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# RESEARCH AND APPLICATION OF A DUAL FILTERING MUSIC HYBRID RECOMMENDATION MODEL BASED ON CATBOOST ALGORITHM AND DCN

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**Abstract.** With the increase of Internet users, the traditional music recommendation model can not meet the increasing personalized needs of users. The single deep cross network model has some defects in music recommendation, such as poor stability and inability to process complex data. To overcome the shortcomings of existing models, a new hybrid music recommendation model combining CatBoost algorithm and deep cross network is constructed to improve the recommendation performance and better meet the individual needs of users. Then the performance of the hybrid model is compared with other algorithms. The results showed that the accuracy of the proposed hybrid algorithm was up to 92.7%, which was superior to the comparison algorithm. In comparison with other single model and hybrid model, it is found that the proposed model was more than 0.05% higher than other models in the four indices of AUC area, accuracy, precision and recall. The above results showed that the proposed hybrid music recommendation model could efficiently process data information and provide users with accurate personalized music recommendation. This study not only promoted the development of music consumption and creation, but also found that the CatBoost-DCN hybrid model was significantly effective in improving recommendation performance. This finding provides a more efficient recommendation strategy for music platforms and has far-reaching significance for improving user experience and satisfaction.

**Key words:** Music recommendation; CatBoost; DCN; Data modeling; Machine learning

**1. Introduction.** With the rapid development of the internet and mobile internet, music recommendation systems have become an indispensable part of the music industry [3]. Music recommendation systems can help users discover new music and increase user engagement on music platforms. The current music recommendation system mostly adopts collaborative filtering algorithm, which recommends music liked by similar users according to their historical behaviors and preferences [6]. However, traditional collaborative filtering algorithms ignore the emotional and stylistic characteristics of music, as well as the subtle preference differences of users, thus limiting the accuracy and personalization of the recommendation system (Sterman et al. 2021). To improve the quality and accuracy of music recommendation, a new hybrid recommendation model is proposed to meet the individual needs of users more comprehensively and accurately capture the emotional and stylistic characteristics of music. This hybrid recommendation model combines CatBoost algorithm and Deep Cross Network (DCN) model. Among them, CatBoost algorithm can balance personalized recommendation and music popularity, while DCN model can dig deeply into the emotion and style characteristics of music, and predict user preferences more accurately by integrating music metadata and historical behavior data of users [17, 13]. The innovation of this research lies in integrating CatBoost and DCN algorithms into the music hybrid recommendation model at the same time. Compared with the traditional recommendation system, it not only significantly improves the personalization and accuracy of recommendation, but also enhances the user experience and brings higher user stickiness and broader profit space to the music platform. This study has important implications for the development of music recommendation systems and also demonstrates the positive role of advanced technology in meeting social and cultural needs. The research is divided into four parts. The first part is to analyze the research status of DCN algorithm and music recommendation model. The second part describes CatBoost and the process of building a music recommendation model after merging with DCN. The third part is to compare and analyze the performance of CatBoost-DCN hybrid algorithm and CatBoost-DCN music recommendation model. The last part is the summary of the full text.

**2. Related Works.** In the era of big data and information, the growth of social media is accompanied by the rapid growth of a variety of data and information. In the context of imperfect information filtering

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mechanisms, how music users can obtain information of interest has become a major challenge for music recommendation systems. To effectively identify and predict the prone sites of cancer, Pandey developed an amino acid sequence feature model using a DCN. After cross validation, the results showed that the model could predict the prone sites of diseases with 81.6% accuracy [14]. To improve the detection accuracy of phishing websites, Anitha and Kalaiarasu proposed a phishing detection system based on mixed deep learning algorithm, and tested the detection system. The results showed that the accuracy of the detection system on phishing websites was much higher than that of the traditional detection model. It also had high robustness and strong prediction ability in distinguishing phishing websites from legitimate websites [1]. To obtain the optimal approximation error characteristics, [11] used DCN to correct the linear unit network. Experimental results showed that after being corrected by this network, the deep linear unit network with different depths exhibited non collinearity. To solve the problem of automatic recognition of different levels of glioma during brain tumor surgery, [2] proposed a deep learning model based on DCN automatic deep learning network. After sample experiments, the model classification produced a sensitivity of 88.9%, an F1 score of 0.906, and 100% specificity. To understand how the number and spacing of communities affect postal delivery, [16] used a mixed effects model based on CatBoost for detection and analysis. After analyzing the sampling points, the metacommunity structure was influenced by natural and human landscape scale variables. To overcome the overfitting problem caused by the small native language data set in the mixed speech environment, Gupta's team proposed a classification model based on CatBoost algorithm and fine-tuned it. The results showed that the model can effectively avoid the overfitting problem. [9]. In addition, for the problem that diabetes is difficult to predict accurately in the early stage, Jenefer and Deepa proposed a CatBoost classifier based on firefly optimization to predict diabetes. The comparison test between this classifier and other similar classifiers showed that CatBoost classifiers had higher accuracy and lower loss values [10].

