in Real Life and Advertising. Chinese traditional culture is like nectar and jade liquid. It is beautiful and unique. It walks into modern times with a long-standing history and shocks the world. Traditional culture includes thought, writing, language, followed by six arts, i.e., ritual, music, archery, imperialism, calligraphy, and numbers. Then, there are calligraphy, music, martial arts, quyi, chess, festivals, folk customs, etc., derived from the rich life. Designers will apply various characteristic elements of traditional Chinese culture to their own works, such as the Miao embroidered silk scarves designed and produced by Hermes. The emergence of Chinese elements makes the advertising system not only limited to a single design but also makes the products full of Chinese charm and vivid life rhythm. The emergence of Chinese elements makes the design of the advertising system more diversified. Figure 5 shows the design of traditional cultural elements in the product.

The colors of Hui style architecture seem to be natural, and the ancient rhyme is solemn. It is like a fine brush and ink, with white walls and black tiles as the main color, which not only highlights the overall color but also integrates with the surrounding natural environment and coexists in harmony. It is what the design says to be in harmony with nature. Hui style buildings use brick, wood, and stone as raw materials, and they mainly use wood frame. The beam frame is mostly made of huge materials and pays attention to decoration. Brick, wood, and stone carvings are also widely used, showing a superb level of decorative art. Huizhou architecture well-reconciles traditional culture and natural environment, making the overall picture tend to be harmonious. It is shown in Figure 6.

In advertising design, the beauty of traditional culture is everywhere, for example, the Dunhuang Feitian designed by the game characters, holding a pipa in silky ribbons, with a good posture like a fairy. The shades of blue and purple are resplendent with aura, and the contrasting colors have a great visual impact. In the advertising design of the pen holder, blue and white porcelain and brushes are used, which is very beautiful. Just like the cheongsam woman in the alley in the south of the Yangtze River came slowly, ethereal and clear. It is shown in Figure 7.

The beauty of traditional culture is polished by time. It is beautiful in the charm of the old and time-honored brand,



Miao Embroidery Hermes scarf

Figure 5: Design of traditional cultural elements in products.

neat aesthetics messy aesthetic

Figure 6: Huizhou architecture in traditional culture.

game advertisement Pen holder advertisement

Figure 7: Application design of traditional cultural elements in advertising.

and it is even more attractive after it is integrated into the advertising design. Of course, it is difficult to obtain evidence just by saying it out of thin air, and it is more convincing to cooperate with the experiment.

4.2. Comparative Experiment of Advertising in the Perspective of Traditional Culture and Modern Fashion. This experiment ran ads with traditional cultural elements on three different platforms. We call it k1, and different ads with modern elements. We call them k2 and k3. Judging the details of the ad in terms of duration control, screen rotation, color tone, endorsement, and delivery time. 200 people were randomly selected to judge the three kinds of advertisements, and then different people were selected to test, and 5 favorite tests were carried out, respectively. The full score is 1, it can score decimals, it can like two or three ads at the same time, or it can like one or neither. To evaluate the purchase intention, the three platforms are platform 1, platform 2, and platform 3, and the data obtained are shown in Figure 8.

From Figure 8, i.e., customer preferences and purchase intentions on platform 1, it can be seen that the public is fonder of advertisements with traditional culture implantation and has a higher purchase intention. Compared with

