Research Article

Research on the B2C Online Marketing Effect Based on the LS-SVM Algorithm and Multimodel Fusion

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The comprehensive B2C online marketing is analyzed, and the current situation and shortage of comprehensive B2C online marketing strategies are summarized. Then, based on the relevant theories of consumer behavior and online marketing, the model of influencing factors in the purchasing decision-making process of online consumers is preliminarily constructed, the online purchasing behavior of consumers is studied by means of questionnaire survey, and the model is revised and improved through data collection and verification. Finally, based on the model, the online marketing strategy is discussed from the aspects of comprehensive B2C online marketing construction, product positioning, price strategy, channel construction, website design, and so on. It has important guiding significance to comprehensive B2C online marketing practice. Aiming at the B2C online marketing problem of multimodel fusion with multiobservation samples, a new multimodel fusion B2C online marketing algorithm based on LS-SVM is proposed, which is suitable for multiobservation samples. In each B2C online marketing of multimodel fusion, the mode of B2C online marketing to be multimodel fusion is represented by the multiobservation sample set. Firstly, the label of the multiobservation sample set is assumed, and this assumption condition is taken as the constraint condition of the optimization problem in LS-SVM. Thus, the B2C online marketing error of multimodel fusion is obtained. The category of multiobservations samples was determined by comparing the B2C online marketing errors of multimodel fusion under two assumptions. The B2C network marketing prediction method, stacking integrated learning method based on multimodel fusion, is adopted to build a multimachine learning algorithm embedded into the stacking integrated learning B2C network marketing prediction model. Through verification, it shows that the lower the correlation degree, the better the model prediction effect. Compared with the traditional single-model prediction, the B2C network marketing prediction method based on multimodel fusion stacking integrated learning method has higher prediction accuracy. The model prediction effect is better.

1. Introduction

The development of the internet has brought about profound changes in marketing; the emergence and development of online marketing theory with B2C enterprises as the core has brought a huge impact on the traditional marketing theory. First of all is the change of marketing environment; the development of the Internet strengthens the continuity of time and shortens the sense of space distance, which makes the macroenvironment more sensitive, and the microenvironment also shows new characteristics under the impact of the development of the Internet. Secondly, the enterprise marketing concept changes. With the development of online marketing, the traditional marketing theory has been unable to meet the needs of enterprise marketing under the new situation, which puts forward new requirements to enterprises. The transformation from 4P to 4C and then to 4R shows the change of enterprise marketing concept under the new form. Thirdly is the impact on consumers. The development of the Internet has prompted consumers to increase their personalized consumption needs and enhance their initiative in consumption. More and more consumers
pay more attention to the convenience and interest of consumption. However, it should also be noted that the current B2C enterprise online marketing is still in a relatively low stage, its development is still extensive, and there are various problems.