In modern society, music plays an important role in relaxing the mood and bringing people beautiful enjoyment. However, due to the numerous categories and quantities of music itself, as well as the different personal preferences of the audience, music recommendation is very difficult. To classify music and effectively recommend it to users, Elbir A et al. constructed a new Deep Neural Network (DNN) model based on acoustic features of music to extract representative features. After training the dataset, the results showed that the model could effectively classify music types and recommend music [6]. In view of the problems of cold start and new user recommendation in music recommendation, Yadav et al proposed a self-focused deep music recommendation model based on MIDI content data, and tested the model. The results showed that this method could effectively improve the recommendation effect by using MIDI content information. It outperformed other advanced models in several comparisons [20]. To obtain the ideal sound of the most popular DJs in search tools and perform DJ classification, Ziemer et al. (2020) [24] constructed a model that includes third octave mixing analysis, peak factor meter, phase range, and channel correlation coefficient functions. Through machine learning experiments, it was found that the accuracy of model detection was 73% [3]. To calculate, model, and classify music emotional content, the Chapaneri team proposed a structured regression framework that uses a single regression model to model the potency and arousal emotional dimensions of music. After training the benchmark dataset, the proposed work achieved significant improvements in R2 of arousal and valence dimensions [24]. To avoid the "one size fits all" phenomenon in music recommendation, Jin et al. constructed a system to optimize user control level based on visual memory and music maturity features. After detecting the interactive visual design system model of the music recommendation system, the results showed that music complexity would enhance the impact of UI on perceptual diversity [4]. To solve the problems of cold start and content feature extraction in Music classification and recommendation, Mao et al proposed a music-CRN model to optimize classification and recommendation by learning audio content features. Empirical analysis of the model found that this method performed better in music classification and recommendation tasks than previous methods [12]. Aiming at the problem that the existing music recommendation system fails to fully capture the correlation between internal and external information, the Xu team proposed a hierarchical multi-information fusion recommendation method, and tested the method. The experimental results showed that compared with the baseline method, the method performed best on the NOWPLAYINGRS dataset. The validity and rationality of the model were verified [19].

Based on the above related studies and the comparison of the advantages and disadvantages of the proposed

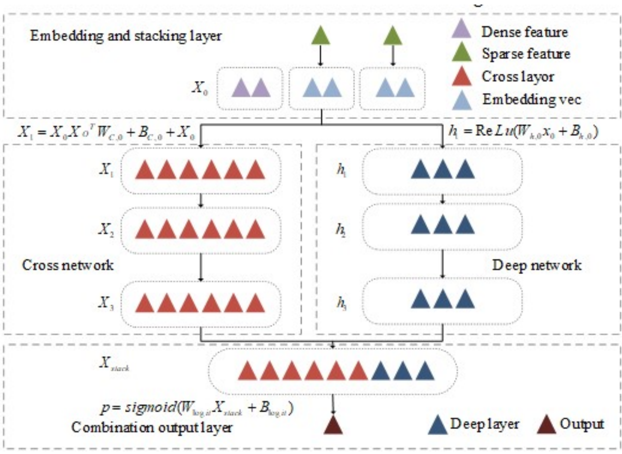


Fig. 3.1: Network model structure of DCN

method, Table 2.1 is obtained.

From Table 2.1, the proposed method integrates CatBoost algorithm and DCN model in the music recommendation system, aiming to meet users' individual needs more comprehensively and accurately capture the emotional and stylistic characteristics of music. The significant advantage of this method is that it can take into account both personalized recommendation and in-depth mining of music characteristics, so as to improve the accuracy and personalized degree of recommendation. Compared to the methods in other references, the proposed method focuses more on how to more accurately capture the intrinsic characteristics of user preferences and music. Although other relevant methods perform well in their respective fields, they have little to do with the direct application of the music recommendation system, and the methods applied in the field of music recommendation cannot meet the personalized needs of users. Therefore, the proposed music recommendation model based on CatBoost algorithm and DCN algorithm aims to fill the knowledge gap, and significantly improve the personalization and accuracy of music recommendation by integrating advanced algorithms, so as to enhance user experience and improve user stickiness of music platform.

## 3. Methods and Materials.

**3.1. Construction of a DCN-based music recommendation model.** DCN consists of a DNN and a Cross Network (CN) in parallel [7]. The drawback of traditional DNN is that only a combination of partial features can obtain better features, and its implicit learning features are inexplicable, resulting in low learning efficiency [23]. The main principle of DCN is to consider discrete and continuous features separately, encode and embed discrete features, and then concatenate and combine them with continuous features. The network model structure of DCN is shown in Figure 3.1.

From Figure 3.1, the original data in the DCN model is first divided into discrete and continuous features. Then at the embedding layer, the discrete features are transformed into real value vectors by building a random initialization vector lookup table. Subsequently, the transformed real value vector and the continuous feature are perfectly fused in the stacked layer to form the final output vector. This design not only optimizes the feature processing, but also improves the expressiveness and flexibility of the DCN model. The stacking function in the DCN model is shown in equation (1).

$$X_0 = \left[x_{\text{embed },1}^T \cdots, x_{\text{embed },k}^T, x_{\text{dense}}^T\right] \tag{1}$$

In equation (1), $x_{\text{embed },k}^T$ means the vector of the $k$ th feature after embedding operation; $x_{\text{dense}}^T$ denotes the transposed continuous value eigenvector; $X_0$ refers to both CN and DNN inputs. The DNN is composed of $n$ layer networks and is a fully linked neural network system. Each layer of the deep network can be represented

Table 2.1: Comparison of the advantages and disadvantages of the research methods in this paper with those in different references

| Author | Research method | Application field | Advantages | Disadvantages |
|---|---|---|---|---|
| Research in this paper | Music recommendation model integrating CatBoost and DCN | Music recommendation | Both personalization and music feature mining can significantly improve the personalization and accuracy of recommendation | / |
| Pandey [14] | Amino acid sequence feature model based on CatBoost | Disease prediction | High accuracy in predicting disease prone sites | Only applicable in the field of cancer prediction |
| Anitha and Kalaiarasu | Phishing detection system based on CatBoost | Phishing site detection | High accuracy, robustness and predictive power | The correlation with music recommendation system is weak It has little |
| Lu et al. [11] | DCN algorithm | Deep linear unit network correction | The corrected network has non collinearity | relevance to the application of music recommendation system |
| Bagyaraj et al. [2] | Deep learning model based on DCN | Automatic recognition of gliomas of different grades | High sensitivity, F1 score and specificity | Focus on glioma recognition, not music recommendation |
| Jenefer and Deepa [10] | CatBoost classifier | Diabetes prediction | High accuracy and less loss value | Applied to diabetes prediction, not directly related to music recommendation |
| Elbir A et al. [6] | DNN model based on acoustic features | Music classification and recommendation | Effectively classify and recommend music genres | Too much reliance on acoustic features |
| Yadav et al. [20] | Self-focused deep music recommendation model | Music recommendation | Effectively solve the problem of cold start and new user recommendation | Too much dependency on MIDI content data |
| Ziemer et al. [24] | Classification model based on third octave mixing analysis | DJ sound classification | Help with DJ retrieval tools | The accuracy rate is 73%, with room for improvement |
| Mao et al. [12] | Music-CRN model | Music classification and recommendation | The effect of music classification and recommendation is good | Rely on audio content feature learning |
| Xu et al. [19] | Hierarchical multi-information fusion recommendation method | Music recommendation | Fully capture information internal and external associations | Implementation can be complex |