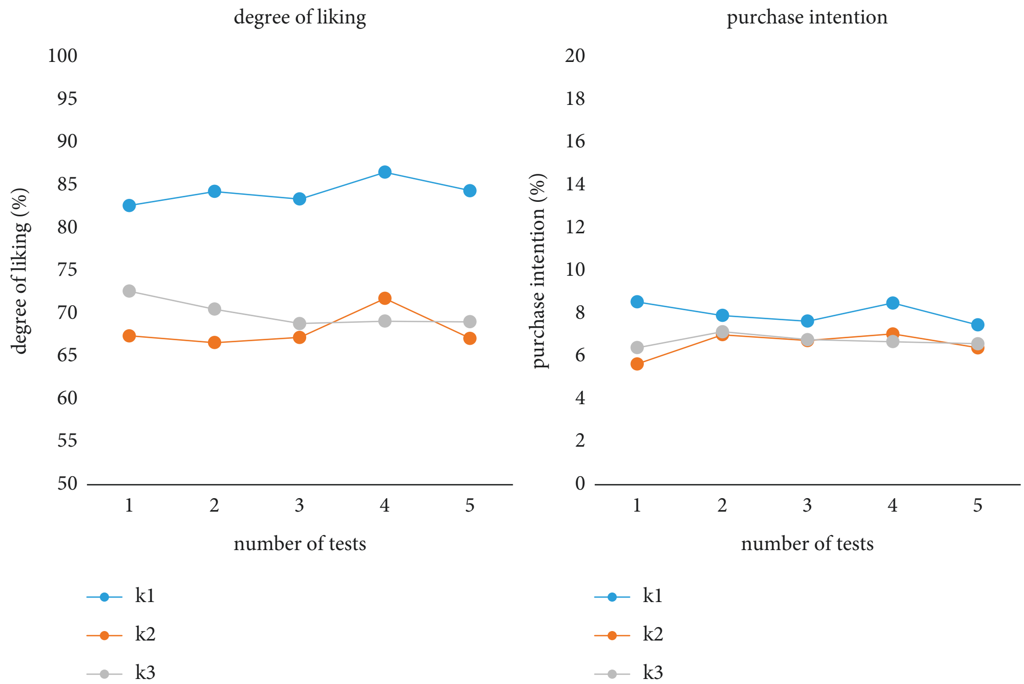


Figure 8: Test customer preference and purchase intention on platform 1.

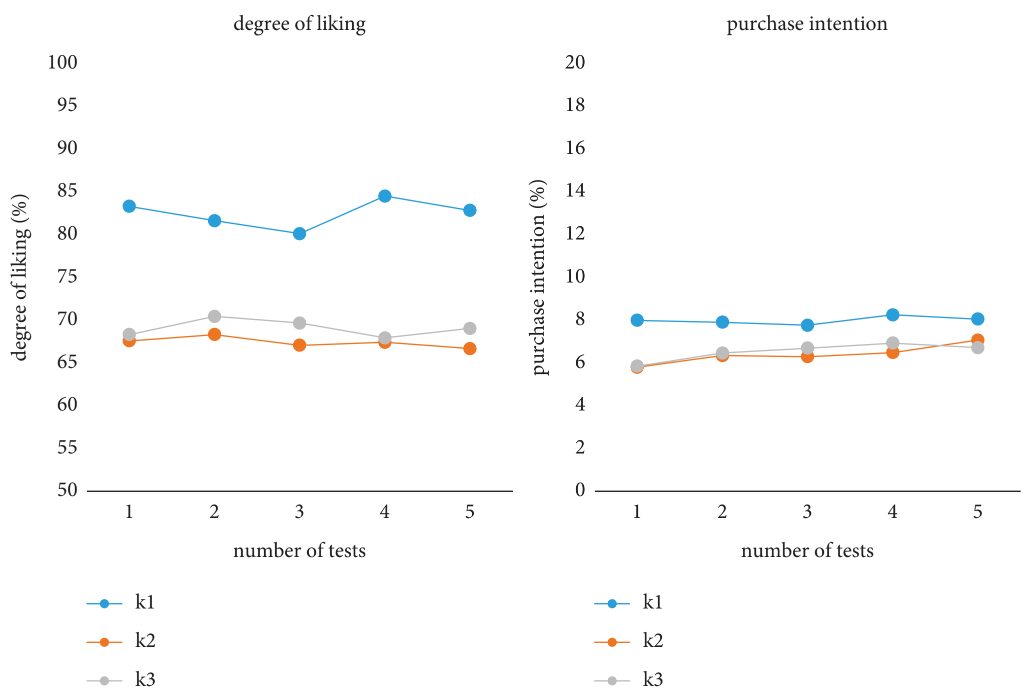


Figure 9: Test customer preference and purchase intention on platform 2.

the other two pure modern elements, the ad likeness increased by about 17%, and the purchase intention increased by about 1.4%.

From Figure 9, i.e., customer preferences and purchase intentions on platform 2, it can be seen that the public is fonder of advertisements with traditional culture implantation and has a higher purchase intention. Compared with the other two pure modern elements, the ad likeness increased by about 15%, and the purchase intention increased by about 1.7%.

