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Recursive Neural Network-based Audience Behavior Prediction Model in Music Communication in the Era of Integrated Media

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Abstract The rapid development of the era of melting media has made the dissemination and creation of popular music more free, thus promoting the combination of life and art, and further narrowing the distance between audiences and music creators. The article combs through the changes of popular music communication characteristics and interaction modes in the era of melting media, and explores the specific manifestations of audience behavior in the process of music communication. The audience participating in music short video communication in DY short video platform is taken as the research object, and its dynamic behavioral characteristics are captured to produce data for audience behavior prediction. Combining 3D-CNN network with GRU in recurrent neural network, Conv3D-GRU model was constructed for predicting audience dynamic behavior in music communication. The results show that compared with GMSDR, the RMSE and MAE of this paper's model are significantly improved by 13.08% and 14.77%, respectively, and the PCC value of the model can reach up to 97.79%.The Conv3D-GRU model possesses a better two-category error and accuracy, and the overall dynamic analysis efficiency reaches 87.44%. Combining neural network technology with music communication audience behavior prediction helps to expand the scope of music communication in the melting media environment.

Index Terms music communication, 3D-CNN network, recurrent neural network, Conv3D-GRU model, audience behavior prediction

I. Introduction

In order to ensure the survival of music culture, it needs to be fully disseminated, and only after dissemination can it be recognized and known by the public, and its dissemination needs the full support of the media. In the era of integrated media, Internet information technology and big data technology become the main medium of communication, which has a key role in promoting the inheritance and dissemination of music culture [1], [2]. The difference with the traditional media is that the specific communication process of music culture under the integrated media becomes no longer single, so that the immediacy of its communication is guaranteed, and the scope of communication is also wider, and the ways of communication are also more diverse [3]-[5]. The emergence of fusion media makes the original way of communication appear obvious changes, and makes the subsequent development of music culture face new challenges and opportunities [6].

In the traditional music recommendation rating model, users are generally asked to rate the music played, and by calculating the similarity between users or music sets, the user's interest preferences are defined by estimating the ratings of similar users on the music, and ultimately the recommended content is decided based on the ratings [7]-[9]. Due to the problems of missing user ratings and large subjective variability in this model, its music recommendation and prediction effect is not satisfactory [10]. In the face of the massive music products contained in the fusion media, the personalized music recommendation method based on user behavior has outstanding advantages [11]. By obtaining records of users' daily listening, playing, favoriting, and other operational behaviors, it taps into users' potential and fixed interests, and helps users quickly and accurately obtain music of interest from the music that springs up every day [12]-[14]. The process uses recursive neural networks to predict the user's behavioral type rather than music ratings, according to which music recommendations are made without requiring specialized knowledge as a prerequisite for recommendation [15], [16]. And this method starts from the user's implicit feedback information and focuses on mining the more fixed behavioral preferences and changing trends from the user's daily music playing data [17], [18]. In behavioral prediction, recurrent neural networks have a natural advantage, solving the problem of sparsity of data, which is conducive to improving the impact of prediction effect [19], [20].

Since the user's behavioral habits reflect the user's interest well, by analyzing the user's behavioral information, the user's potential psychology and interest intention can be mined. For this reason, related scholars have carried out research on audience behavior prediction based on recursive neural networks to provide assistance for music recommendation. Literature [21] uses recursive neural networks to establish a user behavior model based on music consumption items, and through semantic representation and feature capture, it can effectively predict the user's music preference in short-term or long-term time. Literature [22] studied the sequence modeling method based on recurrent neural networks, extended the sequence modeling of consumption items, and introduced a novel gated loop unit that represents user behavior, thus significantly improving the objective prediction performance of the recommender system. Literature [23] addresses the inefficient recommendation problem caused by heterogeneous music data and proposes to establish a user-music interaction network entity based on graphical, textual, and visual data, combined with a recurrent neural network with an attentional mechanism to obtain the user's short-term music preference, thus improving the music recommendation effect. Literature [24] examined two extraction techniques for obtaining music contextual information, in which the contextual information generated from long sequences of songs is improved by utilizing a dual recurrent neural network, which effectively improves the situational recommendation of music. Literature [25] proposes a recurrent neural network based session recommendation framework, while integrating session parallel system and ranking loss function to further improve the efficiency of user session based music recommendation. Literature [26] emphasizes that contextual information reflecting users' activities and moods will greatly improve the effect of music recommendation, and employs deep residual bi-directional gated recurrent neural networks to identify sensor-based user behaviors in order to carry out rhythmic music classification and recommendation in line with user behavioral preferences. Literature [27] not only considered user behavioral characteristics when constructing a music recommendation system, but also analyzed the user's listening audio history characteristics by building an AIN RNN network recommendation list with user profiles to achieve higher music recommendation accuracy. The user's operation, movement, and history of listening data can describe the user's behavioral characteristics for behavioral analysis, and the recursive neural network can provide the basis for music recommendation by discovering the patterns of the user's music playback.

