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Research Article

E-Commerce Precision Marketing Model Based on Convolutional Neural Network

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With the rapid development of network and informatization of the consumer market in my country, the application and maturity of technologies such as the Internet, terminal equipment, logistics, and payment and the continuous improvement of people's consumption concepts, online shopping has gradually become the mainstream purchase method for Chinese consumers, and e-commerce has gradually become one of the important driving forces to promote the sustained and vigorous development of China's economy. Under the traditional marketing model, companies do not fully understand the needs of users. The sales staff's thinking is only how to sell products to users. They do not know the specific consumer needs, so they can only focus on the product. Based on these foundations, this research uses convolutional neural networks and applies this model to precision marketing to obtain accurate portraits of consumers, thereby increasing the company's turnover. After comparing different models and conducting some experiments, it is concluded that (1) through the collection and analysis of W enterprise data, the training and testing conditions of the CNN model, LSTM model, LSTM attention model, and CNN + LSTM attention model are compared. It is concluded that the CNN + LSTM attention model and the LSTM attention model perform better, and the accuracy of testing and training is higher. (2) Through the fitting of the model, it is found that Sn(%) = 70.71, Sp(%) = 86.25, Acc(%) = 81.07, and MCC = 0.752 of the CNN + LSTM attention model are the best fitting models. The men and women stratification and gender stratification of users are predicted, and it is found that men in the W company are the main purchasing power, and in the age stratification, it is found that the population of 41–50 accounts for the highest proportion. (3) The average accuracy rate of the LSTM attention model is as high as 66.6%, the average recall rate is 82.3%, and the F1 score is 73.1%. This model has met expectations for precision marketing forecasts. (4) Using the CNN + LSTM attention model to predict the marketing input for the next year, it is found that the use of precision marketing will increase the profit of W company. The average annual data show that the monthly revenue of precision marketing has increased by 73.5%.

1. Introduction

In the past ten years, with the rapid development of network and informatization of China's consumer market, the application and maturity of technologies such as the Internet, terminal equipment, logistics, and payment and the continuous improvement of people's consumption concepts, online shopping has gradually become the mainstream purchase method for Chinese consumers. E-commerce has gradually become one of the important driving forces to promote the sustained and vigorous development of China's economy [1, 2]. Based on the analysis and statistics of the marketing models that currently exist in our society, it is concluded that the growth rate of e-commerce online marketing is getting faster and faster. The refined and precise marketing model will be the mainstream model in the future. Literature [3] only makes good use of big data to paint portraits of consumers. The precision marketing model can greatly promote offline marketing and online marketing. The function of marketing is to act as a communication bridge between the company and consumers. It can not only help consumers understand the company and make these consumers become loyal customers of the company but also play a role in publicity, allowing the company to better understand its audience. Therefore, it is necessary to learn and improve marketing concepts and transform from ordinary marketing to precision marketing. Precision marketing is a concept that may help promote collective thinking and understanding of the criteria used for segmentation and positioning. The purpose is to better serve customers, thereby highlighting the competitiveness of products and bringing profits to the company. Only by formulating sales strategies from person to person can the effect of precision marketing be maximized. Control the results and costs of communication as much as possible, give scientific standards, and avoid randomness. Convolutional neural networks are used to predict the detection index system of multilabel systems. The prediction model is superior to other existing prediction models in almost all five indicators of performance. The most outstanding performance in the "absolute truth" rate and "absolute truth" rate [4]. A multilabel classifier system is based on deep learning features of convolutional neural network to infer the classification of goods. The system is based on the two-dimensional representation of the sample: first, obtain a one-dimensional feature vector, extract the characteristics of the marketing amount and marketing model, find out the interaction and the structure and feature similarity information with other products of different categories, and then reshape the original one-dimensional feature vector to obtain a two-dimensional matrix table of commodities. Finally, using feature extractors, two general classifiers designed for multilabel classification are trained using deep learning features. The scores obtained are fused by the average rule [5, 6]. With the continuous breakthroughs in computer technology, deep neural networks and other technologies are becoming more and more widely used in our daily life applications. People process the acquired information with computer algorithms. Convolutional neural networks (CNN) are currently the mainstream computer network analysis means. Convolutional neural networks can be used to automatically learn structured data, extract effective features, and then use the extracted effective features to make predictions and make correct decisions, which can help manage company employees, predict consumer preferences, etc. Predictive classification of unknown consumers is of great significance to existing research. The ATC system is a multilabel classification system that classifies consumers according to their consumption preferences. The system includes five levels, and each level includes several levels; the first level includes 14 main overlapping categories. The ATC classification system also considers the distribution of population characteristics, brings into the model effect characteristics, and predicts unknown problems in its category. Such predictions can be used not only to infer the active ingredients of system performance but also to infer other possible active ingredients. Due to the high variability of samples and the overlap between classes, the problem of automatic prediction is very random, and there may be multiple prediction deviations and the complexity of machine learning. Convolutional neural networks are also widely used in the field of biomedical engineering. Medical image analysis is one of the most popular research and development fields. Deep learning has been successfully used as a machine learning tool. Neural networks have the ability to automatically learn features [7]. The rapid growth of data has enabled statistical modeling and machine learning methods to predict the information of some compounds in bioinformatics and chemoinformatics and contribute to various applications of metabolic engineering and drug discovery [8]. Convolutional neural networks have been successfully applied to network big data predictions. Using four different experimental network models and dual graphs with different sparsity and degree distributions, high prediction performance is achieved in the case of relatively dense, but the performance becomes worse in the case of extreme sparseness. Human decision-making processes usually rely on the use of visual information from different perspectives or perspectives. However, in image classification based on machine learning, we usually only infer the category of the object from a single image showing the object. Especially for challenging classification problems, the visual information conveyed by a single image may not be enough to make accurate decisions. The optimization scheme relies on the fusion of visual information captured by images depicting the same object from multiple angles [9]. Convolutional neural networks are used to extract and encode visual features from multiple views, to fuse this information to study the feature maps of different network depths for fusion convolution, to fuse potential bottlenecks before classification, and to score fusion. These strategies were systematically evaluated on three data sets from different fields. The discovery emphasizes the benefits of integrating information fusion into the network instead of performing it through the postprocessing of classification scores [10–13]. A case study that has been trained proves that the network can be easily expanded through the best fusion strategy, which is much better than other methods. The CNN model can be used to decode the hidden focus of attention related to EEG events in the object selection process. It compares the performance of CNN and the commonly used linear discriminant analysis (LDA) classifier, applies it to different dimensional data sets, and analyzes the transfer learning ability. Using CNN can conduct in-depth analysis of e-commerce data, convert the characteristics of each product into recognizable computer instructions, and use these characteristics to predict sales. The impact of individual model components can be verified by systematically changing the model, and the saliency map can be used as a tool to visualize the spatial and temporal characteristics that drive the output of the model. The effect of different attribute training sets on the sparse rate of the CNN output feature matrix is verified, and the improved Grad-CAM algorithm is used to train the key features to improve the stability and accuracy of the CNN model. Convolutional neural networks were originally discovered in biological laboratories. They were computer simulations and transformations of neural networks of humans or animals with brains. With the continuous exploration of science and technology by human beings, CNN is also undergoing continuous innovation and transformation, with more extensive applications and continuous enhancement of computing capabilities [14, 15].

