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Research Article

Forecast Model of TV Show Rating Based on Convolutional Neural Network

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The TV show rating analysis and prediction system can collect and transmit information more quickly and quickly upload the information to the database. The convolutional neural network is a multilayer neural network structure that simulates the operating mechanism of biological vision systems. It is a neural network composed of multiple convolutional layers and downsampling layers sequentially connected. It can obtain useful feature descriptions from original data and is an effective method to extract features from data. At present, convolutional neural networks have become a research hotspot in speech recognition, image recognition and classification, natural language processing, and other fields and have been widely and successfully applied in these fields. Therefore, this paper introduces the convolutional neural network structure to predict the TV program rating data. First, it briefly introduces artificial neural networks and deep learning methods and focuses on the algorithm principles of convolutional neural networks and support vector machines. Then, we improve the convolutional neural network to fit the TV program rating data and finally apply the two prediction models to the TV program rating data prediction. We improve the convolutional neural network TV program rating prediction model and combine the advantages of the convolutional neural network to extract effective features and good classification and prediction capabilities to improve the prediction accuracy. Through simulation comparison, we verify the feasibility and effectiveness of the TV program rating prediction model given in this article.

1. Introduction

The audience rating refers to the proportion of the target audience users who watch a certain TV program in a certain period of time to the total target users [1]. Although the audience rating represents a proportional relationship between users' viewing behavior of a certain program and the total number of users, the audience rating indicator is actually a sample data based on a sample survey. In the actual survey and statistics process, all the viewing behaviors of all users in the survey area are not counted [2]. Instead, randomly selected TV viewing users with a certain scale are used as samples to conduct a sample of the viewing behaviors of the sample users. The result of mathematical statistics is used to calculate the probability that a certain program in a specific viewing area is watched by the user. With the rating data, it is possible to calculate the number of users who watched a program at a certain time period or point in time and to understand the degree of the audience's preference for the program and measure the market competitiveness of different TV program types [3]. The formula for calculating the ratings is as follows: TV ratings = number of users who watch a program in the sample/total number of TV users in the sample 100%

The ratings are often referred to as TV ratings by TV people. 1% of the ratings is a rating point. Assuming that the total number of TV users in a certain viewing area is 10 million, the result of a certain program's rating survey shows that it is 6%. In other words, this program has six points of viewing, and it can be calculated that a certain program is viewed by 600,000 viewers in the surveyed area during this period. Under the marketization of TV media ratings, program ratings mainly play the following roles. First, the number of viewers and the characteristics of the audience group can be mastered at a macrolevel: on the one hand, the program ratings can be calculated by simple calculations. The total number of users can be used as an important basis for judging the influence of the program; on the other hand, the raw data of the ratings in the hands of the rating survey company also covers the personal information of the audience's gender, age, occupation, and education level [4]. The column understands the basis of its audience structure characteristics and provides effective help for the positioning and improvement of different types of programs. The second is a microlevel interpretation of viewing habits, audience loyalty, market competitiveness, and prejudged program ratings: the audience's viewing behavior will change with the broadcast of the program [5]. It is the changing trend between time points, reflecting a kind of viewing habit of the target user, which can provide a reference for adjusting the content of the program or improving the programming; from the audience's viewing time of a certain TV program, it can be judged whether the user is a loyal viewer of a TV channel or a program can understand the needs and preferences of the target audience for a certain type of column by analyzing the time invested by different target audiences in different types of columns; the audience can only be viewed at the same time and choose a program of a certain channel to watch, and the distribution of different channel programs in the same time period can be used to analyze the types of channels that viewers like to watch and understand the market share of each channel in the same TV viewing market to determine the channel's competitiveness in the viewing market [6].

Data mining needs to realize the processing of massive data and analyze the type and combination of data, all the mining processes are organized according to the characteristics of the data, and the discrete data is organized into a logical arrangement. These data can perform secondary processing to form target data. In the process of data, the data needs to be preprocessed, selected, extracted, and finalized. In this process, you need to understand the integrity and validity of the data and formulate an efficient mining rule. The realization of ratings analysis and prediction requires a large amount of data support, and general data analysis methods are difficult to extract scientific and reasonable information from a complex database. Therefore, the use of data mining algorithm screening is the main means to achieve its purpose. The process of data mining can be divided into four steps.

First, the data is preprocessed; that is, the data definition function is completed. This step requires preliminary screening of the massive data. The screening rules are derived from the rating analysis and prediction to determine the demand for data. After the demand is determined, it is based on the demand. The characteristics are used for data processing, and the required data is defined after the data processing.

The second step is to perform some basic classification, identification, and the related processing of the data. After the screening process and the definition process in the previous step, we can obtain the data set that is initially required, then, which data type in this data set is more in line with the requirements, and the data of the viewing segment in the data type that is required to meet the requirements. For further analysis, this step completes the further processing of the data.