Relying on the rapid development in the era of integrated media, popular music has penetrated into the public, which promotes the high-quality development and wide dissemination of popular music. The article proposes a Conv3D-GRU model that combines 3D-CNN and recurrent neural network, and applies it to the prediction of audience behavior for music dissemination in the melting media environment. Taking the audience related to music communication in DY short video platform as the research object, the audience behavior dataset is constructed through data crawling and preprocessing. Then modeling for the audience dynamic behavior characteristics in the process of music communication, so as to clarify the audience dynamic behavior prediction features. The 3D-CNN model is used to extract the audience dynamic behavior features, and combined with the GRU of recurrent neural network to capture the time-dependent and sequential features of the audience dynamic behavior data in the process of music dissemination, so as to realize the accurate prediction of the audience behavior in the process of music dissemination.

II. Dissemination of music and audience behavior in the age of integrated media

The high development of the Internet and computer technology has not only personalized the technology, media, channels and platforms of music communication, but also accelerated the efficiency of music communication and optimized the effect of music communication. The integration of music communication and new media technology under the environment of integrated media is becoming more and more common and in-depth, and the means, methods and forms of music communication have also undergone great changes as a result of integrated media. The audience needs to fully grasp the future direction of music communication in the melting media, and promote the high-quality development of music in the melting media in an all-round way.

II. A. Music Communication Characteristics and Interaction Patterns

II. A. 1) Characteristics of popular music communication

(1) Enhancing the speed and breadth of communication. In the era of integrated media, all kinds of new communication ideas, products and forms are emerging. Massive content storage, convenient social interaction, and efficient and rapid transmission performance have greatly improved the dissemination speed and breadth of popular music compared with the traditional media era. The popularization of fusion media technology has lowered the threshold of listening to music as well as music production and dissemination, and the all-round dissemination matrix created through websites, mobile terminals, short videos, and self-media can further enhance the breadth of music dissemination [28].

(2) Expanding communication channels and space. In the era of integrated media, the relationship between popular music and the public has also been transformed from one-way communication to multi-directional communication. Instead of only passively accepting it as in the past, the public can be more involved in the dissemination of popular music, become one of the disseminators of popular music, and even have an impact on popular music from the source.

(3) Refinement of communication circles and fields. The era of integrated media brings a huge amount of information, and people can quickly find what they are interested in through efficient and convenient information retrieval, which makes people with common interests quickly gather together to form a small circle, showing the trend of segmentation and verticalization. Driven by the segmentation of circles, popular music dissemination has begun to pay more attention to user thinking, and disseminate with users' preferences and needs.

II. A. 2) Interactive Modes of Popular Music

Popular music under traditional media is disseminated through traditional media such as radio and television, which in turn introduces popular music to mass consumers. Through traditional media, large-scale and orderly promotion can be carried out to the target audience, thus enhancing the popularity of pop music and increasing its influence. And in the melting media environment, with the rise of network media, pop music began to evolve towards interactive direction. The interaction of pop music based on melting media platform usually utilizes social media networks and other network media platforms to realize the sharing and discussion of songs, the classification of singers and songs, as well as the release of videos and pictures related to pop music, and so on, so that the audience can directly participate in the open network media platform interaction The audience can directly participate in the interactive discussion of the open network media platform. In essence, the interactive mode of popular music in the view of network media platform is mainly reconstructed from three aspects: interactive mode of music comment, interactive mode of music short video, and interactive mode of music live broadcast.

The new change and dissemination of popular music is inseparable from the development trend of integrated media, and the integration and crossover of the two is an important embodiment of the music culture and creative industry from traditional to modern. Nowadays, the interactive mode of music review, short video interactive mode and live interactive mode spawned by the network media environment are widely used, and the overall communication structure of the popular music system has changed significantly compared with the past. It is necessary to optimize the music environment, accurately locate the audience, innovate the communication content, integrate the network resources, collect the feedback data and other strategic directions together, to give full play to the positive promotion effect of network media on the development of popular music, and to lay a good foundation for the consolidation of the status of Chinese music.

II. B.Performance of Audience Behavior in Music Communication

II. B. 1) Transformation of the identity of the addressee

(1) The Internet has brought communicators and recipients closer together. The development of the interactive mode of music short video has even changed the identity of the recipients, who have become active from passive. In the era of integrated media, everyone is a transmitter and receiver, and the boundaries between transmitter and receiver are gradually blurred.

(2) The identity of recipients and communicators are converging. In the era of integrated media, many audience research results have shown that the identity of recipients and communicators are getting closer and closer. After creating media content, they share short videos through various social software, and in the process, they form their own communication channels. The interactive mode of music short video mainly focuses on the “short video + music” mode, and reduces the threshold of content production through the video processing tools on many applications, so that individuals or small teams of UGC (personal user content production) can produce PGC (professional content production) quality content, reflecting the strong attributes of content tools. The dissemination of music information in the melting media is two-way, and each audience is both the receiver and the disseminator of music information. Each person becomes the publisher of music information, expresses his or her own opinion and spreads the information he or she cares about in a personalized way. The change of audience identity enhances the interactivity of music communication, and also brings far-reaching effects on the construction of music communication ecosystem.