2. Materials and Methods

2.1. Convolutional Neural Network (CNN). The basic composition of the existing neural network model group is composed of the following parts: the input layer (100×1) is used for the input of the original data grid conversion and the convolutional layer 1 is the basic data grid layer of the model. Data filtering and sorting play an important role, and the specific parameters are shown in Figure 1. Convolutional layer 2 (Conv2) is to perform secondary sorting and reverse confirmation on the data grid of the first layer [16–18]. The residual network and the expansion convolution are performed in the stretching layer, and the accuracy of the ConvNet architecture predicting contact is judged by the F1 connection layer. The basic flow of the experiment is shown in Figure 1.

2.2. Data Grid Conversion. Data grid conversion is to classify data in ascending dimensions to facilitate data extraction for subsequent research. Use the DNCON2 data set (V1, V2, and V3) for training and test on the CASP12 data set (V4, V5, and V6). The structural equation model is shown in Figure 2, which has strong connections and close connections. ‘S association. A, B, and C are hidden variables, and A and B correspond to neurons in the convolutional layer. Y1 and Y2 are also observed variables. Figure 3 shows a convolution process diagram with a convolution kernel size of 1×3. This convolution process can simulate the convolution process of the first two layers, and the input related variables can be constructed as latent factors.

2.3. Precision Marketing and Convolutional Neural Network. In the W enterprise, a large amount of personal data is collected, extracted from the enterprise database, and then simulated by a convolutional neural network to simulate accurate consumer portraits. For a small number of anonymous users who cannot obtain accurate data, through simulation and prediction of previous data sets, the hidden data are extracted by looping and replying experiments. Integrate centralized data resources, establish an enterprise-level big data center, and realize “normalization” and “resourceization.” Convolutional neural networks can be used to assist companies in precision marketing models. The general process is to sort out the collected raw data and check the data, including the adjustment of the content format and the change of logic errors. In the rewriting of the basic label, the basic customer information is rewritten, and the threshold is set [19–21]. Perform label classification on the basis of basic label rewriting, based on characteristics such as crowd consumption habits. Then, use the convolutional neural network to predict the customer’s behavior to form a three-dimensional label. The last is the output of the results, providing customers with personalized services and exporting detailed information items.