The third step is the process of executing the formulated data mining method. There are many rules for data mining methods. The common ones are the decision tree method, neural network method, ant colony algorithm, neural network algorithm, and other algorithms to achieve this. Part of it needs to determine the specific algorithm to execute according to the characteristics of the target. In addition, you can customize the data mining algorithm to establish a data mining model. As long as you can quickly extract the characteristic data from the numerous data, this is the first step of data mining.

The fourth step is to interpret the conclusions of data mining execution and form data mining content that meets the needs of ratings analysis and prediction. In many cases, the data mined from data is abstract and cannot directly face users. In this case, it is necessary to interpret the conclusion of the data mining algorithm, that is, form the target data conclusion that is actually needed. Generally speaking, the program ratings are analyzed, and the reasons and changes of the programs broadcast by the column are not welcomed by the audience. Regardless of channel or program competition, the main focus is on the content market, which is also the result of viewers' choice of TV content.

2. Based on Convolutional Neural Network

2.1. Convolutional Neural Network. Convolutional Neural Network (CNN) is a type of feed-forward neural network that contains convolution calculations and has a deep structure [9]. The research on CNN can be traced back to the 1980s and 1990s. TDNN is generally considered to be the earliest convolutional neural networks. Since the 21st century, with the concept of deep learning and the continuous improvement of related hardware accelerators and software platforms, CNN has developed rapidly and has become one of the most representative algorithms for deep learning [10]. CNN was born for images, but its application is not limited to images. It has been widely used in many fields such as computer vision, speech recognition, and natural language processing. The CNN network model training and testing flowchart is shown in Figure 1.

In order to avoid the problems caused by traditional neural networks such as huge parameters, loss of information between pixels, and limited network depth development, CNN does not adopt a fully connected method like artificial neural networks but arranges in an image matrix and introduces the idea of "local perception, weight sharing, downsampling," etc., which has greatly improved its performance and application scenarios [12]. The three cores are briefly introduced as follows:

(1) *Local Perception.* Each neuron in CNN is no longer connected to all neuron nodes in the next layer like a traditional neural network but only connected to some of the neurons, which greatly reduce the weight

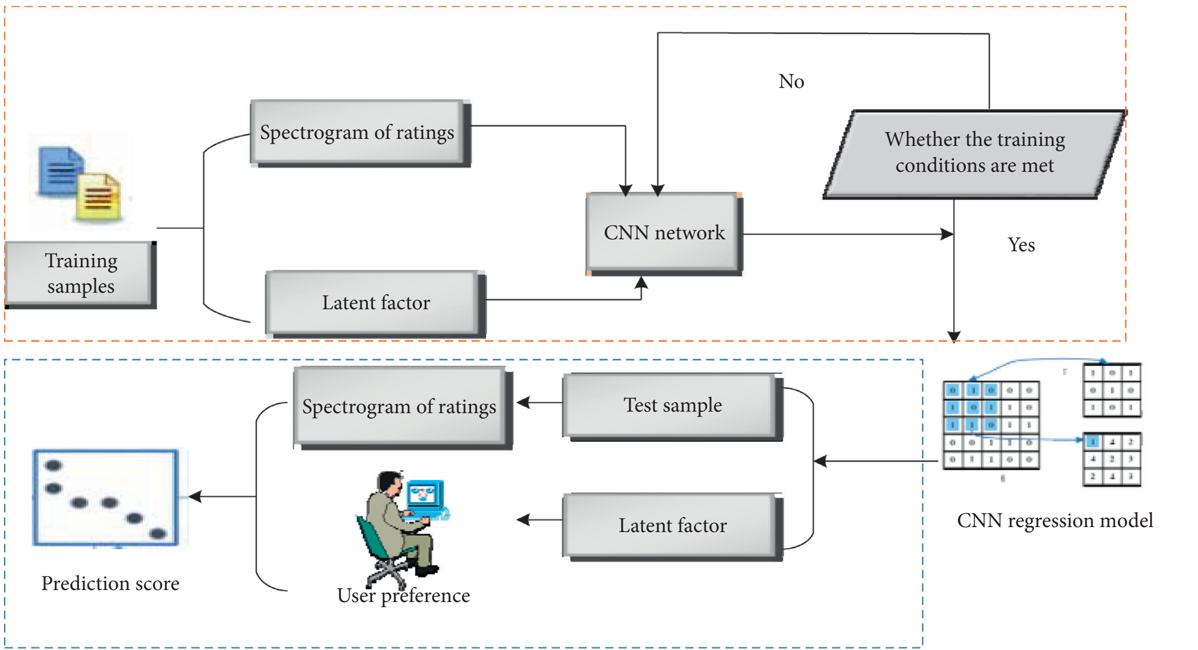

Figure 1: CNN network model training and testing flowchart.

parameters. For an image, the relationship between local pixels is usually relatively close, and the correlation between pixels that are farther apart is relatively weak, so there is no need to perceive the global image, but only the local information of the image. As the network level gradually deepens, the deeper network will continue to extract local information from the image of the previous layer and finally obtain the global information of the image.