For B2C enterprises, the cultivation of their core competence needs a gradual process. However, the development history and development scale of B2C enterprises are insufficient, and the accumulation and development degree of core competence is low, so it is difficult for any enterprise to have core competitiveness. At the same time, a lot of B2C e-commerce enterprises can get the clear market positioning, blindly pursuing “instead of” business model; a lot of vertical class B2C companies in niche after initial success started the comprehensive transformation of B2C enterprise, so as to lose their unique position in the market, then just set up the core competence that has been scattered [1, 2]. Foreign online marketing research and practice started earlier, for online marketing theory research is relatively more accumulating a wealth of experience. The theoretical results and experience summaries of overseas online marketing have certain reference significance for the overall development of integrated B2C enterprises’ online marketing [3]. This paper systematically studies the relationship between the marketing strategy, service quality and cost of online retail enterprises, and the purchase intention of online consumers and analyzes the influencing factors of online consumers’ purchase behavior from different perspectives [4]. Online retail enterprise to do reasonable website design, construct excellent network facilities, provide excellent service quality and standardization of operation management is an important factor to attract network consumers [5, 6]. The reasons for the above problems is that the enterprise did not make full use of good resources in the Internet, and launch of the marketing of the Internet network resources is imminent. As a whole marketing system, online marketing resources are very rich, and the key lies in whether the enterprise can make reasonable and full use of it. According to the theory of enterprise basic resources, an enterprise is an aggregation of various resources, but the heterogeneity of the resources owned by the enterprise is caused by different resources, and the heterogeneity of resources determines the difference of enterprise competitiveness. Generally speaking, the resource-based theory mainly includes the following three aspects: first, special heterogeneous resources are the source of enterprise competitive advantage; second, the unimitability of resources is the key to sustainable competitive advantage; third, resources should be managed and integrated. The resource marketing theory developed on the basis of the resource-based theory solves the problem of the integration of Internet resources well. Based on the basic theories of e-commerce and precision marketing, this paper analyzes the marketing status quo of B2C e-commerce model and finds out the problems existing in marketing of B2C e-commerce. Combined with the characteristics of precision marketing, this paper focuses on discussing how to carry out precision marketing under the B2C e-commerce model. It is pointed out that strengthening the application of modern information technology, doing a good job in market positioning, flexibly applying various marketing means and marketing strategies, and improving communication services and customer relationship management are important means to help enterprises to do a good job in marketing and increase enterprise profits.

This paper starts with the theoretical review of online marketing: the emergence and development of online marketing are introduced, the concept of online marketing is defined, the comprehensive B2C e-commerce enterprises are analyzed, and then the theoretical basis of online marketing is elaborated in detail. Based on the theory of consumer purchasing behavior, a model of the influencing factors of online consumer purchasing decision-making process is preliminarily constructed. A questionnaire is designed to investigate the purchasing decision-making process of online consumers. According to the data collected from the questionnaire, the purchasing decision-making process of online consumers is analyzed and the influencing factors in the purchasing decision-making process of online consumers are summarized. The built model is perfected. Then, based on the decision-making process of online consumers, the comprehensive marketing strategies of B2C e-commerce enterprises are extracted from the five aspects of brand building, product positioning, price strategy, channel building, and website design.

2. Related Work

This paper systematically studies the relationship between the marketing strategy, service quality and cost of online retail enterprises and the purchase intention of online consumers and analyzes the influencing factors of online consumers’ purchase behavior from different perspectives. Reasonable website design, construction of excellent network facilities, service quality, and standardized operation and management are important factors for online retail enterprises to attract online consumers [7]. It is pointed out that the key factors influencing consumers in the network environment include product quality, product price, comprehensive online shopping experience, and risk perception [8]. It is believed that trust is an important factor restricting the development of online shopping. Many consumers are suspicious of online shopping, which requires a more mature and convincing trust mechanism for online marketing websites [9]. Among the driving factors of price setting of online retail enterprises, it is found that online marketers’ website design, convenience of shopping process, enterprise brand, service, enterprise credit, and price setting have certain influence [10]. It is proposed that service quality is an important factor for online retail enterprises to successfully attract customers. These services include product purchase service, distribution service, and after-sales service [11]. The model of consumers’ shopping behavior in e-commerce environment is established and tested with examples, and the conclusion is drawn that consumers’ behavior is closely related to consumption risk, shopping convenience, and other factors [12].

Under the condition of low complexity, the extended GMM (Gaussian Mixture Model) method can further
improve the performance of the algorithm by embedding local features [13]. In the subspace method, the similarity between subspaces is used as the basis for B2C online marketing of multimodel fusion. For example, the MSM (Mutual Subspace Method) proposed in [14] represents each sample set of each category with PCA feature subspace. The principal component angle of subspace is calculated to realize B2C online marketing with multimodel integration. Literature [15] proposed the KMSM (Kernel Mutual Subspace Method) algorithm and solved the nonlinear distribution problem of data by introducing kernel function. The joint local linear model is used to represent the manifold described by the subspace, while the multimodel fusion B2C online marketing method based on popular learning mainly utilizes the local and global distribution information of the space. Gao et al. [16] studied the global distribution and local distribution of logarithmic data points in popular space and proposed a B2C online marketing algorithm based on nonuniform similarity measure embedding discriminant analysis with multiple observation samples and multiple model fusion.