3. Application of Convolutional Neural Network in Precision Marketing

3.1. CNN Model

$$\begin{aligned}\mu_1 &= v_1 w_1, v_2 w_2, v_3 w_3,\\ \mu_2 &= v_4 w_1, v_5 w_2, v_6 w_3.\end{aligned} \tag{1}$$

Euclidean distance

$$d_{ij} = \left(\sum_{k=1}^{n} (X_{ki} - X_{ki})^2\right)^{1/2}. \tag{2}$$

Pearson correlation distance

$$d_{ij} = 1 - |\rho_1 A_i|. \tag{3}$$

Let D_X denote a matrix composed of elements d_{ij}:

$$p_{ij} = \sqrt{(r_i - r_j)^2 + (c_i - c_j)^2}. \tag{4}$$

Let D_Y represent the matrix composed of elements p_{ij}:

$$\widetilde{D}_x = \frac{D_x}{\max(D_x)}, \tag{5}$$

$$\widetilde{D}_y = \frac{D_y}{\max(D_y)}. \tag{6}$$

Formula (5) calculates the number of users before correction, and formula (6) calculates the number of users after correction.

The convolution operation can be expressed by the following formula:

$$Y^{[l]} = f\left(\sum_{n=1}^{n^{[l]}} W^{[l],} + b^{[l]}\right), \tag{7}$$

where y_c represents the marketing forecast profit, and the calculation method is as follows:

$$y_c = \frac{\exp(z_c)}{\sum_j \exp(z_j)}, \quad c = 1, 2, \ldots, c. \tag{8}$$

3.2. LSTM Model

$$Y_{conv} = f\left(\sum_{j=0}^{J=1}\sum_{i=0}^{I=1} x_{m+i,n+j} w_{ij} + b\right). \tag{9}$$

The value range of n in formula (9) is (0, n).

Among them, the interval of the activation parameter m is between positive and negative m, f is the activation function; b is the additional offset (or offset); Y_{conv} is its output.

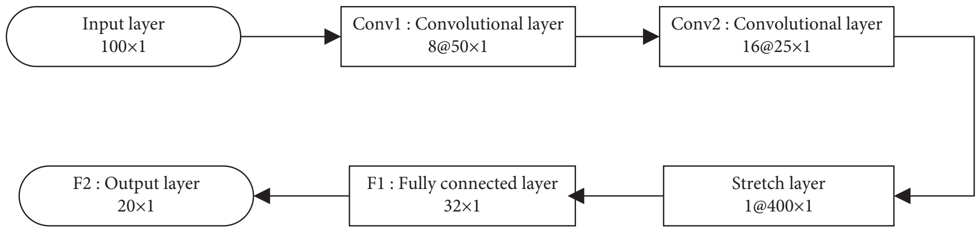

Figure 1: Convolutional neural network model.

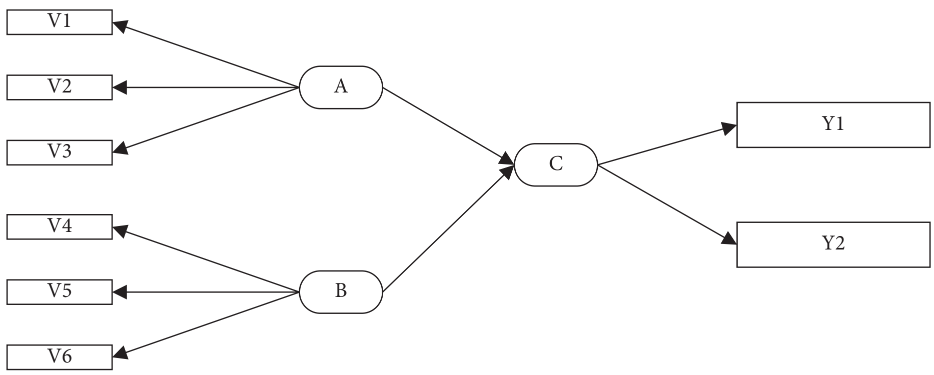

Figure 2: Structural equation simulation path diagram.

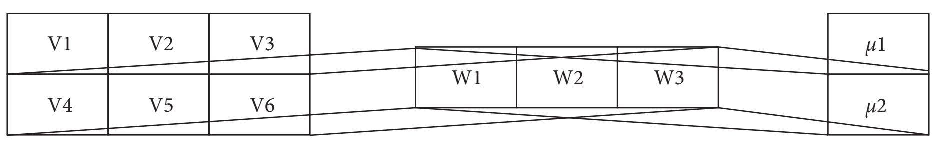

Figure 3: Convolution process with a 1×3 convolution kernel.

$$F_i = \frac{1}{N} = \sum_{x=1}^{N} f_i(x), \tag{10}$$

where $f_i(x)$ is the monthly profit income of W enterprise and N is the quarterly total profit income.

$$s_c = \sum_{i=1}^{M} F_i \times w_i^c. \tag{11}$$

The output of Softmax σ (S prediction result represents the gender and age of the consumer group).

$$\sigma(S_c) = \frac{e^{s_c}}{\sum_{j=1}^{c} e^{s_j}} \text{for } c = 1, \ldots, c,\ s = (S_1, \ldots, S_c) \in \mathbb{R}^c. \tag{12}$$

In order to avoid overfitting, a regularized model is used to constrain

$$\text{loss} = -\frac{1}{n}\sum_{n=1}^{N}\left[y_n \log \hat{y}_n + (1 - y_n)\log(1 - y_n)\right] + \lambda\|w\|^2. \tag{13}$$

Comprehensive judgment of the model

$$\begin{aligned} s_c &= \sum_{i=1}^{M} F_i \times w_i^c = \frac{1}{N}\sum_{x=1}^{N}\sum_{i=1}^{M} w_i^c \times f_i(x), \\ M_c(x) &= \sum_{i=1}^{M} w_i^c \times P_i(x), \end{aligned} \tag{14}$$

The specific formula for the maximum sales of an enterprise is as follows:

$$f_{pool} = Max\left(x_{m,n}, x_{m,n+l}, x_{m+l,n+l}\right), \tag{15}$$

where f_{pool} is the predicted result of the largest sales.