by equation (3.1).

$$D_{l+1} = f\left(W_l D_l + B_l\right) \tag{3.1}$$

In equation (3.1), $D_l$ is the output of the previous layer network; $W_l$ indicates the weight term; $B_l$ denotes the bias term of bias, and ReLu is selected as the activation function $f; l$ represents the number of layers. If $d$ is set as the input dimension, the number of neurons in each layer is $m$, and there is a $l$ layer network, then the total parameter complexity of the DNN is shown in equation (3.2).

$$P(dl) = d \times m + m + \left(m^2 + m\right) \times \left(L_d - 1\right) \tag{3.2}$$

In this study, the CN is applied to the explicit feature cross, and the network output expression of each layer

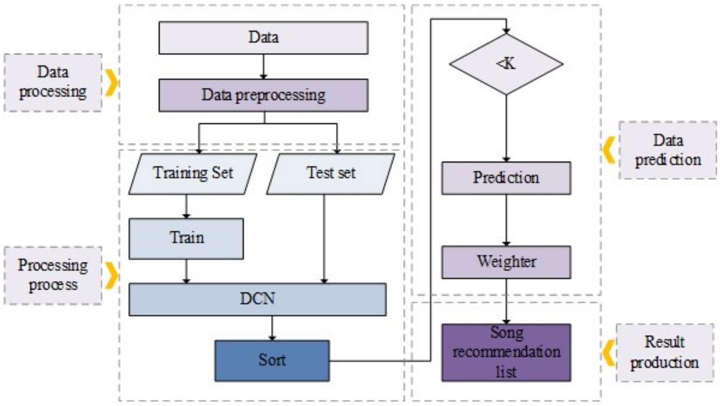


Fig. 3.2: Flow chart of music recommendation model based on DCN

is shown in equation (3.3).

$$x_{l+1} = x_0 x_l^T w_l + B_l + x_l \tag{3.3}$$

In equation (3.3), $x_l$ is the output of the previous layer network; $w_l$ and $B_l$ represent the connection parameters between the two layers of networks; $x_0 x_l^T w_l$ denotes the feature crossover completed in the $l+1$ layer, and all variables in the above equation are column vectors. The residual between the output of the fitting layer and the previous output, plus the input data $x_l$ of that layer, can be regarded as the residual of the two-layer network. Next, in the connection layer, the final outputs of the two networks are connected, and after weighted summation, the final probability value is generated by the Sigmoid function, as shown in equation (3.4).

$$x_{\text{stack}} = \operatorname{concat}\left(w\left[C_{L_1}^T, D_{L_1}^T\right]\right) \tag{3.4}$$

In equation (3.4), $C_{L_1}^T$ and $D_{L_1}^T$ are the outputs of the CN and $DNN$, respectively; $L_1$ and $L_2$ respectively mean the number of layers in two networks; $w$ expresses the weight parameter of the CN. DCN can learn the interactions between effective features and has lower computational costs. Therefore, the study applies DCN to music recommendation models to reduce the complexity of the music recommendation model. The flowchart of the music recommendation model based on DCN algorithm is shown in Figure 3.2.

From Figure 3.2, the music recommendation model based on DCN algorithm first needs to desensitize user information, extract hidden features of music from it, and build an information matrix. Then the music data set is split and passed into the DCN classifier for parameter setting. Parameters are initialized by equation (6) to reduce the dependence between parameters.

$$L = \operatorname{sqrt}\left(\frac{6}{n_{\text{input}} + n_{\text{output}}}\right) \tag{3.5}$$

In equation (3.5), $L$ indicates the range of uniform distribution; $n_{\text{input}}$ denotes the amount of input units for the weight tensor; $n_{\text{output}}$ represents the amount of output units of the weight tensor. Then at the connection layer, the Sigmoid function is used to calculate the probability output, the expression of which is shown in equation (3.6).

$$S(x) = \left(\frac{1}{1+e^{-x}}\right) \tag{3.6}$$

In equation (3.6), $S(x)$ means probability and $x$ indicates variable parameters. After the DCN model is constructed, the Adam optimizer is used to calculate the gradient of the loss function and update the parameters.