In addition, Xu et al. [17] proposed a B2C online marketing algorithm based on joint weighted sparse representation of multiple observation samples and multimodel fusion, considering the different information content contained in each single observation sample that constitutes multiple observation samples. The prediction methods for online marketing mainly include neural network [18], support vector machine [19], and wavelet analysis theory [20]. In addition, cutting-edge artificial intelligence technologies represented by tree integration algorithm and deep learning algorithm have also achieved good application effects in B2C online marketing prediction. Zhongda et al. [21] introduced the grey projection improved random forest regression algorithm into the field of short-term B2C online marketing prediction, aiming at the weak generalization performance of traditional B2C online marketing prediction and the difficulty in determining parameters and model structure. Tsai and Ma [22] compared and analyzed XGBoost (Extreme Gradient Boosting) with multiple algorithms, showing that the online marketing XGBoost prediction model built by us has advantages in computational speed and prediction accuracy compared with random forest, Bayes, and KNN methods. Xie and Ma [23] introduced the deep confidence network algorithm into the B2C online marketing prediction problem and compared and analyzed the prediction results with the shallow model. Sulochana et al. [24] used the long short-term memory (LSTM), a classical algorithm in deep learning, to predict the short-term online marketing on the user side. They [24] adopted variational modal decomposition technology to decompose the original historical B2C online marketing sequence into a series of modal functions with different features and adopts improved particle swarm optimization algorithm to optimize the weight of deep belief network. Li et al. [25] analyzed the prediction demands of various heterogeneous energy sources in the integrated energy system and proposed a joint prediction method of short-term electricity, heat, and gas B2C online marketing based on deep structure multitask learning.

Although the rapid development of artificial intelligence and machine learning technology provides a new solution for B2C online marketing prediction. However, the above literature only adopts a single way to make B2C online marketing prediction. Due to the large hypothesis space of B2C online marketing prediction, there may be multiple hypotheses achieving the same performance on the training set. If a single model is used, the generalization performance may be poor due to randomness. Therefore, literature [26, 27] seeks to use combination prediction to further improve the accuracy of model prediction.

As can be seen from the above, the research on B2C online marketing problems based on the integration of multiple models with multiple observation samples has made certain achievements. However, the above methods still have certain limitations and deficiencies, and the recognition rate needs to be improved. Support vector machine (SVM) based on statistical learning theory is a kind of machine learning method, which maximizes its generalization ability according to the principle of structural risk minimization, and can effectively solve problems of small samples, nonlinearity, and high dimensions. As an extension of the standard support vector machine, the least square support vector machine (LS-SVM) is relatively fast, can solve large scale problems, and has good generalization and robustness. Based on the B2C online marketing idea of multimodel fusion with multi-observation samples and LS-SVM, this paper proposes a new B2C online marketing algorithm of multimodel fusion. Its core idea is to take all the observation samples of the B2C online marketing model to be multimodel fusion as the multiobservation samples of the model. Then assume the category of the multiobservation sample set, and take it as the constraint condition of the optimization problem in LS-SVM. Finally, compare the B2C online marketing errors of multimodel fusion under different category assumptions, so as to realize the B2C online marketing of multimodel fusion. A model of the factors influencing the purchasing decision-making process of online consumers is constructed. This paper designs a questionnaire of online consumers’ purchasing behavior, analyzes the stages and characteristics of online consumers’ purchasing decision-making process, and constructs a model of influencing factors of consumer purchasing decision-making process, which provides necessary empirical support for comprehensive B2C online marketing strategy analysis.