II. B. 2) Audience Cognitive Behavioral Performance

Music will form a cognitive effect in the process of dissemination, which is generated in the stage of people's use of APP and is greatly influenced by the agenda setting of short video platforms. For example, in the short video platform, in order to standardize the video release orientation and achieve the operational purpose of the video platform, it influences the user's choice by setting up assistants, topics, etc., so that the user establishes his or her own perception of the release of the popular music video, and forms a cognitive system of the popular music video oriented to the rules of the platform.

The formation of the music communication effect mainly comes from user behavior, the high frequency of user viewing, forwarding and liking frequently, will not only increase the communication effect, but also form a benign short video platform communication effect with the help of short video platform communication mechanism. Secondly, many audience groups in watching short videos, the platform will form a recommendation mechanism, this recommendation mechanism recommended to the user's information are oriented information, targeted, so the user will be caught in the cycle of watching the information, this phenomenon will promote the spread of short music videos, resulting in a strong dissemination effect. And this communication-oriented recommendation mechanism also provides a direction for the production of short music video communication, you can choose the audience style of music system when the music production, to promote the dissemination of music to provide favorable conditions.

III. Recursive neural network-based audience behavior prediction

The era of integrated media is characterized by immediacy, openness, freedom, diversification, convenience, massive information and integration. Digitalization, big data, mobile smart terminals and so on have had a profound impact on contemporary music communication activities, especially in the online and virtual characteristics of the viewing object, the universality of network communication and a tendency to data-oriented description of music communication activities, such as manifested in the music industry statistical research reports and so on. It is also worthwhile for us to rethink and apply new research concepts and methods to solve various problems in the field of audience behavior in the process of music communication and promote the construction of corresponding theories.

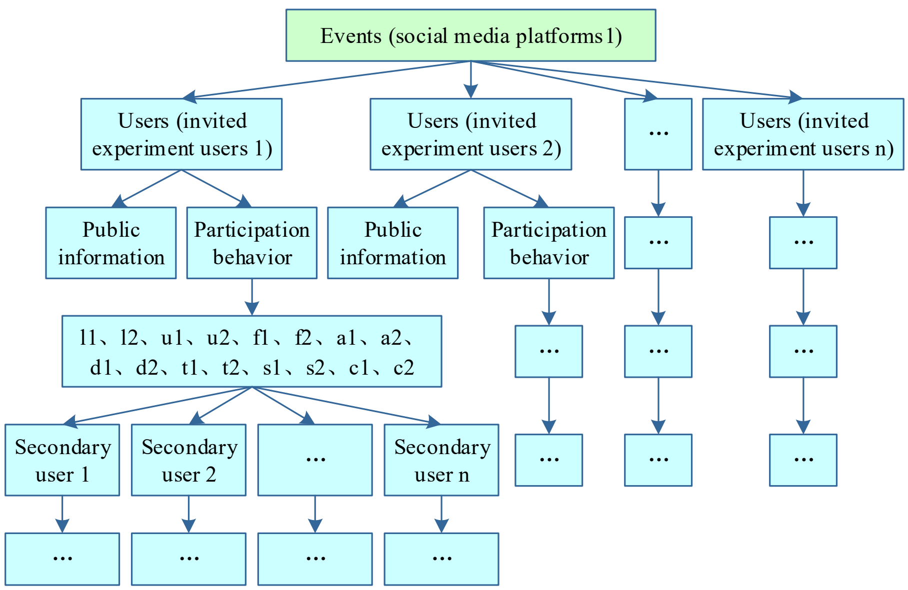


Figure 1: Audience behavior data fetching model framework

III. A. Data capture and pre-processing methods

III. A. 1) Audience Behavior Data Capture

In order to solve the problems of huge data volume and cleaning difficulty, this study carries out directed data capture for the research topic. Taking the user data of DY short video platform as an example, the event data, user data and user participation behavior data related to music dissemination in DY short video platform are directionally captured through questionnaire survey, observation experiment and web crawler. Event data refers to the relevant event data related to music dissemination. User data refers to the public data that can be captured from publishers, commenters, forwarders, etc. of events related to music dissemination, including user nicknames, genders, ages, number of friends/followers, label preferences and other related data. Participation behavior data refers to the platform's related like message content and quantity, posting content and quantity, commenting content and quantity, retweeting content and quantity, favoriting content and quantity, @ content and quantity, sharing content and quantity and other related data in music dissemination, with a total of seven different types of behaviors (BE1~BE7).

The data capture framework is shown in Figure 1, which can be divided into sub-modules such as events, users and engagement behaviors. As the basis of all subsequent models, the crawled data must be cleaned and pre-processed. In the process of data capture, due to the data originating from different platforms and other issues, there will be certain data garbled, duplicated, inconsistent format, default values, etc., so data cleaning is essential to ensure that the data is usable. For the captured dataset, the text, numbers and dates are organized by setting specific formats respectively. For the presence of spaces, the strip function is applied to remove them. The default values are uniformly dealt with by deletion.