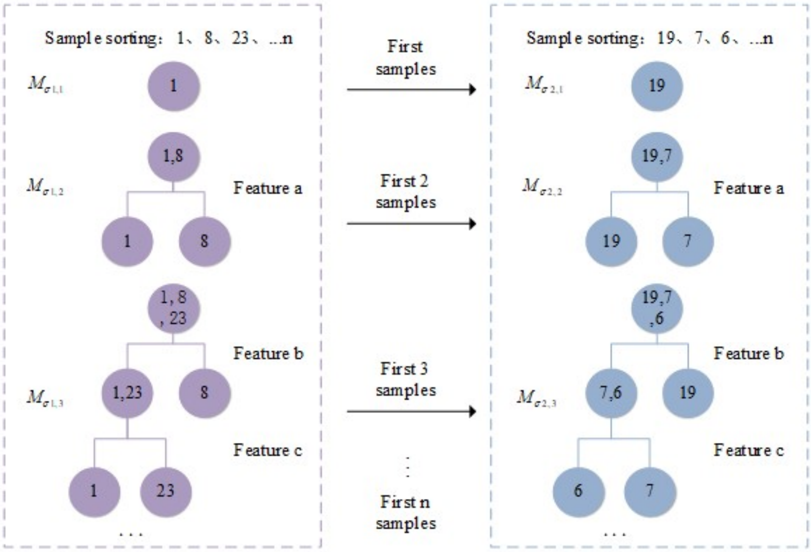


Fig. 3.3: CatBoost model structure

After the model configuration is completed, the number of iterations is set, the model is trained by the number of samples in each iteration, and the music recommendation list is finally obtained. Through the above steps, the music recommendation model based on DCN algorithm can recommend music according to the needs of different users, and ensure high recommendation accuracy.

**3.2. Design of a dual filtering music recommendation model integrating CatBoost and DCN.** In traditional DCN music model recommendations, the number of music songs is large, the types are diverse, and the duration is not uniform. Moreover, the DCN model cannot effectively process discrete features, making it difficult for the model to provide personalized recommendations for users [15, 22]. Based on this dilemma, the study integrates the integrated learning CatBoost classification model with the DCN to construct a music recommendation model based on the DCN-CAT algorithm. CatBoost is a type of decision tree that can efficiently and reasonably process categorical features, thereby improving the accuracy of the algorithm [8]. The CatBoost symmetric tree structure is shown in Figure 3.3.

From Figure 3.3, the core of CatBoost algorithm is the design of symmetric tree, and it will build an initial tree structure according to the selected sample in the first iteration, and then determine the value of each leaf node through calculation. This initial tree structure is reused in subsequent iterations to continuously optimize the model. The design form of CatBoost enables it to efficiently process category-type features, thus making up for the shortcomings of DCN model in processing discrete features, and finally forming a complete recommendation model through multiple iterations, improving the accuracy of music recommendation. At the same time, CatBoost proposed the use of TS-based ordered transport stream (Ordered TS) and a new classification feature processing algorithm to solve the problem of target leakage and prediction offset in Boosting algorithm, and improve training speed and accuracy. The Ordered TS coding principle is shown in Figure 3.4.

From Figure 3.4, in Ordered TS coding principle, the classification feature values of samples are converted into a sequential coding. For a particular sample, its coded value is calculated based on the sample that comes before it. When one of the classification features of the sample is the same as that of the previous sample, the corresponding Ordered TS encoding value is adopted.

This method can help solve the problem of target leakage and prediction deviation in Boosting algorithm, and improve the training speed and prediction accuracy of the model by considering the order relationship between samples. Ordered TS code principle in the sample $x_i$, under the classification feature $k'$ is $x_{i'}^{k'}$, and the

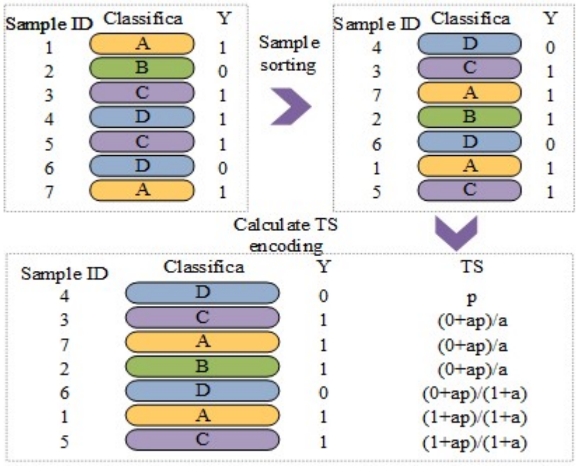


Fig. 3.4: Ordered TS encoding principle

encoding value of $x_{i'}^{k'}$ is calculated based on the sample $D_\sigma$ that ranks first in the value. The TS encoding value of the same sample as $x_{i'}^{k'}$ under the classification feature k in $D_\sigma$ is the Ordered TS encoding value. CatBoost uses the target count method in the gradient enhancement algorithm to group categories and estimate the expected target value of each category, processing classification features with minimal information loss. The specific equation for estimating the expected target is shown in equation (3.7).

$$\hat{x}_{k'}^{i'} \approx E\left(y/x = x_{k'}^{i'}\right) \tag{3.7}$$

In equation (3.7), $y$ means the expected goal. When the $i'$ feature values of other samples are equal to $x_{k'}^{i'}$, the expected value of this category is used to replace the $i'$ feature of the $k'$ sample, which means that the discrete feature is reassigned. Because $x_{k'}^{i'}$ is calculated from the target values of the samples, there will be conditional biases when splitting the test set and training set. The expression for obtaining a prior value is shown in equation (3.8).

$$P_1\left(y = 1/x^i = C\right) = 0.5 \tag{3.8}$$

In equation (3.8), $P_1$ denotes the TS value; $C$ indicates the category. Therefore, it assumes that there is a category feature with all feature values taking different values, the numerical values for replacing category features in the classification category are shown in equation (3.2).

$$\hat{x}_{k'}^{i'} = \frac{yC + aP_1}{1 + a} \tag{3.9}$$

In equation (), $a$ represents a constant, but for the test set, if all TS values are 0.5 , it is not possible to classify and predict the test data. Therefore, a threshold is used for classification, and the threshold expression is shown in equation (11).

$$t = \frac{0.5 + aP_1}{1 + a} \tag{3.10}$$

In equation (), $t$ denotes the threshold. Afterwards, the training samples are randomly sorted, and the prior values and weight coefficients of the prior values are added to the mean of the category labels before the samples, thereby reducing the impact of low-frequency category features. The expression for defining the encoding value