ReLu is a consumer characteristic factor:

$$f_{(x)} = \max(0, x). \tag{16}$$

3.3. LSTM Attention Model. Correlation coefficient of two vectors:

$$
\begin{aligned}
PCC(\overrightarrow{X},\overrightarrow{Y},) &= \frac{s_{\overrightarrow{X}\overrightarrow{Y}}}{s_{\overrightarrow{X}}s_{\overrightarrow{Y}}},\\
s_{\overrightarrow{X}\ \overrightarrow{Y}} &= \frac{1}{N-1}\sum_{k=1}^{N}(x_k-\overline{x})(y_k-\overline{y}),\\
s_{\overrightarrow{X}} &= \sqrt{\frac{1}{N-1}\sum_{k=1}^{N}(x_k-\overline{x})^2},\\
s_{\overrightarrow{Y}} &= \sqrt{\frac{1}{N-1}\sum_{k=1}^{N}(y_k-\overline{y})^2},\\
\overline{x} &= \frac{1}{N}\sum_{k=1}^{N}x_k,\\
\overline{y} &= \frac{1}{N}\sum_{k=1}^{N}y_k.
\end{aligned}
\tag{17}
$$

Here, x_k and y_k are the kth element of the vector. Finally, the precise demand profile of consumers is simulated [22].

3.4. CNN + LSTM Attention Model. Euclidean distance for two features

$$E\ D(\overrightarrow{X},\overrightarrow{Y}) = \sqrt{\sum_{k=1}^{N}(x_k-y_k)^2}. \tag{18}$$

The maximum distance is recorded as

$$\max MD_i = ED_i\,(1 \le i \le M). \tag{19}$$

The F-score of consumer demand characteristics is defined as

$$F-\text{score}(j) = \frac{\left(\overline{x}_j^{(+)}-\overline{x}_j\right)^2+\left(\overline{x}_j^{(-)}-\overline{x}_j\right)^2}{1/m^+ - 1\sum_{k=1}^{m^+}\left(\overline{x}_{k,j}^{(+)}-\overline{x}_j^{(+)}\right)^2 + 1/m^- - 1\sum_{k=1}^{m^-}\left(\overline{x}_{k,j}^{(-)}-\overline{x}_j^{(-)}\right)^2.} \tag{20}$$

$\overline{x}_j$, $\overline{x}_j^{(+)}$, and $\overline{x}_j^{\ (-)}$, respectively, represent the average value of all, positive, and negative predictions and actual eigenvalues. m^+ and m^- are the error interval between forecast and actual. The larger the value, the more obvious the consumer's demand characteristics, and q_i is the frequency of appearance.

$$q_i = \frac{m_i}{M}. \tag{21}$$

M is the total number of consumer features in all training data sets [23]. The probability in the male population and the female population can be defined as

$$
\begin{aligned}
p\left(n_{1,j}\right) &= \sum_{m=n_{1j}}^{N_j}\frac{N_j!}{m!\left(N_j-m\right)}q_i^m(1-q_i)^{N_j-m},\\
p\left(n_{-1,j}\right) &= \sum_{m=n_{-1j}}^{N_j}\frac{N_j!}{m!\left(N_j-m\right)}q_i^m(1-q_i)^{N_j-m}.
\end{aligned}
\tag{22}
$$

where $n_{1,j}$ and $n_{-1,j}$ is the number of users.

Finally, according to the following formula, the company's turnover through precision marketing is predicted:

$$P_j = \min\left(p\left(n_{1,j}\right), p\left(n_{-1,j}\right)\right). \tag{23}$$

4. Simulation Experiment

4.1. Training and Testing of the Model. As shown in Table 1, the training and testing of the CNN model, LSTM model, LSTM attention model, and CNN + LSTM attention model are compared in detail. The data source is the commercial marketing data of W company. After filtering the data, we input it to our model. Choose from July to July, July to August, July to September, July to October, July to November, August to August, August to September, August to October, August to November, and September to September. Data from different months are used; data from September to October are used for testing, and data from September to November are used for training. Based on the results of several models, the CNN + LSTM attention model and the LSTM attention model perform better, and the accuracy of testing and training is higher.

Figure 4 visualizes the training and testing comparison of the CNN model. The training and testing comparison of the LSTM Train model is shown in Figure 5. Figure 6 is the training and testing comparison of the LSTM attention model after LSTM optimization. The comparison of training and testing of the CNN+ LSTM attention model is shown in Figure 7. The comprehensive icon result CNN + LSTM attention model is the optimal model [24–27].