(2) *Weight Sharing.* A group of connections or multiple groups of connections in CNN can share the same weight parameter or the same convolution kernel, instead of each connection having its own weight. Because if a convolution kernel obtains a specific texture feature in a small area of the image, then this convolution kernel can also be used in other similar features of the image [13].

(3) *Downsampling.* The downsampling technology is used in CNN to compress the image data originally input to the convolutional layer to reduce the total output pixels. It can reduce the possibility of overfitting due to too many weight parameters, and at the same time, because the image space size is compressed, the amount of calculation is reduced, and the calculation speed is further improved.

As mentioned earlier, CNN has unique advantages in many aspects with its special structure of sharing local weights. Through local perception, the associated information between image pixels can be retained, which is convenient for extracting higher-dimensional features of the image and perceiving richer information in the image. After weight sharing and downsampling operations, the number of network parameters can be further reduced and the model's performance can be improved. Robustness allows the model to continuously expand in depth and continue to increase hidden layers. CNN is a multilayer neural network constructed by imitating biological visual perception mechanisms [14]. Each layer is composed of multiple two-dimensional planes, and each two-dimensional plane contains multiple independent neurons. A complete CNN model can be constructed by using a convolutional layer, downsampling layer (also called pooling layer), fully connected layer, and other three network layers permutation and combination, plus input layer and output layer. A simple example model of a convolutional neural network is shown in Figure 2.

2.2. The Layout of the Deep CNN Model. Compared with the artificial neural network, the layout of the CNN model is closer to the actual biological neural network. The parameter sharing of the convolution kernel in the hidden layer and the sparsity of the connection between layers greatly reduce the complexity of the network, making it possible to specify the completion of calculations in less time and limited memory resources. Its power is also that the multilayer network structure can automatically learn the deep features of the input data [15]. Different levels of the network can learn features of different levels, thus avoiding the feature engineering of feature extraction and the pattern recognition process of feature classification. In the typical network structure of CNN, the input raw data or transformed data enters the fully connected perceptron layer after several convolution and pooling stages and finally reaches the output layer. The input layer neuron of CNN has a three-dimensional structure of width, height, and depth, which can correspond to the width, height, and channel number of the

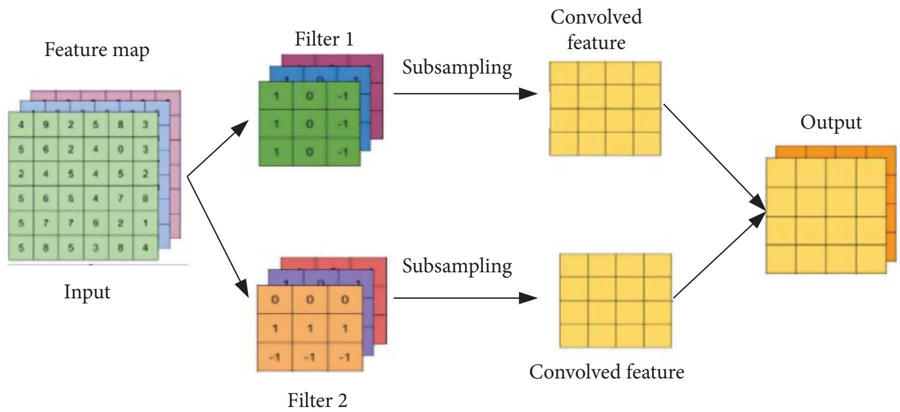

Figure 2: A simple convolutional neural network example model.

input image, respectively. The structure of the fully connected layer is similar to the structure of the artificial neural network. The upper layer and the lower layer are connected to all neurons; that is, the fully connected method is adopted. Due to a large number of neurons, the fully connected layer has the most parameters. Its main function is to make a convolutional layer and pooling. The features extracted by layers are integrated. The two most important network layers in CNN are the convolutional layer and the pooling layer. Convolution is a very important operation in analytical mathematics. The purpose of convolution in CNN is to extract certain features, and it is realized by the convolution kernel. For example, during image processing, each pixel in the output image is obtained by the weighted average of the pixels in each small area in the input image, where the weighted weight is defined by the convolution kernel, which can be regarded as a filter or feature scanner. The convolutional layer is the most core part of the CNN model. A convolutional layer generally has multiple convolution kernels, and each convolution kernel may be high-dimensional, usually consistent with the input dimension. The extracted features of different convolution kernels are different, and the same convolutional layer pixels can obtain different forms of features through multiple convolution kernels [16]. Powerful feature learning ability is the biggest feature of the convolutional layer. Often the first layer of the convolutional layer may only extract some lower-level features from the original data, but deeper networks can iteratively extract more complex features from the lower-level features This greatly simplifies the tedious feature engineering in the past. In addition, CNN is different from a fully connected network. The convolution kernel of the convolutional layer is only connected to certain local areas in the input, and the same convolution kernel will share parameters for the same layer, which not only effectively reduces the network parameters and the quantity but also can obtain rich structural characteristics. A simple convolution kernel performs a convolution operation on the input image to obtain the output feature map as shown in Figure 2. Slightly different from convolution in the field of signal processing, the convolution operation in CNN is more like a linear weighting operation. For an input image X, a convolution kernel K with a size of $m * m$ is used for convolution, and finally, the output of a feature map Y can be expressed as