From Figure 10, i.e., customer preferences and purchase intentions on platform 3, it can be seen that the public is fonder of advertisements with traditional culture implantation and has a higher purchase intention. Compared with the other two pure modern elements, the ad likeness increased by about 11%, and the purchase intention increased

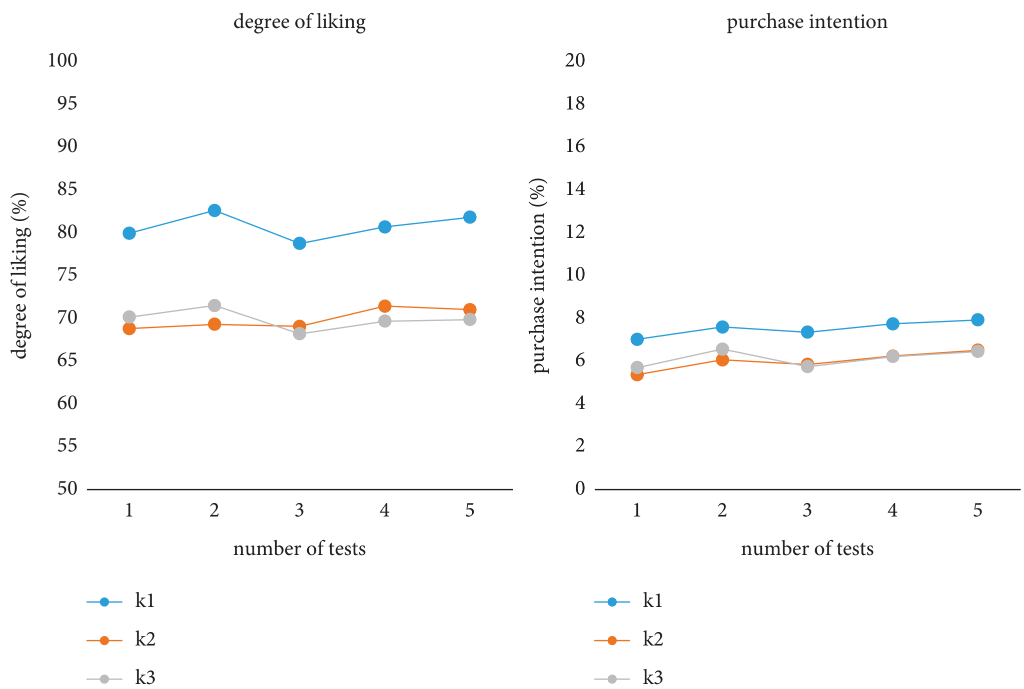


Figure 10: Test customer preference and purchase intention on platform 3.