Table 1: Comparison of training and testing of different models.

Month	CNN		LSTM		LSTM attention		CNN + LSTM attention	
	Train	Test	Train	Test	Train	Test	Train	Test
7–7	0.75	0.74	0.69	0.68	0.71	0.73	0.72	0.72
7–8	0.61	0.62	0.53	0.52	0.58	0.56	0.59	0.57
7–9	0.62	0.63	0.61	0.6	0.69	0.68	0.69	0.69
7–10	0.65	0.64	0.6	0.59	0.69	0.68	0.67	0.69
7–11	0.61	0.62	0.65	0.64	0.66	0.65	0.66	0.65
8–8	0.75	0.76	0.77	0.76	0.78	0.77	0.77	0.79
8–9	0.81	0.8	0.79	0.78	0.8	0.81	0.84	0.8
8–10	0.76	0.77	0.75	0.74	0.76	0.78	0.77	0.77
8–11	0.75	0.74	0.72	0.71	0.73	0.74	0.73	0.74
9–9	0.85	0.84	0.8	0.79	0.81	0.81	0.83	0.79
9–10	0.74	0.73	0.75	0.74	0.76	0.74	0.75	0.76
9–11	0.65	0.69	0.68	0.67	0.69	0.7	0.68	0.7

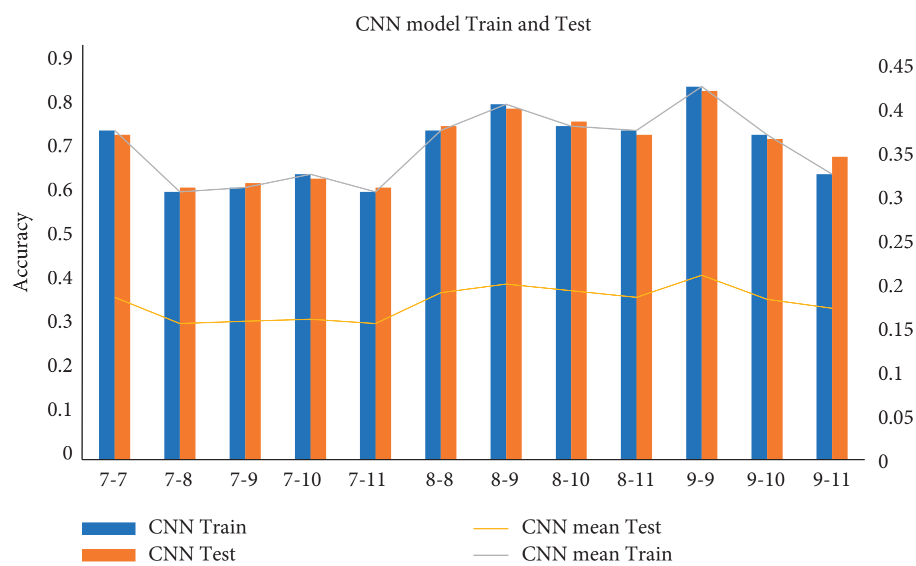

Figure 4: Comparison of training and testing of CNN model.

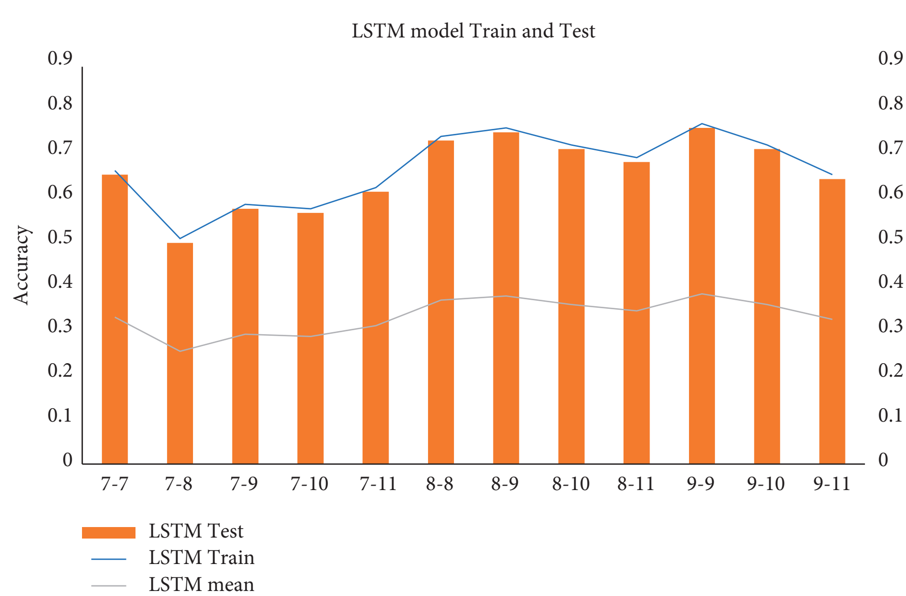

Figure 5: Comparison of training and testing of LSTM train model.