$$Y_i = g\left(\sum_m X_i \times K_i + C\right). \tag{1}$$

In the formula, C is the offset, and $p * q$ is the size of the output feature map, which is related to the processing method of the image edge during convolution and the step length of the convolution kernel movement in the image convolution process. It can be simply understood as the sliding convolution operation of some points to be convolved with the convolution kernel. Assuming that the edge pixels of the image are discarded and the moving step is 1, the offset is 0, and the first feature value in the figure is $0 * 1 + 1 * 0 + 0 * 1 + 1 * 0 + 0 * 1 + 1 * 0 + 1 * 1 + 1 * 0 + 0 * 1 = 1$. The other feature values can be deduced by analogy, and the entire original image is gradually convolved to obtain the final convolution feature map. Of course, in practice, the number of convolution kernels in each convolution layer is more than one and may be high-dimensional.

2.3. Convolutional Neural Network Structure Design. The CNN model is different from the traditional artificial neural network model. All of its weights are obtained through backpropagation algorithm training. The classification or prediction is exactly like being placed in a black box, and the required parameters of the network are obtained through continuous optimization. The work is a feature extractor that automatically synthesizes its own. Therefore, following some existing rules when designing the architecture for different scenarios, which is beneficial to the structural design of the CNN network, is the solution of the network. Generally, what needs to be focused on is the arrangement law between network layers and the design law of network parameters.

The most common in the CNN model structure is the convolutional layer followed by the pooling layer. Its purpose is to reduce the size of the input image during the next convolution, then repeat the process several times to further extract the high-dimensional features of the image, and finally get the output through the fully connected layer. Therefore, the most common CNN model structure rules are as follows. The parameter definitions in the CNN model are more complicated than traditional models, and the general rules of parameter design can be summarized as follows:

(1) In order to facilitate the calculation of the convolutional layer and the pooling layer, the size of the input layer matrix should be divisible as many times as possible. For example, the feature map generated by each pooling layer is half of the input, which can reduce the reduction caused by data lost

(2) The convolution layer should try to use a convolution kernel with a small size, and the deeper the number of network layers is, the smaller the size of the convolution kernel should be set. Because in terms of space, as the network level deepens, the smaller the output feature map, the larger the perception area, which means the larger the convolution kernel. The increase of the convolution kernel will further reduce the feature map, and the perception area in the image is too large to extract high-dimensional features of the input data. In terms of performance, the smaller the convolution kernel, the fewer weight parameters required, which can effectively increase the computing speed [17]

(3) The convolution step size should be set as small as possible. Smaller step size is better for extracting features. For example, when the step size is set to 1, the downsampling operation of the spatial dimension is responsible for the pooling layer, and the convolutional layer only is responsible for extracting features of input data

(4) The boundary of the matrix should be filled with the same padding zero in the convolutional layer so that the output data of the convolutional layer and the size of the input data can be kept unchanged. If the convolutional layer only performs convolution operations without zero paddings, as the network level continues to deepen, the size of the data volume will gradually decrease, and the edge information of the image will be lost too quickly. The setting of padding is related to the size of the convolution kernel. For any convolution kernel size k, setting $\text{padding} = (k-1)/2$ can maintain the size invariance. For example, when the size of the convolution kernel is 3, set $\text{padding} = 1$. When the size of the convolution kernel is 5, set $\text{padding} = 2$

(5) The pooling layer often uses a $2 * 2$ pooling window, and it is the maximum pooling operation. Because the pooling layer is mainly responsible for spatial dimensionality reduction of the input data, when the pooling operation is too intense, it is easy to cause data information loss, resulting in a sharp decline in network performance

(6) Generally, the number of fully connected layers should not exceed 3 layers, because the more fully connected layers, the more difficult it is to train, and the easier it is to cause overfitting and gradient dissipation. Most CNN models are two consecutive fully connected layers plus an output layer [18]

The model is a CNN model designed to recognize computer-printed characters and handwritten fonts. This model is a very classic convolutional neural network model. It has been widely used in various image recognition scenarios such as license plates and house numbers. This article is based on the network model architecture, referring to other excellent convolutional neural network models, and following the general rules for the design of CNN network architecture summarized above, it is designed to predict the potential factors. The structure of the layer network model is shown in Figure 3.