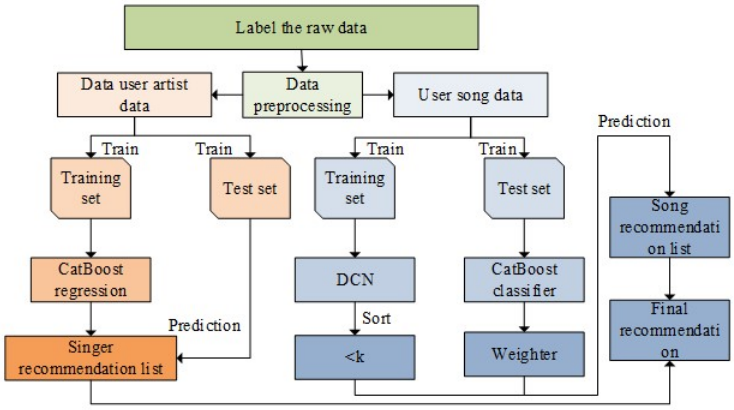


Fig. 3.5: Flow chart of hybrid recommendation model

is shown in equation (3.11).

$$\hat{x}_{k'}^{i'} = \frac{\sum_{x_j \in D_k} I\left[x_j^{i'} = x_{k'}^{i'}\right] \Box y_j + aP_1}{\sum_{x_j \in D_{k'}} I\left[x_j^{i'} = x_{k'}^{i'}\right] + a}, D_{k'} = \{xj : \sigma(j) < \sigma(k')\} \tag{3.11}$$

In equation (3.11), $D$ refers to all datasets available for model training; $D_{k'}$ indicates a subset of $D$; $\sigma$ represents a constructed random sequence; $y_j$ is the eigenvalues of sample $j$. To achieve more accurate and personalized recommendation algorithms, music recommendation is divided into two parts: song and singer recommendation. In the dataset prediction section, mixed classification models and regression models are used for prediction. This generates a music recommendation list for different users, and the hybrid recommendation model flowchart is shown in Figure 3.5.

From Figure 3.5, the hybrid recommendation model proposed in this study combines deep learning and machine learning technologies. The model achieves accurate recommendation through four main stages. The first stage is to label the raw data to extract key information and hidden features. In addition to basic song information and user behavior data, the research also focuses on users' historical listening records, song emotional labels, rhythms, genres and other additional information, so as to provide a more comprehensive view of user preferences and song characteristics, which is conducive to accurate recommendation in the future. At the same time, in the process, the research also extracts singer information from the original data, forms a new singer data set, and splits it into a training set and a test set. Then, in the second stage, the song training data is input into DCN and CatBoost classifiers for training and parameter tuning. DCN, with its powerful feature crossover ability, helps capture complex relationships between songs. In order to improve the generalization ability and accuracy of the model, additional information such as sentiment analysis data of songs, user comments, and community tags are also introduced at this stage of the study to enable the model to understand songs and user preferences from multiple dimensions. At the same time, the singer training set is input into the CatBoost regression model for training, which is able to efficiently process the classification features and prevent overfitting with specific enhancement techniques, thus ensuring the accuracy of the recommendations. In the third stage, the trained DCN model is used to predict the song test set, generate a list of predicted values, and set the filtering range to form a new data set. The trained CatBoost regressor is used to predict the score of the singer test set and generate the singer recommendation list. This process incorporates the user's recent listening behavior and feedback, which is used as an important reference for dynamically adjusting the recommendation list. Then, the CatBoost regressor is used to predict the score of the singer test set and generate the singer recommendation list. Finally, in the fourth stage, CatBoost classifier is used for secondary classification prediction, and additional information such as users' social network information and geographical location data is integrated in this stage, so as to provide users with more personalized and

Table 4.1: Performance comparison of various algorithms

| Dependent variable | Variable | Dependent variable | Variable |
|---|---|---|---|
| User information | User-id<br>Gender<br>Bd<br>City<br>Registered -via<br>Registration -time<br>Expiration-date | Operation information | User-id<br>Song-id<br>Source-screen-name<br>Source-system -tab<br>Source-type |
| Song information | Song-id<br>Genre-ids<br>Artist-name<br>Composer<br>Lyricist<br>Song-length<br>Isrc | Song additional information | Song-id<br>Name<br>Isrc |

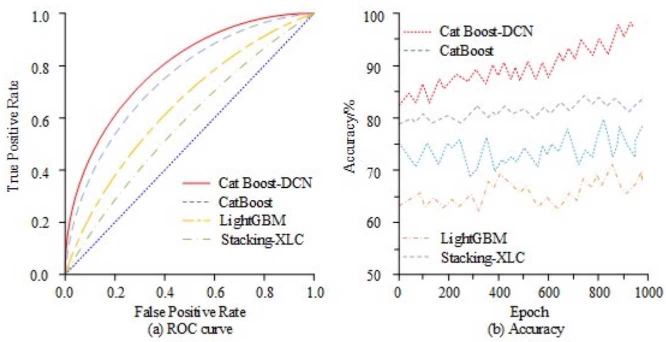


Fig. 4.1: ROC and accuracy of four algorithms results

localized music recommendations to further refine the recommendation results. Finally, the recommended list of songs and artists is combined to generate personalized music recommendations for users.

## 4. Results.

**4.1. Parameter design and performance evaluation of CatBoost-DCN.** After constructing the CatBoost-DCN hybrid music recommendation model, to verify the superiority of the constructed CatBoost-DCN algorithm, it attempted to compare CatBoost-DCN with CatBoost, LightGBM, and Stacking-XLC algorithms in the same dataset. The experimental dataset included four parts: user, song, operation and song additional information tables. The dataset variables for music recommendation are shown in Table 4.1.