III. A. 2) Preprocessing of behavioral data

In this paper, relevant music audience behavior data captured from the DY short video platform was comprehensively collected. In order to meet the in-depth analysis requirements of the study, a series of key steps, i.e., data cleaning and data preprocessing, are mainly executed. Data cleaning mainly includes the following steps:

(1) Remove duplicate data. Duplicate content in the dataset was checked and duplicate comment information posted by the same user at the same time was removed to ensure the uniqueness of the data. The de-duplication of data is realized by writing Python code, if there is a situation where the same user posts the same content at the same time, only the first data is retained and all the duplicated data after that is deleted.

(2) Traditional to Simplified Chinese. Use Python's OpenCC library to realize the conversion of Chinese Traditional to Simplified Chinese, OpenCC is an open source Chinese Simplified-Traditional conversion project, which supports character-level and vocabulary-level Traditional-Simplified conversion.

(3) Dealing with missing values. Check whether there are missing values in data items such as “user name”, “comment time”, “comment content”, etc., and delete the data containing missing values.

(4) Remove irrelevant content. Remove data not related to music dissemination events, such as advertisements, links, and non-text content.

(5) Text normalization. Convert audience behavior text data into a uniform format, such as removing redundant spaces, useless punctuation marks, etc.

On the basis of data cleaning, duplicate text data is removed by mechanical compression de-lexing, and a customized word list of participle words is established to ensure the accuracy of subsequent text segmentation. Combined with the Jieba module in Python and the customized lexicon, we realized the lexicon of music audience behavior data. The deactivated word list of Baidu, deactivated word list of HIT, deactivated word list of Chinese, and deactivated word database of Machine Intelligence Laboratory of Sichuan University were also collected, and the deactivated word list of this experiment was formed by merging and de-weighting. Finally, the deactivation word processing of music communication audience behavior text is realized by combining the deactivation word list [29].

III. B. Modeling Audience Behavior in Music Communication

III. B. 1) Key factors in audience behavior

In the prediction of audience behavior based on social platforms, the primary problem is to excavate the correlation factors related to the audience's music communication impact, and then to build the music communication impact calculation model and communication model based on these factors. Therefore, which factors to mine and how to model and calculate music communication impact are the main issues. First, from the input data, including social relationships, user preferences and basic user information, the factors related to the user's music communication influence are mined, which are expressed as mathematical expressions:

$$g\left(G,P,U_{profile}\right)\Rightarrow\left(f_1,f_2,\cdots,f_k\right) \tag{1}$$

where G represents the music dissemination network, including nodes and user relationships, and P represents user preferences, such as user tags, keywords, and participation topics can be used as user preferences. $U_{profile}$ represents the basic information of the user, including gender, age, occupation and so on. With this information, relevant factors can be mined to describe the user's music communication influence, such as the degree of the user, topic distribution, etc.

Utilizing the mined relevant factors, the music spreading influence calculation and spreading model is constructed to get the social music spreading influence of users on each other, i.e.:

$$f\left(f_1,f_2,\cdots,f_k\right)\Rightarrow SI \tag{2}$$

where SI then represents the mutual social music dissemination influence matrix between users as an N-dimensional square matrix, N represents the number of users, and its element (i,j) represents the amount of influence that user u_i receives from user u_j, and in general (i,j) is not equal to (j,i) because the mutual influences of the users are asymmetric for the most part of the user.

III. B. 2) Dynamic Behavioral Prediction Characteristics

The Common Neighbors metric assumes that the similarity between two audiences is proportional to the number of common neighbors they have, and the Salton metric adds the degree information of two users to the Common Neighbors metric [30]. In this paper, the ratio of audience inbound link and outbound link metrics is used to reflect the user characteristics, and it is used as the Salton independent standard eigenvalue within an independent time slice. According to the dynamic characteristics of the music short video platform, this paper regards it as a dynamic time-slice stream, where each time-slice represents a day and the longer a time-slice is, the more important it is. Then the calculation of Salton values of user u and user v on the i th time slice t_i is denoted as:

$$Sa(u,v,t_i)=\frac{\left|\Gamma^{in}(u,t_i)\cap\Gamma^{in}(v,t_i)\right|\Big/\sqrt{\left|\Gamma^{in}(u,t_i)\right|\times\left|\Gamma^{in}(v,t_i)\right|}}{\left|\Gamma^{out}(u,t_i)\cap\Gamma^{out}(v,t_i)\right|\Big/\sqrt{\left|\Gamma^{out}(u,t_i)\right|\times\left|\Gamma^{out}(v,t_i)\right|}} \tag{3}$$

where $\Gamma^{in}(u,t_i)$ and $\Gamma^{in}(v,t_i)$ are the set of inbound linked users on time slice t_i for user u and user v respectively, and $\Gamma^{out}(u,t_i)$ and $\Gamma^{out}(v,t_i)$ are the set of outgoing linked users on time-slice t_i for user u and user v, respectively. The incoming and outgoing links are determined by the attention relationship between users, and $|\cdot|$ denotes the number of elements in the set. Then, the Salton values of user u and user v on the time-slice stream $[0,t_n]$ are computed as:

$$Sa^{[0,t_n]}(u,v)=\sum\nolimits_{i=0}^{n}\beta^{n-i}\times Sa(u,v,t_i) \tag{4}$$

where $\beta\in[0,1]$, β^{n-i} denotes the weight of time-slice t_i, and n denotes the total number of time-slice contained on time-slice stream $[0,t_n]$.