It can be seen from the figure that the CNN model has 4 convolution + pooling layers, the convolutional layer, and the pooling layer alternate, and finally, there are two fully connected layers and a prediction output layer. The input image of the input layer is the Mel spectrum feature map extracted from the audio, and its pixel size is all $256 * 256 * 1$. The convolution operation implements local perception and weight sharing, the convolution step length is set to 2, and the matrix edge is filled with zero paddings. The pooling layer uses the maximum pooling algorithm, and the pooling window size is set to $2 * 2$. The specific network parameter settings of the convolutional layer and the fully connected layer are shown in Table 1.

Among them, k is the dimension of the latent factor. This article will compare the effects of different values on the results through experiments. In addition, in order to prevent overfitting, the regularization method adopted is to introduce a dropout layer between the fully connected layers and set the dropout probability to 50%. The random initial value of each layer weight adopts the default initialization method in the Keras library [18]. In addition to the abovementioned parameters related to the network model, other parameters related to model tuning training, such as activation function, loss function, optimizer, and learning rate, will be compared and selected in the following sections.

3. Experimental Results and Analysis

3.1. System Evaluation Index. Recommendation systems usually run in a specific environment. The requirements and performance of recommendation systems in different environments are quite different. Therefore, there are many indicators to evaluate the performance of a system. However, no matter what the situation is, the system requires high recommendation accuracy and effectiveness as the goal. For the recommendation system studied in this article and the recommendation produced by the recommendation algorithm, the evaluation of the recommendation quality is mainly achieved by verifying the accuracy of the recommendation algorithm to produce recommendation results on a given data set, and it can be measured from the two perspectives of predicting scoring accuracy and generating recommendation list accuracy.

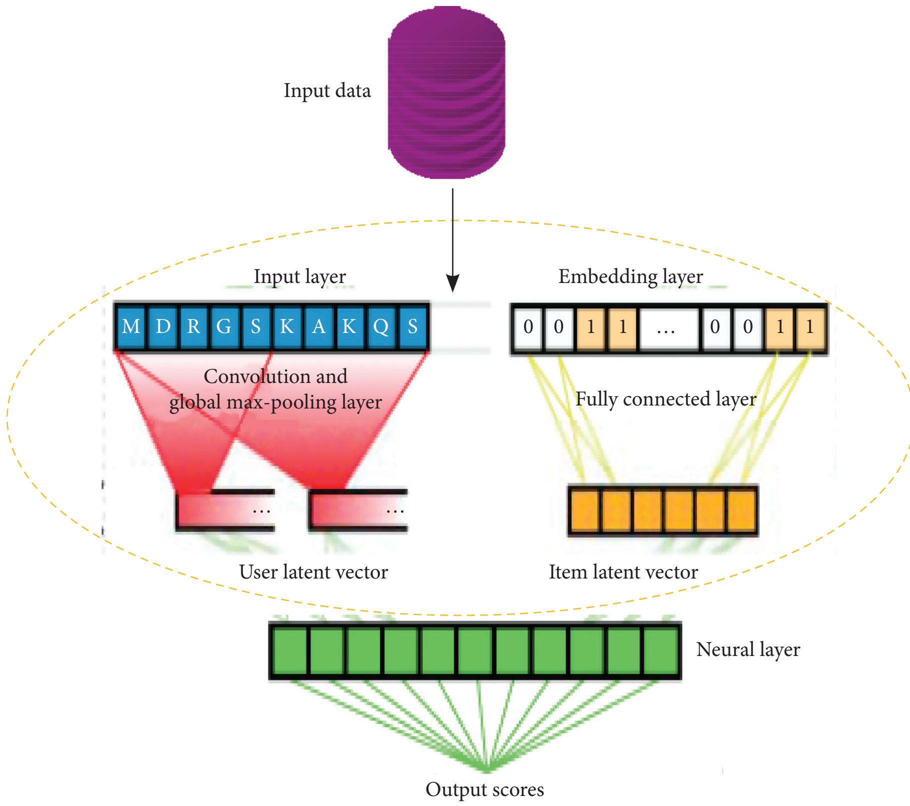

Figure 3: CNN network model structure for latent factor prediction.

Table 1: CNN model convolutional layer parameters.