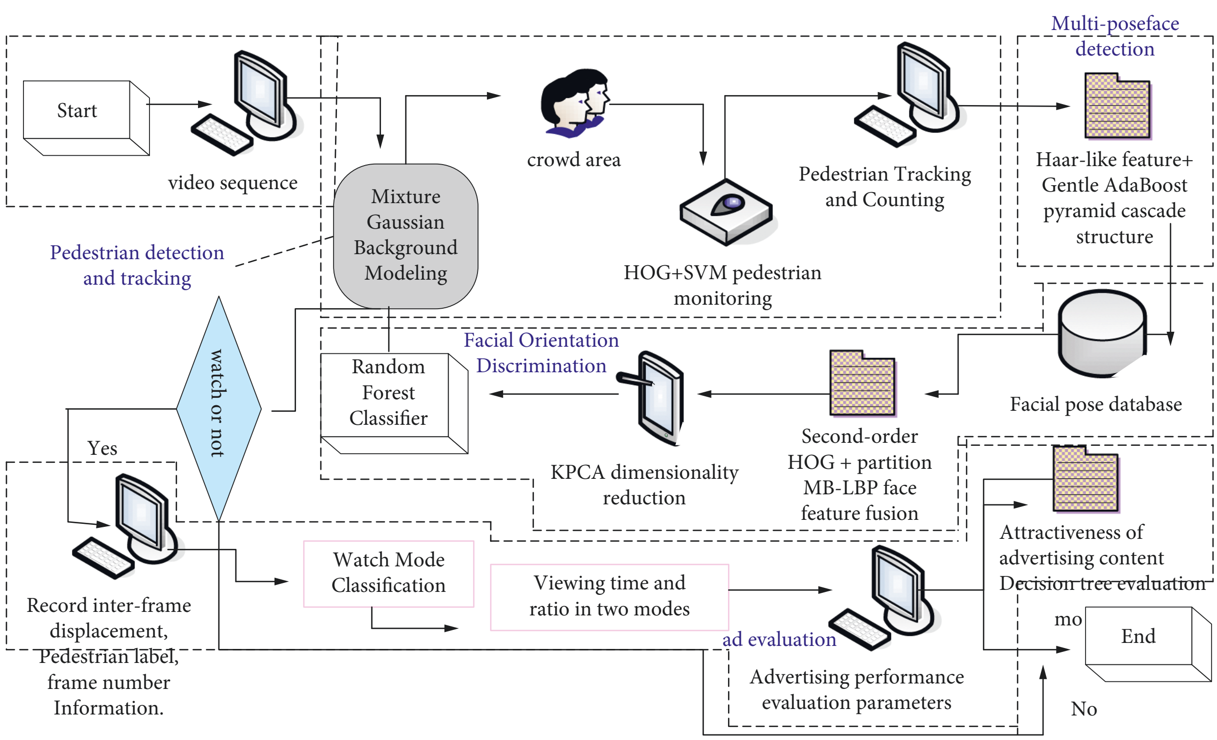


Figure 11: Outdoor advertising effect evaluation system.

by about 1.5%. Therefore, on the whole, people have a high degree of acceptance and love for traditional cultural input into smart advertisements. It tends to be a visual feast with traditional colors, and is also willing to consume it.

4.3. Evaluation System of Facial Gesture Recognition Effect Based on Outdoor Advertising. After placing the billboards, the staff will set up surveillance cameras at suitable locations nearby. Through existing mature technologies, such as face recognition, dynamic tracking, and behavior recognition, it can identify pedestrians who pay attention to the content of billboards and obtain effective data, i.e., the evaluation parameters that can automatically and independently obtain the advertising effect can be realized. With a sufficient data

Table 1: Statistics of advertising effect evaluation system.

Number of times	Statistical methods	Human traffic	Stop and watch	Walking and watching	Viewing ratio (%)	Stop and watch the ratio (%)	Look at the proportions (%)
1	System statistics	24	6	8	58.33	25.00	33.33
2		19	5	6	57.89	26.32	31.58
3		16	5	3	50.00	31.25	18.75
4		20	6	6	60.00	30.00	30.00
5		26	7	7	53.85	26.92	26.92
6		23	7	9	69.57	30.43	39.13
7		24	6	7	54.17	25.00	29.17
8		19	6	4	52.63	31.58	21.05

Table 2: Manual calculation results of advertising effect evaluation.

Number of times	Statistical methods	Human traffic	Stop and watch	Walking and watching	Viewing ratio (%)	Stop and watch the ratio (%)	Look at the proportions (%)
1	Manual statistics	24	6	7	54.17	25.00	29.17
2		16	5	5	62.50	31.25	31.25
3		16	5	3	50.00	31.25	18.75
4		20	5	5	50.00	25.00	25.00
5		24	7	5	50.00	29.17	20.83
6		23	7	7	60.87	30.43	30.43
7		26	7	5	46.15	26.92	19.23
8		21	6	4	47.62	28.57	19.05

base, an evaluation model for the attention of advertising content can be established. The model can carry out a thorough and effective analysis and processing of the advertising effect evaluation parameters so that the overall evaluation effect of the advertisement can be improved more. The overall algorithm of the intelligent analysis advertising effect evaluation system used in this paper is shown in Figure 11.

Random forest repeatedly selects n samples randomly from the original training sample set N to generate a new training sample set to train a decision tree. Then, follow the above steps to generate m decision trees to form a random forest. The classification result of the new data is determined by the score formed by the votes of the classification tree.

It places surveillance cameras on the 9 m-high roof and randomly selects a certain number of advertising viewers. These people are guided back and forth within the range that the surveillance cameras can detect in this way to simulate actual pedestrians passing by to watch the advertisement. The time to watch back and forth is about 4 minutes, for a total of 8 back and forth viewings. Statistics are made according to the above data, as shown in Tables 1 and 2. The experimental data counts the number of people who stopped to watch, the flow of people, and the number of people who watched while walking. At the same time, the viewing ratio corresponding to these data was counted, and the data detected by the surveillance camera was compared with the manually counted data.

The 8 groups of data obtained from the above experiments were compared with the manually obtained data. From this, it can be concluded that, to a certain extent, the monitoring and detection system is more sensitive to the recognition and evaluation of pedestrians watching advertisements, although there may be certain errors. However, on the whole, the number of people who have watched the advertisement detected by the monitoring and detection system is significantly higher than the number of people who have been manually counted. According to the further calculation of the obtained data, it can be obtained that the monitoring accuracy rate of the monitoring and detection system for the pedestrian viewing ratio is 96.7%. Therefore, the corresponding error is 3.3%, and the system can meet the qualified standard in practical application.