The interaction frequency of user u and user v on the i th time slice t_i is calculated as:

$$Fre(u,v,t_i)=\frac{c(u,v,t_i)}{p(u,t_i)+p(v,t_i)} \tag{5}$$

where $p(u,t_i)$ and $p(v,t_i)$ denote the total number of music dissemination topics posted by user u and user v on t_i, respectively, and $c(u,v,t_i)$ denotes the total number of interactions between user u and user v on t_i (one interaction is one time for one user to retweet a topic posted by another user). According to the dynamic nature of social platforms, similar to the dynamic Salton metric feature computation on the time-slice stream $[0,t_n]$, in this paper, we denote the weight of time-slice t_i by the same β^{n-i}, then, on the time-slice stream $[0,t_n]$, the dynamic interaction frequency of user u and user v is calculated as:

$$Fre^{[0,t_n]}(u,v)=\sum_{i=0}^{n}\beta^{n-i}\times Fre(u,v,t_i) \tag{6}$$

In this paper, whether or not the social platform contains a URL is used as a user dynamic posting content feature, then the URL feature of user u on the i th time slice t_i is calculated as:

$$isURL(u,t_i)=\frac{url(u,t_i)}{p(u,t_i)} \tag{7}$$

where $p(u,t_i)$ denotes the total number of music dissemination topics posted by user u on t_i, and $url(u,t_i)$ denotes the total number of topics containing URLs posted by user u on t_i. According to the dynamic characteristics of music propagation on social platforms, similar to the calculation method of the Salton metric feature dynamic on the time slice stream $[0,t_n]$, this paper uses the same β^{n-i} to represent the weight of the time slice t_i, then, on the time slice stream $[0,t_n]$, the URL feature calculation formula of user u is as follows:

$$isURL^{[0,t_n]}(u)=\sum\nolimits_{i=0}^{n}\beta^{n-i}\times isURL(u,t_i) \tag{8}$$

In addition, in this paper, whether the social platform contains Hashtag or not is also considered as one of the user's dynamic posting content features, and the Hashtag feature of user u on the i th time slice t_i is computed as:

$$isHashtag(u,t_i) = \frac{hashtag(u,t_i)}{p(u,t_i)} \tag{9}$$

$hashtag(u,t_i)$ indicates the total number of hashtags in music communication topics posted by user u on t_i. According to the dynamic characteristics of music transmission on social platforms, similar to the calculation method of the dynamic Salton metric feature on the time slice stream $[0,t_n]$, this paper uses the same β^{n-i} to represent the weight of the time slice t_i, then, on the time slice stream $[0,t_n]$, the calculation formula of the hashtag feature of user u is as follows:

$$isHashtag^{[0,t_n]}(u) = \sum\nolimits_{i=0}^{n} \beta^{n-i} \times isHashtag(u,t_i) \tag{10}$$

III. C. Prediction of audience's music communication behavior

III. C. 1) Three-Dimensional Convolutional Neural Networks

Convolutional neural networks (CNNs) usually consist of an input layer, a convolutional layer, a pooling layer, a fully connected layer, and an output layer [31]. The details are as follows:

(1) Input layer. Input to the network model, preprocessed data or raw data are applicable.

(2) Convolutional layer. Typically, the convolutional layer is composed of several convolutional kernels. Convolution is the weighted summation of input data using convolution kernels, which are used to compute different feature maps. Convolution of different dimensions is used to process data of different dimensions. Convolution consists of two parts: computing the inner product product of a matrix and summing the inner product product. The procedure of the convolutional layer is as follows:

$$x_j^l = f\left(\sum\nolimits_{i\in M_j} x_i^{l-1} * W_{ij}^l + b_j^l\right) \tag{11}$$

where f denotes the activation function, W_{ij}^l represents the weight corresponding to the convolution filter at the l th layer (i,j) position, b_j^l denotes the bias, x_i^{l-1} represents the feature maps obtained in the previous layer, M_j is a set of feature maps, and x_j^l it is a feature map of the current layer.

3D Convolutional Neural Network (3D-CNN) uses 3D convolutional kernels with more depth channels than 2D convolution. It requires the depth of the filter to be less than the depth of the input layer, that is, the number of convolution kernels is less than the number of channels in the input layer.3D-CNN requires sliding the input layer in the three directions of length, width, and height, and getting a value for each slide. In the filtering process, the 3D structure is also generated.