Convolutional layer	Convolution kernel size	Number of convolution kernels	Fully connected layer	Number of inputs	Number of outputs
1	3 ∗ 3	64	1	512	128
2	3 ∗ 3	128	2	128	32
3	2 ∗ 2	256	3	32	K
4	2 ∗ 2	512			

3.1.1. Prediction of the Accuracy of Scoring. The main function implemented by the recommendation algorithm is score prediction. The system finally completes the task of generating recommendations for relevant users based on the predicted score. Therefore, the difference between the system's predicted score and the user's true score is a very important indicator to measure the accuracy of a recommendation system. Common standards used to measure the accuracy of prediction scores are mean absolute error MAE, normalized mean absolute error NMAE, mean square error MSE, and root mean square error RMSE [16]. It is generally believed that RMSE can increase the penalties for inaccurate predictions to a certain extent and impose stricter requirements on the system. Therefore, this paper uses RMSE as a metric for the accuracy of system score prediction to verify the experiment. The RMSE calculation formula is as follows:

$$\mathrm{RMSE} = \sqrt{\frac{\sum_m \left(r_i - \hat{r}\right)^2}{|r|}}, \tag{2}$$

where r represents the test data set.

3.1.2. Accuracy of the Recommendation List. The recommendation system studied in this paper can realize the N recommendation function for users; that is, for each user, first rank the input, then select the top N to form a recommendation list, and finally, recommend it to the target user. In order to verify the accuracy of the recommendation list generated by the system, this paper uses the widely used indicators in recommendation quality evaluation such as accuracy rate precision, recall rate, and F value as the evaluation criteria of recommendation results to verify the experiment.

The accuracy calculation formula is

$$\text{accuracy} = \frac{\sum_m |A(i) \cap B(i)|}{\sum_m |A(i)|}. \tag{3}$$

In the formula, $A(i)$ represents the list generated by the system for each user on the test set, and $B(i)$ represents each user on the test set. The formula for calculating the recall rate is

$$\text{recall} = \frac{\sum_m |A(i) \cap B(i)|}{\sum_m |B(i)|}. \tag{4}$$

In the formula, $A(i)$ and $B(i)$ have the same meaning as above, and the difference between them and the accuracy calculation formula lies in the denominator. The recall rate represents the proportion of the music that the user listens to by the system after the recommendation. The formula for calculating F value is

$$F = \frac{2\alpha\beta}{(\alpha + \beta)}. \tag{5}$$

In the formula, α stands for precision and β stands for recall. It is relatively one-sided to evaluate the performance of the recommendation system from the perspective of accuracy or recall rate, because there will be conflicts between accuracy rate and recall rate. The longer the recommendation list, the lower the accuracy rate and the higher the recall rate, and vice versa. Therefore, the F value is the result of the balance between the accuracy rate and the recall rate and is a more comprehensive evaluation index.

In addition to the evaluation indicators used in the above experiments in this article, coverage, diversity, novelty, etc. are usually used to evaluate certain aspects of the performance of the recommender system, which will not be repeated here.

3.2. Result Analysis. As mentioned earlier, this experiment uses the mean square error MSE as the loss function and uses the training set data to train the CNN network model. The training results are shown in Figure 4. It can be seen from the figure that as the number of iterations continues to increase, the loss error of the network model decreases rapidly at the beginning and then gradually becomes slower, and approximately, when the epoch reaches 10, the error drops to 0.143, and the function tends to convergence. Only from the loss value curve, the training process of the model basically meets the expected requirements. In order to better verify the predictive ability of the model, the following will conduct a more comprehensive evaluation of the experimental model from different perspectives.

3.2.1. The Influence of Latent Factor Dimension k and Iterative round Epoch on Score Prediction. The last layer in the CNN network model structure used in this experiment is the prediction output layer. The output dimension should be determined by the dimension of the feature vector of the potential factor, which is determined by the analysis in the section showing that the general requirement of the latent factor dimension $k < r$ represents the rank of the scoring matrix R, $r < \min(m, n)$. The number of users n in the data set used in the experiment is 12, so it is planned to set k to vary from 3 to 11, and the increment step is 2 to evaluate the influence of the number of dimensions of potential topics on the model's prediction score. In addition, when training the model, the training effect of the model is usually affected by the epoch of the training round, so this paper conducts a comparative experiment of different training rounds.

During the test, we first input the spectrum in the test set into the CNN regression model to predict the k-dimensional potential factor and then combine the user preference model to finally calculate the model's prediction score. The experiment uses the root mean square error RMSE to measure and predict the accuracy of the score. The RMSE results of the model prediction score under different latent factor feature dimension k and training round epoch are shown in Figure 4.