Two groups of pedestrian samples are taken, and the attention of pedestrians to advertisements is taken as the reference object. The statistical statistics of the viewing process behavior of its advertisements can be obtained in Table 3. From 2 groups of pedestrians, each group randomly selects 3 pedestrians and analyzes these selected samples. In this way, it is judged whether the monitoring and detection system is accurate when counting the viewing time.

In all samples, the data of six pedestrians are randomly selected. The proportion of the time spent watching advertisements when they stopped and the proportion of time spent watching while walking were tabulated as shown in Table 3. Although at the third pedestrian, the error is as high as 22%, the average statistical error is 3.76%. Therefore, the detection results show that the monitoring and detection system can more accurately record the duration of pedestrians watching advertisements.

5. Discussion

The outdoor advertising effect evaluation system designed in this paper is mainly based on the video recorded by the monitoring camera. The system analyzes and processes the

Table 3: Viewing time and ad attractiveness.

	Statistical methods	Total duration/ frame	Stop and watch duration/frame	Watch while walking duration/frame	Stop and watch	Walk and watch (%)	Attraction
1	System	96	0	96	0	100	Ordinary
	Manual	106	0	106	0	100	Ordinary
2	System	83	0	83	0	100	Ordinary
	Manual	68	0	68	0	100	Ordinary
3	System	119	46	59	38.66%	50	Moderate
	Manual	122	48	34	39.34%	28	High degree
4	System	105	66	28	62.86%	27	High degree
	Manual	124	68	39	54.84%	31	Moderate
5	System	120	73	40	60.83%	33	Moderate
	Manual	129	75	34	58.14%	26	High degree
6	System	131	115	30	87.79%	23	High degree
	Manual	136	112	33	82.35%	24	High degree

recorded video by installing special surveillance cameras at the appropriate positions of the billboards. The obtained pedestrian data is classified and evaluated, such as the total number of viewers, viewing behavior, traffic, viewing time, etc. Compared with manual statistics, the system has the characteristics of objectivity and automation. The data obtained by the system can effectively evaluate and predict the effect of an advertisement. Assisted by dynamic tracking technology, the system can accurately count the flow of people in a certain period of time. Dynamic tracing technology is an advanced debugging technology. It can help software engineers answer some difficult questions about software systems at a very low cost and in a very short period of time to troubleshoot and solve problems more quickly. In the face of various scenes and complex backgrounds in reality, the background subtraction algorithm can effectively eliminate the interference of redundant backgrounds. It makes the statistical results more realistic and accurate. At the same time, the interfering background is removed, and the adverse effect on the final result is effectively removed, and the algorithm can further improve the accuracy of the system detection. As for obtaining the flow of people, it is the basic function of system monitoring. In addition, the system further filters the pedestrians who have watched the advertisement. The faces of passing pedestrians are detected and analyzed, and finally, various behaviors are classified and counted. The algorithm used for face detection in this paper is a multipose face detection algorithm with a pyramid cascade structure, which can accurately identify and judge various facial changes in real time. In some crowded scenes, the face detection algorithm will have missed detections, and there could be false detections. The real-time image is quite different from the standard database. At the same time, this paper proposes a further line-of-sight direction analysis on the obtained face images based on the face recognition method that combines the second-order HOG and MB_LBP. This recognition method can simultaneously obtain the face texture features and the gradient information related to the face pose and is finally classified by the random forest algorithm.

6. Conclusions

This paper adopts random sampling to simulate the scene of actual pedestrians watching advertisements. In addition to the statistics of the basic traffic, the number of viewers, and other data, here, we further analyze and explore the viewing patterns of pedestrians. The system analyzes and recognizes various motion trajectories of pedestrians through algorithms and automatically classifies them. According to the data and tables obtained in this paper, it can be seen that the outdoor advertising effect evaluation system designed in this paper can effectively and accurately count pedestrian data. The system has a minimal error and high accuracy, with an average statistical error of 3.76%. Obviously, the system can effectively analyze, process, and classify pedestrian data and information in actual scenarios. At the same time, it has a good reference and evaluation effect for the publicity and distribution of advertisements. The monitoring and detection system has a monitoring accuracy of 96.7% for the pedestrian viewing ratio. Hence, the corresponding error is 3.3%.

Data Availability

No data were used to support this study.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this article.

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