3. Model Construction of Influencing Factors of B2C Online Marketing Based on Multimodel Fusion and LS-SVM

3.1. Multimodel Integration of B2C Online Marketing.

Based on the related theories of consumer behavior and network marketing, this paper discusses the influencing
factors of e-commerce enterprises’ marketing strategies for consumers in each purchasing stage by taking the five stages of the purchasing process of online consumers as the main line and preliminarily constructs the influencing factors model of the purchasing decision-making process of online consumers. The model points out that e-commerce enterprises can stimulate consumers’ attention, interest, and demand through external stimulation, provide consumers with commodities and sales information through traditional and network channels, and influence consumers’ purchase comparison and choice through high-quality commodities, web page commodity display, diversified information provision, and preferential prices. Through online payment and delivery services and other safe and reliable shopping environments to encourage consumers to complete the purchase and finally through the product postpurchase evaluation system, collect consumers’ comments on the product and purchase experience.

This model (see Figure 1) is only built on the basis of relevant theoretical research, and the degree of influence of various factors mentioned in the model on the purchasing decision-making process of online consumers still needs to be tested in practice. This paper will design a questionnaire on online consumers’ purchasing behavior, collect online consumers’ recognition of various factors that affect their purchasing, and analyze the influence degree of each factor from both qualitative and quantitative aspects, to provide empirical support for the subsequent proposal of comprehensive B2C e-commerce enterprise network marketing strategy.

According to the factors that the online consumers pay attention to in the purchasing process and the assumptions of the model construction in this paper, the main content and specific topics of the questionnaire are designed. The questionnaire is divided into three parts. The first part is the basic information of the respondents, mainly including gender, age, education level, occupation, and monthly income of the respondents, a total of 5 single topic selections.

The second part mainly understands the basic situation of the respondents’ online shopping. It mainly includes whether you have online shopping experience, the reasons for choosing online shopping, the frequency of online shopping, the cost, and the types of goods you mainly buy (see Table 1).

Questionnaire reliability analysis is to test the reliability, consistency, and stability of the questionnaire. It means that when the same method is used to conduct an investigation on the same object, the survey results should maintain consistency and stability. In this paper, Cronbach’s alpha coefficient was used to test the internal consistency reliability of the questionnaire. Cronbach’s alpha coefficient is between 0.00 and 1.00, and the greater the value, the higher the reliability of the questionnaire. The best Cronbach’s alpha coefficient of the scale should be greater than 0.80, and it is acceptable when Cronbach’s alpha coefficient is between 0.70 and 0.80. When Cronbach’s alpha coefficient is below 0.70, the questionnaire should be rerevised. The reliability test results of this questionnaire are shown in Table 2.

Based on the prediction ability of the learning machine, this paper is in the first layer of the stacking model in addition to the selection of XGBoost algorithm and LSTM algorithm, also selecting a number of models with better prediction performance as the learning machine. This is because the base model with strong learning ability helps to improve the overall prediction effect of the model. Among them, Random Forest (RF) and Gradient Promotion Decision Tree (GBDT) use Bagging and Boosting as integration learning methods, respectively. With excellent learning ability and rigorous mathematical theory support, it has been widely used in various fields. Support Vector Machine (SVM) has unique advantages for solving small sample, nonlinear and high dimensional regression problems. KNN also has good practical application effect because of its mature theory and efficient training. In the second layer, models with strong generalization ability are selected to summarize and correct the bias of multiple learning algorithms for the training set, and the overfitting effect is prevented by the way of collection. The model architecture is shown in Figure 2.