(3) Pooling Layer. Pooling layer is usually used for downsampling, by pooling layer, the size of the representation space can be reduced and the network training speed can be improved. There are two common pooling methods, average pooling and maximum pooling. Average pooling refers to taking the average of all elements of each subdomain, while maximum pooling refers to selecting the maximum value of each subdomain element.

(4) Fully Connected Layer. The Fully Connected (FC) layer can integrate the class-distinctive local information in the convolutional or pooling layers and map it into the sample labeling space. To enhance the nonlinear capability of the network, the fully connected layer uses the ReLU activation function. The fully connected layer can be realized by convolution operation, which can be transformed into a convolution with a convolution kernel of 1x1 for the fully connected layer that is fully connected in the previous layer.

(5) Output layer. The output layer is used to output the final classification result of the convolutional neural network, and its output neurons are generally connected to the neurons of the previous layer through the fully connected form, and then SoftMax is used to classify them.The expression formula of SoftMax is as follows:

$$\hat{y}_j = soft\max(z_j) = e^{z_j} \Big/ \sum k^{e^{z_j}} \tag{12}$$

where $\hat{y}_j$ is the predicted output, z_j denotes the feature value of the current layer, and k denotes the number of categories.

III. C. 2) Door control neural network unit

Recurrent neural network (RNN) is connected by a set of recurrent nodes, which is usually used to deal with data with temporal characteristics, compared with the traditional artificial neural network, RNN is able to solve the problem of unidirectional transmission between neurons, so that the historical data also play a role. A cyclic recursive approach is used to compute the neurons, and the results of the weights computed by the node neurons are passed backward to realize the information update and computation.

Gated Recurrent Unit (GRU) is also a kind of recurrent neural network, derived from the improvement of Long Short-Term Memory (LSTM) neural network, which inherits the advantages of LSTM in long-term temporal data processing [32]. However, unlike the LSTM network, the GRU structure has fewer gates within it and has a simpler structure, containing only update gates and reset gates.The output gates are removed from the GRU structure, and the input and forget gates of the LSTM network are integrated into the update gates.

The GRU update gate controls what information needs to be retained for the current moment information input, and the reset gate fuses the previous moment information with the current moment information and decides what information will be discarded, with larger values indicating that less information will be lost from the neuron.

To calculate the update gate and reset gate information, it is necessary to combine the hidden layer unit state output H_{t-1} at the previous moment and the information input X_t at the current moment, and use the activation function to calculate, the specific calculation process is as follows:

$$Z_t = \sigma\left(W_Z \cdot \left[H_{t-1}, X_t\right]\right) \tag{13}$$

$$R_t = \sigma\left(W_r \cdot \left[H_{t-1}, X_t\right]\right) \tag{14}$$

$$H_{t'} = \tanh\left(W_h \cdot \left[R_t \cdot H_{t-1}, X_t\right]\right) \tag{15}$$

$$H_t = \left(1 - Z_t\right) \cdot H_{t-1} + Z_t \cdot H_t' \tag{16}$$

where Z_t is the update gate, σ is the activation function, W_Z is the update gate weight, H_{t-1} is the hidden layer unit state output at the previous moment, X_t is the information input at the current moment, R_t is the reset gate, W_r is the reset gate weight, and H_t is the hidden layer unit state output at the current moment. $H_{t'}$ is the current moment hidden layer update unit state.

GRU inherits the advantages of LSTM to solve the problem of gradient vanishing and gradient explosion of RNN model, meanwhile, the parameters are less, the structure is simpler, and the time consumed will be shorter in the process of modeling operation.

III. C. 3) Audience Behavior Prediction Models

In order to effectively capture the audience behavior features in the audience behavior text data in the process of music dissemination and its changing law over time, this paper proposes a hybrid convolutional-recurrent neural network (Conv3D-GRU) model, which is framed as shown in Fig. 2.The structure of the Conv3D-GRU model consists of 5 layers of 3D-CNN, 1 layer of GRU, and 1 layer of fully-connected layer, which takes the dynamic behavioral prediction features of the audience in the process of music dissemination as the inputs. The model takes the dynamic behavioral prediction features of the audience in the process of music dissemination as input, and the spatial features and temporal dependence of the audience behavioral data in the process of music dissemination can be learned by combining 3D-CNN and GRU.

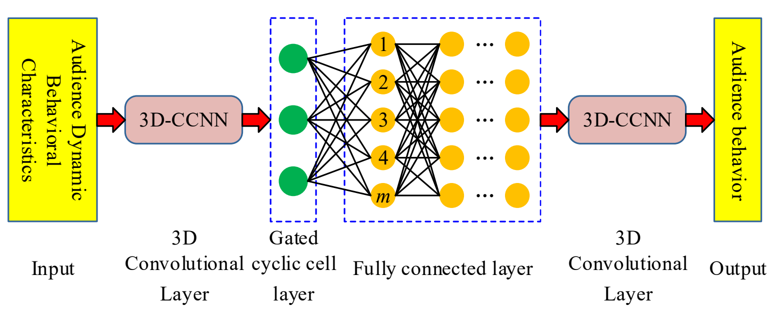


Figure 2: Conv3D-GRU model architecture diagram

(1) 3D-CNN layer. The data of audience behavior during music dissemination show obvious usage differences under different time periods, and 3D-CNN is chosen to effectively process this temporal information.Specifically, the model inputs the processed tensor data into the 2-layer 3D-CNN for identifying and extracting the trends, regularities and features of audience behavior changes over time. A series of feature mappings are computed by performing sliding convolution operations on the date and hour indexes to capture the regularity of the data over time, thus learning the changes in audience behavior over time during music dissemination. Finally, a 3-layer 3D-CNN is introduced to further extract more advanced spatio-temporal features. The hierarchical feature extraction process captures the spatio-temporal complexity of the audience behavior data in a deeper way, which enables the model to more accurately predict audience behaviors during music dissemination.