Table 4.1 shows all the data sets involved in this experiment. The experimental data set included more than 2,000 user song operation records, data labels on whether users listen to songs repeatedly, 150 user attribute information and more than 1,000 song information, ensuring the comprehensiveness and diversity of the data. Then, the four algorithms were tested in the data set, and the ROC curve, accuracy rate, recall rate, error value and other indicators of the four algorithms in the data set were compared and analyzed. The comparison results of ROC curve and accuracy of the four algorithms are shown in Figure 4.1.

Figure 4.1 shows the ROC curves and accuracy plots of CatBoost-DCN, CatBoost, LightGBM, and Stacking-XLC algorithms. As shown in Figure 4.1 (a), compared to the other three algorithms, the CatBoost-DCN algorithm had a maximum area of approximately 0.85 in the ROC curve, while the other three algorithms had areas of $0.75, 0.53$, and 0.51, respectively. The results showed that CatBoost-DCN algorithm had higher

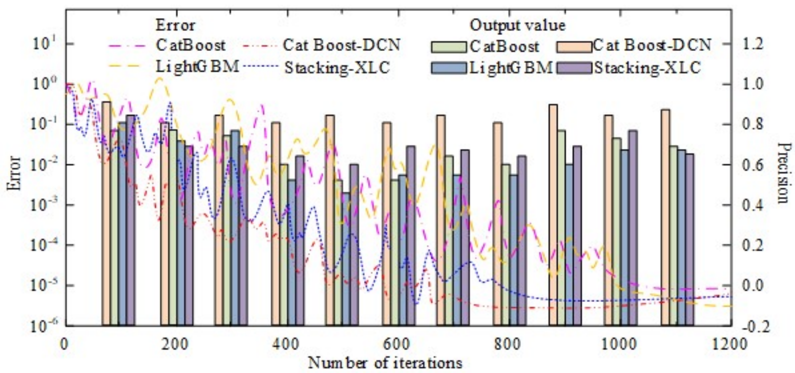


Fig. 4.2: Performance comparison of various models

performance in distinguishing positive and negative samples, and the classification effect was better. From Figure 4.1 (b), from the comparison results of algorithm accuracy, after stable training, CatBoost-DCN had the highest accuracy, at 96.13%, which was 19.91% higher than CatBoost, 29.69% higher than LightGBM, and 12.71% higher than Stacking-XLC. The results showed that the CatBoost-DCN algorithm performed well in the classification task and could correctly classify most samples into the correct categories. Therefore, from the two dimensions of area under the ROC curve and accuracy, CatBoost-DCN showed higher performance than the other three algorithms. This shows that the CatBoost-DCN algorithm can get more accurate classification results in practical applications. The advantages of CatBoost-DCN may come from its unique algorithm design and optimization strategies, which enable the algorithm to extract features more efficiently, reduce the risk of overfitting, and improve generalization ability when dealing with complex data. As shown in Figure 4.2, the error and accuracy of the four algorithms would be analyzed next.

Figure 4.2 shows the error and precision analysis of the four algorithms. The broken line section represents the error curve of the algorithm, and the bar chart section represents the precision of the algorithm. As shown in Figure 4.2, the training error of CatBoost-DCN, LightGBM, CatBoost, and Stacking-XLC was $0.013\%, 0.065\%, 0.034\%$, and $0.023\%$, respectively. The results demonstrated the high precision and low error of CatBoost-DCN algorithm in the process of model training, indicating that the algorithm can fit the data more accurately and reduce the prediction bias. In the precision comparison, CatBoost-DCN had an precision of 95%, approximately $19\%, 17\%$, and 10% higher than LightGBM, CatBoost, and Stacking-XLC, respectively. The results showed that CatBoost-DCN algorithm had excellent precision in classification tasks and could identify all kinds of samples more accurately. In summary, CatBoost-DCN is significantly better than the other three algorithms in the two key indicators of error rate and precision , which indicates that CatBoost-DCN algorithm can provide more precise and reliable classification results in practical applications. Next, the recall and accuracy of the four algorithms were analyzed and sorted, and the results are shown in Figure 4.3.

In Figure 4.3 (a) of the PR curve, the area of CatBoost-DCN was 0.89 , with the largest area, approximately 0.33 higher than LightGBM, 0.17 higher than CatBoost, and 0.11 higher than Stacking-XLC. The results showed that the CatBoost-DCN algorithm had excellent performance in the comparison of PR curves, and could identify positive samples more effectively while maintaining a low false positive rate. As shown in Figure 4.3 (b), the recall rates of CatBoost-DCN, LightGBM, CatBoost, and Stacking-XLC algorithms were $92.7\%, 71.1\%, 76.1\%$, and 83.2%, respectively. This data showeed that CatBoost-DCN algorithm could find out the real positive class samples more comprehensively and reduce the cases of missing reports in classification tasks. According to the comprehensive analysis of Figure 4.3(a) and Figure 4.3(b), CatBoost-DCN showed obvious advantages from the comparison results of PR curve and recall rate. This advantage may be due to its advanced algorithm design and fine parameter tuning, so that the algorithm can more accurately capture the internal structure of the data when dealing with classification problems, thus providing more reliable and comprehensive classification results. The results also further confirm that CatBoost-DCN algorithm is expected to obtain better classification