On the contrary, in order to obtain the optimal prediction effect, in the first layer of the stacking model, it is also necessary to choose the model with a large degree of difference as the basic learner. This is to consider that, for different algorithm models, its essence is to observe data from different perspectives of data space and data structure and then establish the corresponding model according to the observation status of the algorithm and its own algorithm principle. Therefore, the selection of the algorithm with a large degree of difference can reflect the advantages of different algorithms to the greatest extent, so that each differentiation model can learn from the other. In this paper, Pearson correlation coefficient is used to calculate the error difference degree of each model, so as to analyze the correlation degree of different base learners. The Pearson correlation coefficient x calculation method of two-dimensional vector y is as follows:

\[ y_{\text{sh}} = \frac{\sum (x_i - x) (y_i - y)}{\sqrt{(x_i - x)^2 \sqrt{(y_i - y)^2}}} \]  

(1)

In addition, feature selection is often a very important step to establish a model, and the quality of feature plays a decisive role in the prediction effect. In general, the conventional method is to construct feature engineering based on manual experience. In this paper, manual experience and model score were combined to select features. The feature contribution analysis function of tree integrated model is used to calculate the model score. XGBoost, RF, and GBDT models can calculate the score of each feature according to the gain of the tree in the process of training, indicating the importance of each feature to the model training. This function is helpful for the validation of the effectiveness of
feature selection and assists decision-making. In this way, excellent features can be retained and redundant features can be deleted. The training process of B2C online marketing prediction method based on multimodel fusion under the framework of stacking is as follows:

1. XGBOOST, GBDT, and RF algorithms were used to analyze input feature contribution and assist feature selection.

2. The error distribution of each algorithm was analyzed, and the algorithm with great difference was selected as the first-layer prediction model. The original datasets were divided, and the optimal superparameters of each model were optimized by cross validation.

3. Use the partitioned dataset to train the prediction algorithm of the first layer in stacking, respectively, and output the prediction results to generate a new dataset.

4. Using the newly generated dataset, the second layer algorithm in stacking is trained, and the stacking integrated learning algorithm based on multimodel fusion is trained.

| Frequency | On average, once a week or more | On average, one to three times a month | On average, two to five times a year | Once a year or less on average |
|-----------|--------------------------------|--------------------------------------|-------------------------------------|-------------------------------|
| Number    | 47                             | 87                                   | 23                                 | 8                             |
| Percentage| 29.4%                          | 53.4%                                | 13.5%                               | 4.3%                          |

Table 1: Frequency of online shopping of respondents.

Table 2: Reliability test table.
3.2. LS-SVM B2C Online Marketing New Multimodel Fusion B2C Online Marketing Algorithm. Aiming at the dichotomy problem of multiple observation samples, this paper proposes a new B2C online marketing algorithm based on the standard LS-SVM. According to the principle of LS-SVM, the problems to be solved by LS-SVM can be described as the following mathematical problems:

\[
\min_{w,t} J(w,t) = \frac{w^T + \sum t}{2} \tag{2}
\]

According to the problem description of multiple observation samples \(w\), there are only two different types of data in the dataset at this time, so the label set of data set \(Y\) can be expressed as \([-1, +1]\). If the label of multiple observation samples is \(y\), then \(y = -1\) or \(y = +1\); that is, the labels of all samples in the observation sample set are

\[
\min_{i} J(w,t) = \frac{w + \sum t^2}{2}. \tag{3}
\]

With \(y\) values only two cases, so by assuming that the value of \(y\), which for the first of two optimization problems to solve, each corresponding to the solution will get more fusion model of B2C online marketing error. Therefore, the true value of B2C online marketing can be determined only by comparing the errors of multimodel fusion under two different label assumptions. The B2C online marketing error of multimodel fusion can be expressed as

\[
g = c \sum t^2. \tag{4}
\]