(2) GRU layer. Audience behavior in the process of music dissemination is not only related to spatial factors, but also closely related to time. For this reason, the model introduces a GRU layer to capture the dynamic changes and long-term dependencies in the time series data. Specifically, after the spatial features are extracted through the 3D-CNN layer, the GRU is introduced to identify the behavioral features in different time periods in the audience behavior data in the music dissemination process, so that the model is able to comprehensively capture the temporal dependence of the audience behavior in the music dissemination process.

(3) Full connectivity layer. The fully connected layer is mainly used to convert the time series features processed by the GRU layer into high-dimensional feature vectors suitable for further processing, so as to enhance the model's ability to capture the details of changes in audience behavior during the music dissemination process.

IV. Predictive validation analysis of the audience's music communication behavior

Under the current environment of integrated media, the way, platform and content of music dissemination have undergone a great transformation, and integrated media has become an important tool for modern popular music dissemination. The audience's behavior of music communication in the era of integrated media has also become an important driving force to promote the innovative development of popular music. Therefore, it is necessary to adapt to the development of the melting media environment, use new media to innovate the path of music communication, and actively explore the trend of audience behavior in the process of music communication under the melting media environment, so as to promote the innovative development of popular music.

IV. A. Validation and analysis of the validity of the model

IV. A. 1) Effectiveness of 3D-CNNs

In this paper, in the prediction of audience behavior in the process of music dissemination, the predicted features of audience's dynamic behavior are used as inputs, and 3D-CNN is introduced to extract features from them as a means to for predicting the dynamic behavior of the audience. In order to verify the effectiveness of the 3D-CNN model, this paper compares the performance of the model in four cases: CNN, 1D-CNN, 2D-CNN and 3D-CNN. For its performance evaluation, this paper chooses five metrics, MSE, MAE, MAPE, RMSE & R2, for evaluation.

Using the previously captured data about audience behavior in music communication on the DY short video platform as the basis, the validation of the model is carried out, and Figure 3 shows the performance comparison results of 3D-CNN. As can be seen from the figure, the results of the overlapped convolutional neural network compared to the original CNN in the five indicators have different degrees of improvement, the 3D-CNN proposed in this paper in the MSE, MAE, MAPE, RMSE and R2 evaluation indexes are better than the non-stacked CNN, where the values of the MSE, MAE, MAPE, and RMSE were reduced by 41.71%, 38.93%, 38.93%, 40.08%, 28.91%, and 28.91%, respectively, 40.08%, 28.91%, and the R2 value is improved by 14.11%. This shows that the 3D convolutional neural network has a strong ability to extract features, can well extract the text features of the audience dynamic behavior data in the process of music dissemination, so that the learned text features are more accurate, and provide reliable results of audience behavior feature extraction for accurate prediction of the audience dynamic behavior in the process of music dissemination.

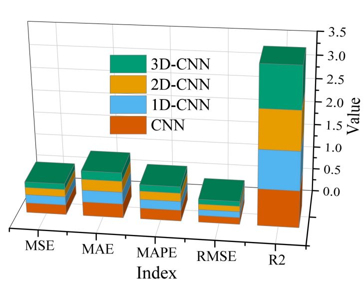


Figure 3: 3D-CNN performance comparison results

IV. A. 2) Hyperparametric effects of models

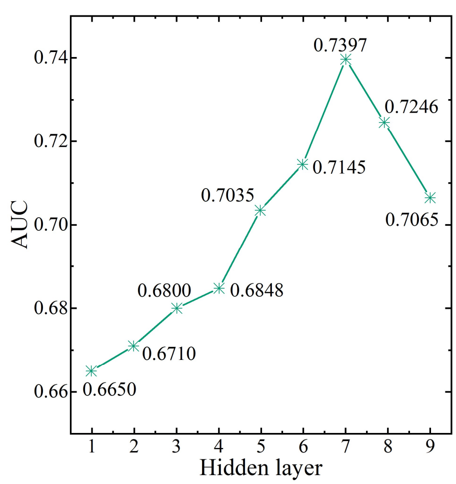
For the Conv3D-GRU model proposed in this paper, in which the number of hidden layers, the number of hidden units, the embedding dimension and the number of Epoch rounds all have an impact on the prediction results of audience dynamic behavior. In order to be able to ensure the best prediction results of the Conv3D-GRU model, it is necessary to study the specific effects of hyperparameters on the Conv3D-GRU model through several experiments, so as to determine the best hyperparameters. The audience dynamic behavior data during music dissemination collected in the previous section were divided into training and test sets in the ratio of 8:2, and the Conv3D-GRU model was tested for the number of hidden layers, the number of hidden units, the embedding dimensions, and the number of Epoch rounds, respectively, and the AUC was chosen as the evaluation index. Fig. 4 shows the test results of the model hyperparameters, where Figs. 4(a)~(d) show the test results of the number of hidden layers, the number of hidden units, the embedding dimension and the number of Epoch rounds, respectively.