It can be seen from the experimental results that when the k value is 3 and 5, the RMSE value of the predicted score is relatively large, which means that the smaller k is not enough to represent the potential theme of music; when the k value is 7 and 9, the predicted score decreases. The difference between the RMSE values is not obvious. The RMSE with a k value of 7 is slightly lower than the RMSE with a k value of 9, and in the best case, the RMSE drops to about 0.6; and when the k value is 11, the RMSE value of the predicted score starts to increase again, which shows that too large latent factor dimensions will dispel the importance of true latent features. At the same time, with the increase of training rounds, when the epoch is between 10 and 20, the RMSE has a certain improvement, while the RMSE between 20 and 30 is basically the same, which shows that the preferred training round in this experiment is 20. After all, large training rounds will increase the training time of the entire model. It can be seen that when the latent factor k is 7 and the training round epoch is 20, the experiment can achieve a better score prediction effect, which will be the basis of the experiment to be carried out hereinafter.

3.2.2. The Impact of Different Recommendation List Lengths on the Accuracy of Recommendation Results. In order to verify the feasibility of the recommendation algorithm in this paper and measure the quality of the recommended results produced by the model, experiments have tested the recommendation accuracy under different recommendation list lengths. In the experiment, the recommended list is set to different lengths such as 5, 10, 15, 20, and 25, and the accuracy, recall, and F values are used to quantitatively evaluate the accuracy of the recommended list. The recommendation results under different recommendation list lengths are shown in Figure 5.

It can be seen from the experimental results that the length of the recommendation list has a certain impact on the recommendation results, and as the length of the recommendation list increases, the accuracy rate is continuously decreasing, while the recall rate and F value are

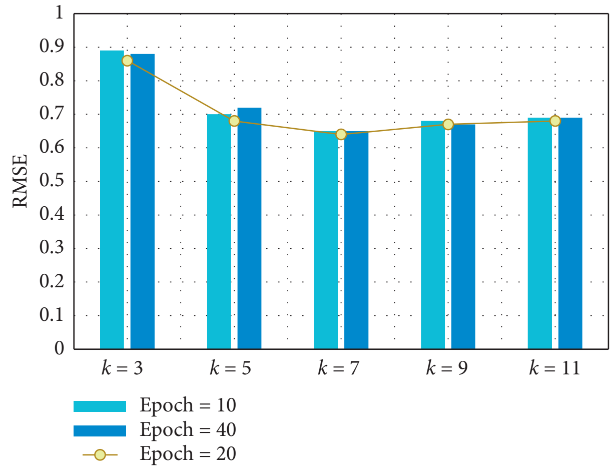

Figure 4: RMSE of prediction score under different k and epoch.

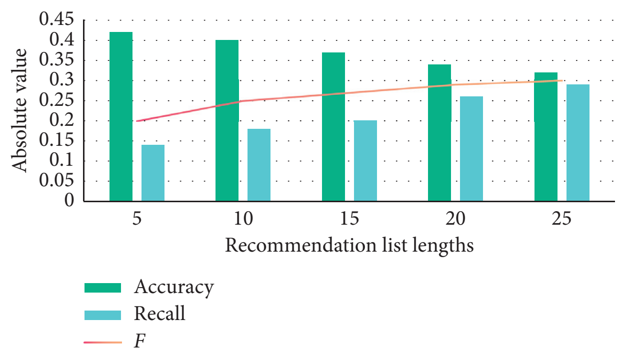

Figure 5: Recommendation results under different recommendation list lengths.

continuously increasing. When the recommended list length is 10, the highest accuracy rate is about 0.412, and the lowest recall rate is about 0.134. When the recommended list length increases to 30, with the data used for 0.308, the recall rate rises to about 0.248, which is basically in line with the decrease in accuracy rate. Because the test users are all data that have not been used for network model training and verification, it can be seen that the recommendation algorithm in this article still has a certain predictive recommendation ability in a cold start environment.

4. Simulation Analysis

In order to verify the effectiveness of the intelligent prediction method of news ratings based on network click data, a simulation comparison experiment was carried out. This experiment needs the help of simulation software to complete the calculation work, because it can not only quickly establish a CNN prediction model but also automatically give related parameters and automatically generate an error function [12]. Assume that the evening news broadcasts of 10 stations are the simulation experiment objects, which are selected by data mining technology. The network click data of news broadcasts from 10 stations between January and October 2019 is used as the model input index, that is, the model input sample. The specific sample data is shown in Table 2.

The maximum number of iterations is set to 15 000, the preset accuracy is set to 0.1%, and the neural network is trained. The average input data of B station is selected as the input of the news broadcast ratings in November. The output value of the neural network is the program ratings in November rates shown in Table 3.

The prediction results of the November program are shown in the output data of Table 3, and the error curve is shown in Figure 6.

It can be seen from Figure 6 that after iteration, the accuracy of the neural network reaches the preset value of 1%. Now, we use the intelligent forecasting method of news audience rating based on network click data and the intelligent forecasting method of news audience rating based on a decision tree to predict the audience ratings of the 10 evening news broadcasts in November. The result is shown in Figure 7.