In the experiment, BinaryB2C online marketing database and USPSB2C online marketing database are selected. The Binary database contains a handwritten image of 10 groups of digits from 0 to 9, each of which has 39 samples, each of which is represented by a Binary image of size \(20 \times 16\). The USPS database includes categories 0–9 representing a total of 10 categories of B2C online marketing, each of which has 1100 samples, each of which is represented by a \(16 \times 16\) grayscale image. The robustness of pattern transformation is an important feature of B2C online marketing with multiobservation samples and multimodel integration. In order to enhance the transformation resistance of the algorithm in this paper, the original labeled samples are transformed to get virtual samples, and then the virtual samples are added to the dataset. In the experiment, the formation method of the training set and test set of each group of numbers is as follows: two samples are randomly selected to form the training set and the remaining samples to form the test set. The two samples in the training set are respectively rotated for four consecutive times, and the eight new samples obtained are added to the training set to obtain the final training set. Rotate each sample in the test set, add the obtained sample to the test set, and get the final test sample set. To avoid confusion between the “6” and “9” numbers, all rotation angles \(B\) are derived from a uniformly sampled sequence. In each experiment, two different types of numbers were used for B2C online marketing with multimodel fusion twice, and there were 45 combinations. The training sets of the two types of numbers were used to obtain the training sets of the algorithm, and the test sets of each type were used as the multiobservation sample sets. The experiment tested a multiobservation sample set of different sizes, and 10 randomized trials were conducted for each test in each combination. Thus, the results of each experiment were the mean of 900 randomized trials, as shown in Table 3 and represented by a bar chart in Figure 3.
As can be seen from the experimental results in Table 3 and Figure 3, the recognition rate of the algorithm proposed in this paper is high on two different handwritten digital databases, close to 100%. In particular, with the increase of the number of samples, the recognition rate of the proposed algorithm in the USPS database reached 100% and remained unchanged. The following conclusions can be drawn from the analysis of the data: with the increasing number of multiobservation samples, the recognition rate of the algorithm is constantly improving. This verifies that multiple observation samples can provide more information about the test mode, thus achieving a higher recognition rate.

4. Example Verification

This paper uses SPSS18 to analyze the variable identity of 161 respondents. The degree of recognition of factors influencing the purchasing decision-making process of online consumers involved in the earlier hypothesis is shown in Table 4. According to the results of variable recognition analysis, it can be concluded that the average recognition degree of traditional advertising channels for the demand stimulation of online consumers is only 1.96, while the average recognition degree of online advertising is as high as 3.77. It can be seen that the traditional advertising channels, such as newspapers, magazines, and TV, have far less influence on the demand for online consumer shopping than online advertising. The average recognition degree of online consumers who choose the retailer with the lowest price of the same commodity as the purchase object is only 2.89, indicating that in online shopping, price is no longer the only factor to attract consumers to buy goods, and online consumers are gradually moving away from the purchase mode of recognizing only low price. In addition to the price standard, the quality and practicability of products, as well as the reputation of merchants, are also important factors affecting consumers’ purchase decisions. In online shopping, the average recognition degree of consumers’ preference for various promotional activities of merchants is only 3.83, indicating that online consumers’ buying rationality is gradually improving. For online consumers, a wide range of promotions is not as attractive as a direct and affordable price offer (4.03). Firstly, B2C online marketing historical information and calendar rules are selected as input data through manual experience. Among them, B2C online marketing information contains the previous 7h history of B2C online marketing data.

As can be seen from Figures 4–6, B2C online marketing historical information often has a greater impact on the predicted target. The closer the historical B2C online marketing information features are to the predicted target, the more important the historical B2C online marketing information features are. The contribution of historical B2C online marketing data features 1h before the predicted target is the highest. At the same time, temperature information, holidays, and weekends have a greater impact on
Table 4: Variable identity analysis table.

| No. | Measure the multi-item                                         | Totally disagree | Do not agree with | Not sure | Basically agree | Totally agree with | Average recognition |
|-----|-----------------------------------------------------------------|-------------------|-------------------|---------|-----------------|---------------------|---------------------|
| 1   | The popularity of shopping websites                             | 1                 | 2                 | 23      | 25              | 112                 | 4.53                |
| 2   | A complete range of goods                                       | 2                 | 8                 | 43      | 87              | 22                  | 3.76                |
| 3   | Traditional advertising                                        | 56                | 61                | 37      | 4               | 2                   | 1.96                |
| 4   | Online advertising                                             | 6                 | 13                | 41      | 61              | 43                  | 3.77                |
| 5   | It is easy to operate                                          | 3                 | 4                 | 42      | 82              | 33                  | 3.83                |
| 6   | Relatives and friends to recommend                             | 4                 | 15                | 56      | 37              | 55                  | 3.76                |
| 7   | Search engines collect product information                     | 2                 | 7                 | 34      | 53              | 64                  | 4.03                |
| 8   | Collect product information on online forums and social networking sites | 9                 | 4                 | 32      | 78              | 17                  | 2.89                |
| 9   | Quality of goods                                               | 7                 | 28                | 5       | 18              | 135                 | 4.87                |