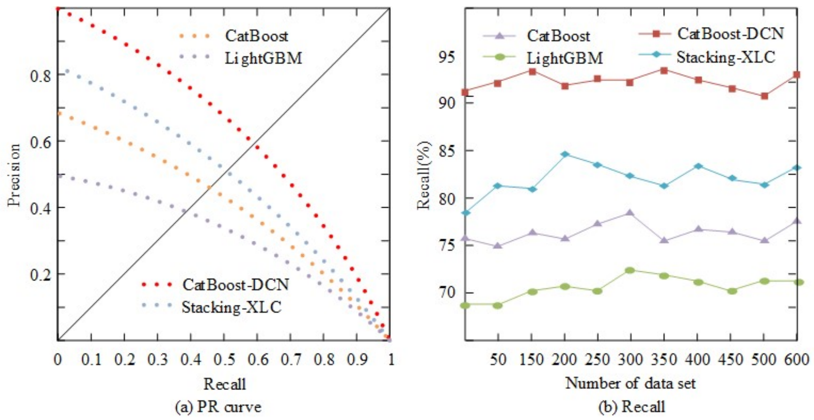


Fig. 4.3: Recall and precision of four algorithms

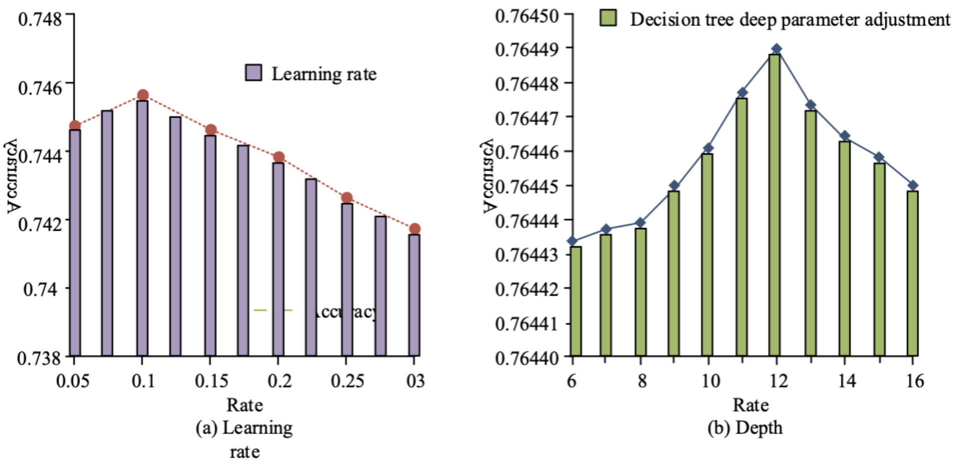


Fig. 4.4: Recall and precision of four algorithms

performance in practical applications.

**4.2. Evaluation of CatBoost-DCN recommendation model results.** To compensate for the low accuracy of a single algorithm, a CatBoost-DCN dual filtering music hybrid recommendation model was constructed. For the binary classification problem of the CatBoost-DCN hybrid model, four indicators, precision, recall, AUC, and accuracy, were used to evaluate and analyze the performance of CatBoost-DCN. To obtain the optimal model and parameters, the above four indicators were used as the evaluation criteria for the model, and testing was conducted based on learning rate and depth. The results are shown in Figure 4.4.

Figure 4.4 shows the final results of learning rate tuning and decision tree tuning. Figure 4.4 (a) shows that when the learning rate was 0.1 , the optimal model score was 0.7516 , and the overall learning rate showed a trend of increasing first and then decreasing. Figure 4.4 (b) indicated that when the decision tree depth was 12, the optimal model score could be obtained, which was 0.76449. When the decision tree depth was 6 , the model score showed an upward trend. When the decision tree depth was within the 9-12 range, the increase in model score significantly increased and reached the highest value. When the decision tree depth was after 12, the score showed a downward trend. The original test set consisted of 1342 pieces of data. The predicted values of CatBoost and DCN in the hybrid model were weighted and fused to obtain the final probability. The

Table 4.2: CatBoost-DCN parameter settings

| Song recommendation | | Singer recommendation | |
|---|---|---|---|
| Parameter name | Parameter value | Parameter name | Parameter value |
| Iterations | 1000 | Iterations | 600 |
| Depth | 12 | Depth | 8 |
| Learning_rate | 0.1 | Learning_rate | 0.2 |
| Eval_metric | AUC | Eval_metric | R2 |
| Max_ctr_complexity | 2 | | |
| Loss_function | Logloss | Loss_function | RESE |
| Boosting_type | Plain | | |
| 12_leaf_reg | 6 | 12_leaf_reg | 3 |
| Bootstrap_type | Bernou lli | Bootstrap_type | Bernou lli |
| Border_count | 31 | Border_count | 32 |
| One_hot_max_size | 255 | | |
| Random_seed | 123 | Random_seed | 123 |
| Task_type | GPU | Task_type | GPU |

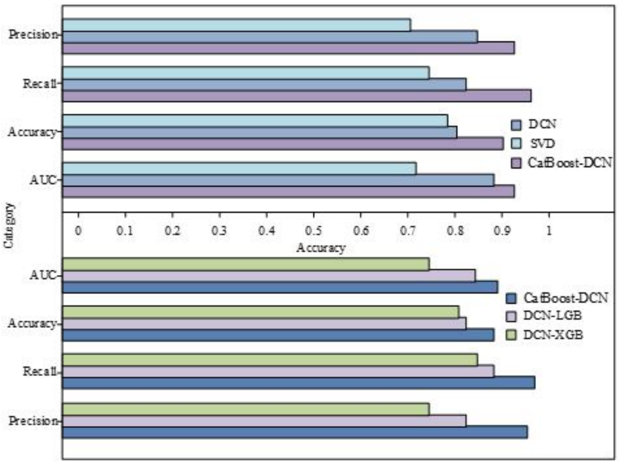


Fig. 4.5: Model comparison test

probabilities were then sorted to form a corresponding recommendation list, and finally recommendations were made to users. The optimal parameter settings for the CatBoost-DCN model for final singer recommendation and song recommendation are shown in Table 4.2.

Table 4.2 shows the CatBoost-DCN parameter settings. The number of trees in the song recommendation bar was 1000. When the depth of the tree was 12, the maximum feature combination tree was 2, the regularization coefficient was 6, the number of numerical feature divisions was 31, and the maximum number of unique hot codes was 255. The number of trees in the singer recommendation column as 600. When the depth of the tree was 8, the regularization coefficient was 3, and the numerical feature segmentation tree was 32. After the parameters were adjusted, the model was called to predict the test set, and the top eight singers with the highest scores were recommended to users. In addition, to further analyze the performance of the CatBoost-DCN model, a comparative analysis was conducted among the CatBoost-DCN hybrid model, the DCN model, and the SVD model. At the same time, to verify the superiority of CatBoost-DCN, models with different algorithms such as DCN-LGB and DCN-XGB were selected for comparison. The results are shown in Figure 4.5.