It can be seen from Figure 7 that when using the intelligent prediction method of news ratings based on network click data to predict the evening news broadcast ratings of 10 stations in November, the average correct rate was 91.34%; while the use is based on decision-making when the tree's intelligent forecasting method of news ratings predicts the ratings of the evening news broadcasts of 10 stations in

Table 2: Sample data.

	Average input data (%)	Average output data (%)
L station	0.241	0.217
B station	0.198	0.211
S station	0.188	0.294
H station	0.203	0.274
A station	0.242	0.204
G station	0.265	0.201
T station	0.221	0.204
C station	0.215	0.205
K station	0.197	0.198
M station	0.187	0.214

Table 3: Predictive calculation input and output.

	Average input data (%)	Average output data (%)
L station	0.217	0.201
B station	0.211	0.205
S station	0.294	0.198
H station	0.274	0.197
A station	0.204	0.202
G station	0.201	0.204
T station	0.204	0.196
C station	0.205	0.205
K station	0.198	0.208
M station	0.214	0.212

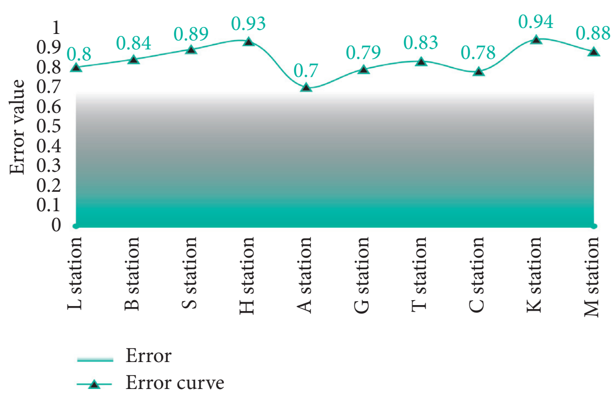

Figure 6: Error curve.

November; the average correct rate is only 84.42%. Compared with the two, the former is 6.92% higher than the latter. In addition, judging from the trends of the two curves in Figure 7, the forecast curve of the intelligent forecasting method for news ratings based on network click data is roughly the same as that of the real results, while the intelligent forecasting method of news ratings based on the decision tree is the trend of the predicted curve that has a large error with the trend of the predicted curve of the real result; from the perspective of curve fluctuations; the prediction curve of the intelligent prediction method of news ratings based on network click data is higher than that of the intelligent prediction method of news ratings based on decision trees. The curve waveform is small. Therefore, from

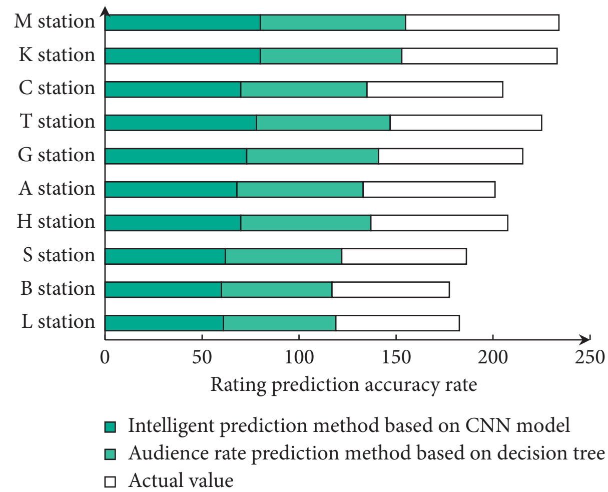

Figure 7: Forecast results of ratings.

the above curve trend and fluctuation, it can be seen that the stability of the intelligent forecasting method of news ratings based on network click data is better than that of the intelligent forecasting method of news ratings based on decision trees.

5. Conclusion

This paper first describes the construction process of the data set used in the system experiment, and the matrix decomposition method of the implicit semantic model is used, respectively. The user preference model and the potential factor features of music are obtained, and the spectrum feature extraction is performed on the data set; then the system environment used in the experiment and the related process of CNN model training and testing are briefly introduced. Finally, the model was trained and tested, and the recommendation quality of the system was comprehensively evaluated from two perspectives: the accuracy of predictive scoring and the accuracy of generating recommendation lists. To sum up, as one of the most important sources for the public to obtain current affairs from the outside world, TV ratings are affected by various factors, among which Internet click data is the most influential factor. Therefore, this research starts with the Internet click data to predict TV ratings. The accurate prediction of TV ratings can not only better complete the program scheduling work but also provide a certain reference for relevant departments when formulating policies. In order to verify the effectiveness of the intelligent prediction method of TV ratings based on network click data, a simulation comparison experiment was carried out. The results show that after a limited number of iterations, the method can achieve the expected accuracy of 0.1%, and the prediction accuracy is better than the intelligent prediction method of TV ratings based on the decision tree. It can provide TV station staff with assistance in programming and adjustment and provide data reference for advertising.

Data Availability

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

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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