Figure 4: Analysis of the contribution of XGBoost features.

Figure 5: Analysis of GBDT feature contribution.
B2C online marketing of electricity. Considering that the mapping of weather type, hour, week, month, and other features adopts the form of unique heat coding, the feature contribution is sparse and scattered, but it all plays a certain role in model training. The effectiveness of feature selection in this paper is verified by analyzing the contribution of feature to the model (see Figures 4–6).

In order to compare and illustrate the generalization ability of the thermodynamic mechanism model and the B2C online marketing model integrated with multiple models, another set of test data (test data 2) was selected. The prediction effects of the two models are shown in Figure 7. Figure 7 shows that performance of thermodynamic mechanism model did not change obviously, and the...
multimodel fusion model of B2C online marketing forecast deviation happened.

By comparing Figures 7 and 8, it can be seen that, compared with the single thermodynamic mechanism model or B2C online marketing model with multimodel integration, the hybrid model has made complementary corrections by taking advantage of the respective characteristics of the mechanism model and the data-driven model, so that the fluctuation range of the predicted value is reduced and the prediction accuracy is improved. After model correction, the output of the mixed model was modified, and the parameters of Kalman filter algorithm were optimized, and the prediction stability was further improved, which could accurately reflect the trend of the polymerization rate in the process of vinyl chloride polymerization.

From the results of this group of experiments, it can be seen that the recognition rate of LS-SVM algorithm in this paper is very high in both VidTIMIT and Honda/UC SD databases, which indicates the feasibility of this algorithm in B2C online marketing problem of face image multimodel fusion. For different number of multiobservation samples, the recognition rate of the proposed algorithm has little change, which indicates that the algorithm has good robustness for different number of multiobservation samples. It can be seen from the results of Figure 9. Even though there are many little observation concentration samples, in this paper, the LS-SVM algorithm can still achieve high fusion model of B2C online marketing more correctly. This is because the algorithm in this paper uses the test set and two classes of data at the same time, all the sample training set, when the number of samples is small, samples still can obtain more information. In contrast, the sample information obtained by the other three algorithms is limited, so the accuracy of B2C online marketing based on multimodel fusion is also low (see Figure 9).

5. Conclusion

Based on the classical LS-SVM algorithm, combined with the idea of B2C online marketing algorithm of multiobservation samples and multimodel fusion, this paper proposes a new B2C online marketing algorithm of multiobservation samples and multimodel fusion based on LS-SVM. The algorithm first assumes the label of the multiobservation sample set, transforms it into the constraint condition of the optimization problem, obtains the B2C online marketing error of multimodel fusion at this time, and takes this error as the basis of the B2C online marketing of multimodel fusion to realize the B2C online marketing of multimodel fusion. Experimental results show that the proposed algorithm is superior to other B2C online marketing algorithms based on multiobservation samples and multimodel fusion and has good robustness. There is still much room for improvement in this paper, for example, how to apply the algorithm to B2C online marketing problem with multimodel fusion. Due to the refinement of B2C e-commerce activities, precision marketing will also become more targeted, and the next step will have more emphasis on marketing segmentation and orientation. Subdivision and targeted marketing will accurately and effectively meet the needs of target consumer groups and promote their continuous purchase behavior, and marketing effect will be better.

Data Availability

All the data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that there are no conflicts of interest.

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