The bar chart in the upper half of Figure 4.5 shows the performance comparison results among DCN, SVD, and CatBoost-DCN models. The results showed that the AUC area of CatBoost-DCN was 0.93, the precision was 0.91, the accuracy was 0.95, and the recall was 0.92. The scores of CatBoost-DCN were higher than those of DCN and SVD models. Compared with the DCN model, the CatBoost-DCN hybrid model improved in all indicators, with an increase of approximately 7.2% in AUC, 3.4% in accuracy, 2.2% in precision, and 2.1% in recall. The above results showed that the combination of CatBoost and DCN could effectively improve the predictive ability and stability of the model. The lower half of Figure 10 shows the comparison of indicator performance among different mixed models. The AUC area of CatBoost-DCN was approximately 0.05% more than DCN-LGB and 0.15% more than DCN-XGB. The precision of CatBoost-DCN was approximately 0.07% higher than DCN-LGB and 0.09% higher than DCN-XGB. The accuracy of CatBoost-DCN was approximately 0.11% higher than DCN-LGB and 0.15% higher than DCN-XGB. The recall rate of CatBoost-DCN was approximately 0.16% higher than DCN-LGB and 0.23% higher than DCN-XGB. The above data fully proved the superiority of CatBoost-DCN hybrid model in various indicators. CatBoost-DCN showed strong prediction and classification ability both in the comparison of single models and in the competition of mixed models. To sum up, CatBoost-DCN hybrid model has significant advantages in the field of music recommendation, and its overall performance improvement is due to the perfect combination of CatBoost and DCN. The hybrid model can not only extract features more effectively and reduce the risk of overfitting, but also improve the generalization ability and prediction accuracy of the model.

**5. Discussion.** From the simulation results, CatBoost-DCN model showed significant advantages in several evaluation indicators. Compared with the other three algorithms (CatBoost, LightGBM, and Stacking-XLC), CatBoost-DCN had significant improvements in ROC curve area, accuracy, error rate, and precision. This is mainly due to CatBoost-DCN's unique algorithm design and optimization strategy, which enables it to extract features more efficiently, reduce the risk of overfitting, and improve generalization. The results of this study were significantly improved compared with the indicators of the music recommendation model proposed by Yun et al. [21]. In comparison with the DCN model and SVD model, CatBoost-DCN also showed excellent performance. The AUC area, accuracy, precision and recall rate were higher than those of the two models. In particular, compared with the DCN model, CatBoost-DCN improved in all indicators, with AUC improving by about 7.2%, accuracy by 3.4%, precision and recall by 2.2% and 2.1%, respectively. These results showed that the combination of CatBoost and DCN could indeed significantly improve the predictive power and stability of the model. The research results were compared with the research results of the music recommendation model proposed by Wang team in 2023, and it was found that the overall performance of the proposed model was better [18]. In addition, the performance of different hybrid models was compared. The results showed that CatBoost-DCN was superior to DCN-LGB and DCN-XGB models in AUC area, precision, accuracy and recall ratio. This result further confirmed the superiority of CatBoost-DCN hybrid model. Compared with other relevant studies, the application of CatBoost-DCN model in the field of music recommendation has significant advantages. This is mainly reflected in its overall performance improvement, including higher accuracy, lower error rate, and better generalization ability [5]. These advantages enable the CatBoost-DCN model to provide users with more accurate and personalized music recommendation services.

In summary, the CatBoost-DCN model shows excellent performance in music recommendation applications. Its advantages come from unique algorithm design and optimization strategies, which enable the model to extract features more effectively, reduce overfitting risks, and improve generalization ability when dealing with complex data. The results of comparison with other algorithms and models further confirm the superiority of CatBoost-DCN. Therefore, in the field of music recommendation, CatBoost-DCN model is expected to achieve better recommendation results and user satisfaction. In addition, because the CatBoost-DCN model performs well in processing complex data with a large number of category characteristics and numerical characteristics, it also has a wide range of application potential in other recommendation fields such as e-commerce product recommendation, video content recommendation, and social network friend recommendation.

**6. Conclusion.** The personalized demand for music recommendations from different users on music platforms is increasing, and traditional music recommendation models have shortcomings such as long-time consumption and insufficient personalization. This study attempted to integrate the CatBoost algorithm with DCN and constructed a CatBoost-DCN hybrid model to recommend personalized music to meet the needs of a large number of network users. During training, CatBoost, LightGBM, and Stacking-XLC algorithms were selected for performance analysis with CatBoost-DCN. In performance analysis, this model was superior to CatBoost, LightGBM and Stacking-XLC algorithms in ROC area, accuracy, error rate, recall area, and precision. Among them, the ROC area of CatBoost-DCN was 0.85 , the accuracy was 96.13%, the error rate was only 0.013%, the recall area was 0.89 , the precision rate was 95%. Compared with single and other models, CatBoost-DCN also performed well in AUC area, precision, accuracy and recall. The results above showed that the CatBoost-DCN hybrid model showed excellent performance in personalized music recommendation, which is significantly better than the traditional recommendation algorithm. This study found that by integrating CatBoost and DCN, the research successfully improved the accuracy and efficiency of the recommendation system, and effectively met the personalized needs of Internet users for music. However, there are also shortcomings in the research. At present, the CatBoost-DCN model does not take into account how user interests may change over time. Future studies can further refine the model by introducing techniques such as time series analysis to more accurately capture users' dynamic music preferences.

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