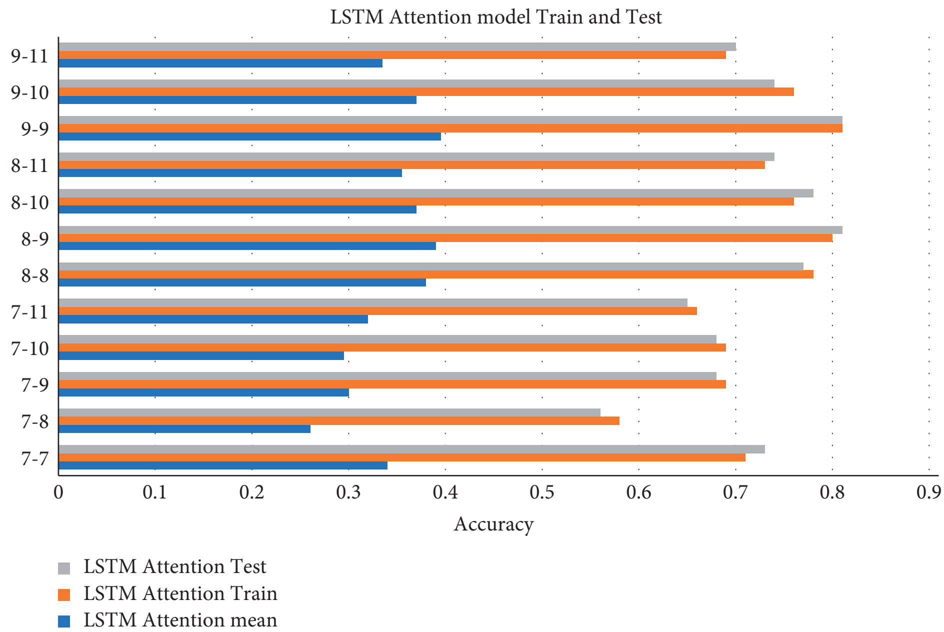

Figure 6: Comparison of training and testing of LSTM attention model.

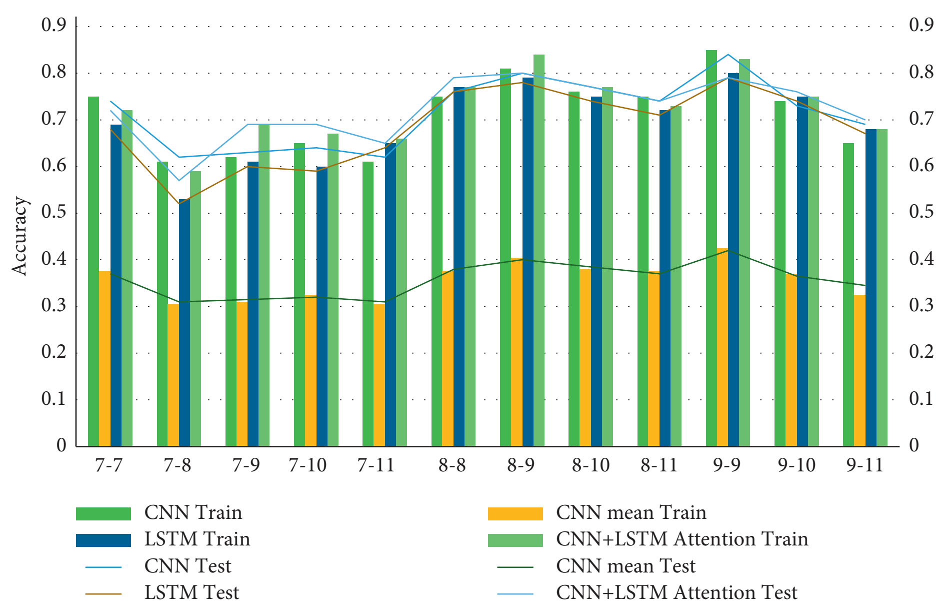

Figure 7: Comparison of training and testing of CNN + LSTM attention model.

4.2. Use Models to Fit Marketing Data. Using the marketing data of W company in previous years, bring in CNN model, LSTM model, LSTM attention model, and CNN + LSTM attention model, and evaluate the model using Sn(%), Sp(%), Acc(%), and MCC indicators. As shown in Table 2 and Figure 8, looking at the four indicators of Sn (%), Sp (%), Acc (%), and MCC, the Sn (%) of the CNN + LSTM attention model = 70.71, Sp (%) = 86.25, Acc(%) = 81.07, and MCC = 0.752 is the best fitting model.

As shown in Table 3, using CNN + LSTM attention to filter user tags, it is predicted that those users have greater buying potential.

As shown in Table 4, the users are classified by gender and gender, and it is found that men in the W company are the main purchasing power, and in the age stratification, it is found that the population of 41–50 accounts for the highest proportion. It can be seen from this that when performing precision marketing, the gender and age of the population must be precisely controlled.

4.3. Prediction of Precision Marketing and General Marketing. As shown in Table 5 and Figure 9, in the marketing input forecast for the next year, it is found that the use of precision

Table 2: Fitting of the model to marketing data.

Method	CNN	LSTM	LSTM attention	CNN + LSTM attention
Sn(%)	69.64	63.57	46.07	70.71
Sp(%)	90	94.46	93.92	86.25
Acc(%)	83.21	84.16	77.97	8l.07
MCC	0.756	0.708	0.384	0.752

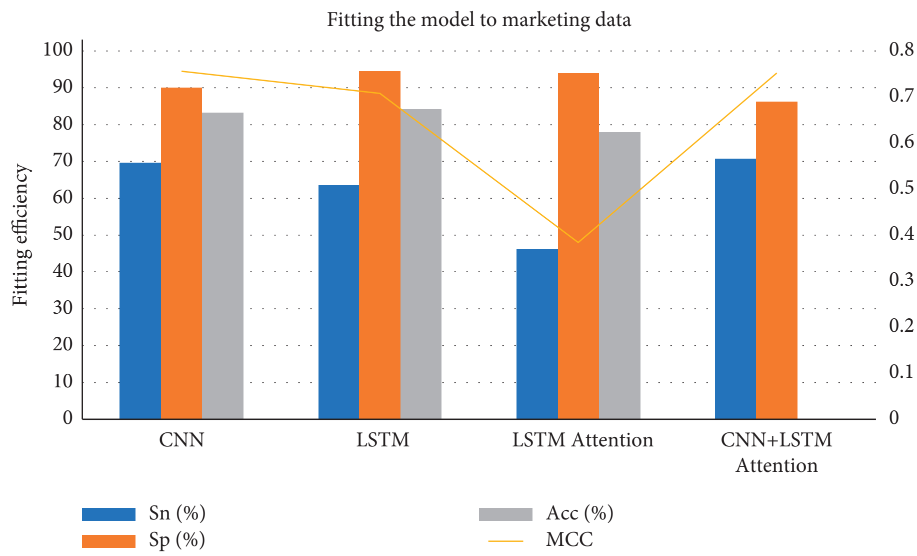

Figure 8: Fitting of the model to marketing data.

Table 3: Using CNN + LSTM attention to predict the number of users.

Serial number	Original log size (G)	Number of original tags	Number of filtered tags	User number
1	19.82	2319905	487180	154727
2	40.35	4450395	934583	297493
3	59.64	6879890	1444777	458726
4	78.92	8812650	1938783	587510
5	101.52	11300270	2486059	747618
6	120.08	13298965	3058762	887931
7	141.28	15470470	3094094	1031298

Table 4: Using CNN + LSTM attention to predict the number of users (male and female stratification and age stratification).

	Attribute value	User number	Percentage of generated data (%)	Proportion of original data (%)
Gender	Man	59190070	59.19	59.19
	Woman	32272265	32.27	32.47
	Others	8537665	8.54	8.54
Age	0–24	17879563	17.88	17.88
	25–30	15928089	15.93	15.93
	31–35	10995266	11.00	11.00
	36–40	9691802	9.69	9.69
	41–50	19059443	19.06	19.06
	>50	17924356	17.92	17.92
	Others	8521481	8.52	8.52

marketing will increase the profit of *W* enterprise. The average annual data shows that the monthly income of precision marketing is 0.735, while that of ordinary marketing is only 0.567.

4.4. Practical Effects of the Model. After downloading the data of W company from July 1 to November 30, 2020, the original data of W company's marketing income through different methods is classified, and the comparative

Table 5: Prediction of precision marketing and general marketing.

Month	Precision marketing	General marketing
1	0.73	0.5
2	0.75	0.51
3	0.68	0.51
4	0.65	0.49
5	0.77	0.68
6	0.81	0.66
7	0.78	0.62
8	0.74	0.59
9	0.81	0.71
10	0.74	0.58
11	0.72	0.56
12	0.64	0.4

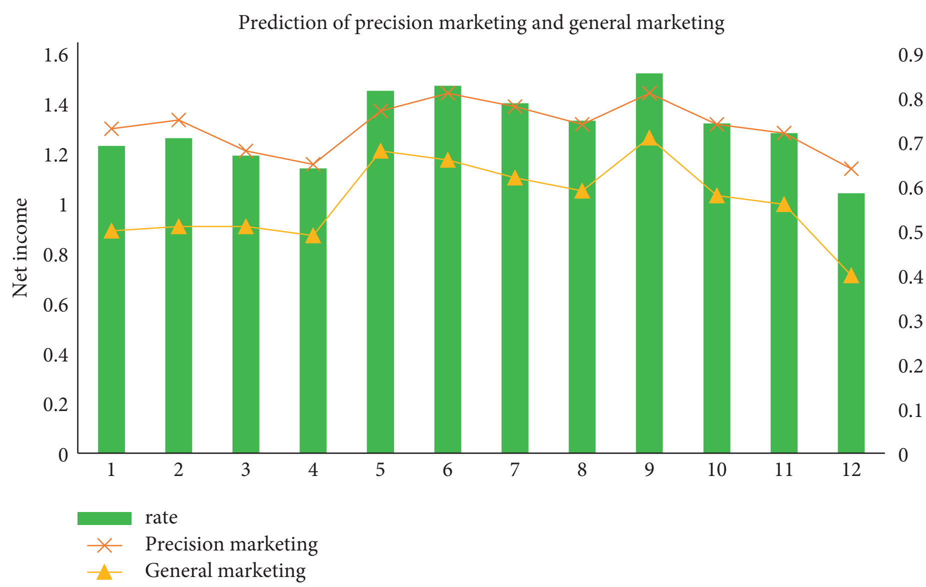

Figure 9: Prediction of precision marketing and general marketing.

Table 6: Practical effects of the model.

Months	Precision %	Recall %	F1-score %
7	73.1	77.6	75.2
8	61	72.3	66.2
9	55.9	91.6	69.4
10	78.3	84.1	81.1
11	64.9	85.7	73.8
Mean	66.6	82.3	73.1

analysis and supplementary analysis are applied to the optimization model. As shown in Table 6 and Figure 10, the results of comparative analysis and supplementary analysis are displayed. Precision, recall, and F1 scores are used to evaluate the comparative analysis and supplementary analysis, and the comparative analysis and supplementary analysis are simulated. The average accuracy rate of additive analysis is as high as 66.6%, the average recall rate of comparative analysis and complementary analysis is 82.3%, and the F1 score of comparative analysis and complementary analysis is 73.1%. This model has met expectations for precision marketing forecasts. Using precision, recall, and F1 scores to predict the W company, it is found that the CNN + LSTM attention model can increase monthly revenue by 50% in peak seasons and about 20% in off-season.

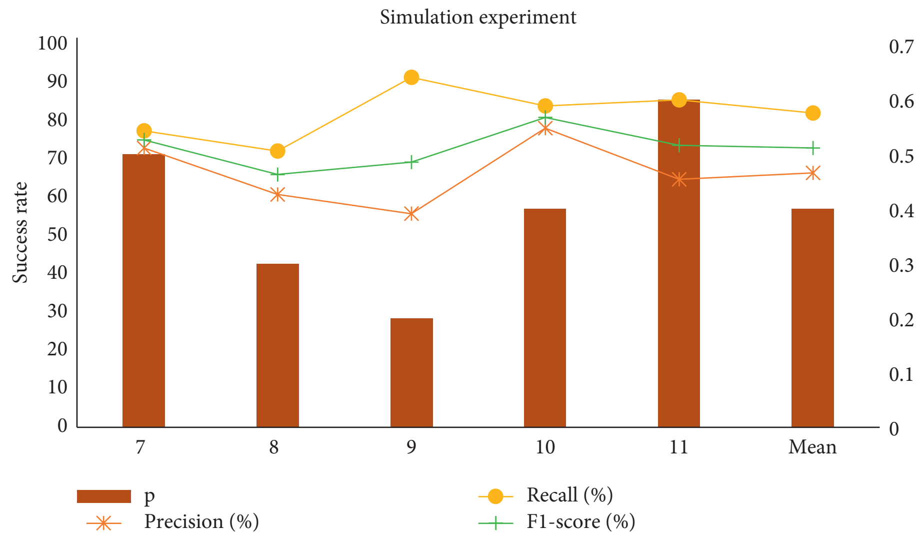

Figure 10: The practical effect of the model.

5. Conclusion

This research is based on curling neural networks, precision marketing, model optimization and construction, comparative analysis, and supplementary analysis and proposes precision marketing in response to the problems of existing marketing methods. Optimize the existing curl neural network model and apply it to e-commerce precision marketing. Through the collection and analysis of W enterprise data, the training and testing of CNN model, LSTM model, LSTM attention model, and CNN + LSTM attention model are compared, and the performance of CNN + LSTM attention model and LSTM attention model is obtained. Better, the accuracy of testing and training is higher. By fitting the model, it is found that Sn(%) = 70.71, Sp(%) = 86.25, Acc(%) = 81.07, and MCC = 0.752 of the CNN + LSTM attention model are the best fitting models. The men and women stratification and gender stratification of users are predicted, and it is found that men in the W company are the main purchasing power, and in the age stratification, it is found that the population of 41–50 accounts for the highest proportion. Using the CNN + LSTM attention model to predict the marketing input for the next year, it is found that the use of precision marketing will increase the profit of W company. Using the CNN + LSTM attention model to predict the marketing input for the next year, it is found that the use of precision marketing will increase the profits of *W* companies. The average annual data show that precision marketing will increase monthly revenue by 42.5%. The simulation shows that the average accuracy rate of comparative analysis and supplementary analysis is as high as 66.6%, the average recall rate of comparative analysis and supplementary analysis is 82.3%, and the F1 score of comparative analysis and supplementary analysis is 73.1%. The model predicts precision marketing as expected.

Data Availability

The experimental data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The author declares no conflicts of interest regarding this work.

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