(1) In the comparison experiments, the number of hidden units per layer is set to 250, and the number of hidden layers is increased from 1 to 9 respectively to verify the effect of the number of hidden layers on the prediction results of the model. From the figure, it can be seen that the model predicts the best results when the number of hidden layers is 7. If the number of hidden layers continues to increase, the effect of the model is decreasing, which is due to the fact that as the number of hidden layers is too large it leads to an overly complex model structure, as well as too many parametrics, which produces the phenomenon of overfitting.

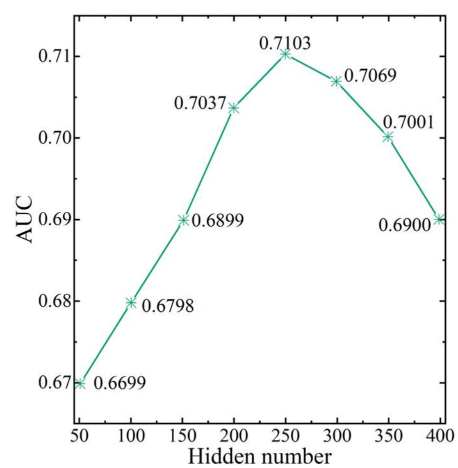
(2) After determining the optimal number of hidden layers, this section conducts multiple sets of experiments on the number of hidden units, increasing the number of hidden units setting from 50 to 400, to verify the effect of the number of hidden units on the prediction results of the model. Generally speaking, the increase in the number of hidden units makes the model fit the features better, but every model has its upper performance limit, and after reaching the upper limit, the model cannot be further improved by increasing the number of hidden units alone. On the contrary, more hidden units will bring more training overhead, resulting in slower iteration process and overfitting phenomenon. From Fig. 4(b), it can be seen that the Conv3D-GRU model learns best when the number of hidden units is [250,250,250].

(3) In this section, multiple sets of experiments are conducted on embedding dimensions, which are set to 2, 4, 8, 16, 32 and 64 to verify the effect of embedding dimensions on the prediction results of the model. From Fig. 4(c), it can be seen that the Conv3D-GRU model increases the number of embedding layers with the increase of embedding dimension, which improves the generalization ability of the model and the prediction accuracy of the model, and the best effect is achieved when the embedding dimension is 16, and the effect becomes worse when the embedding dimension is further increased.

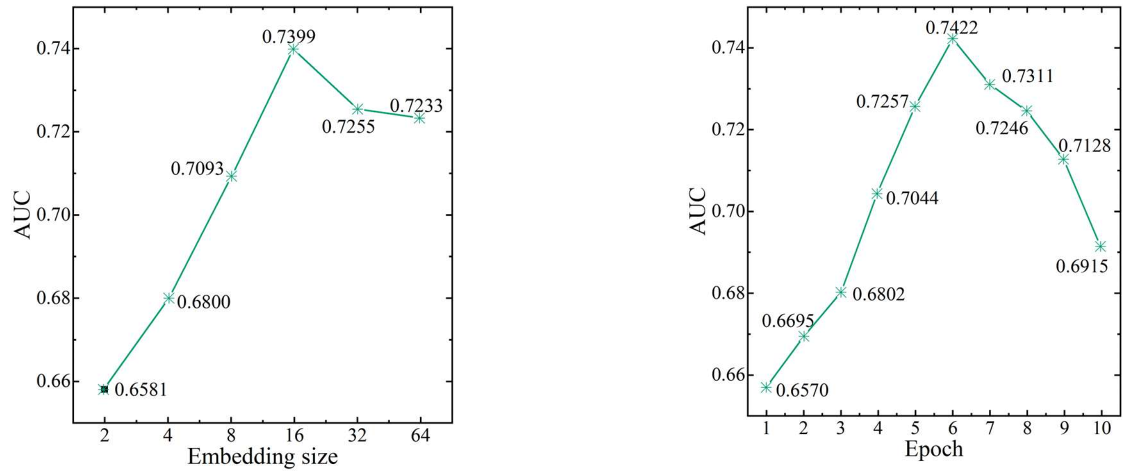
(4) In this section, multiple experiments are conducted on the number of Epoch rounds, and the embedding dimensions are set to 1~10 respectively, to verify the effect of the number of Epochs on the prediction results of the model. From Fig. 4(d), it can be seen that the Conv3D-GRU model works best and has the highest prediction accuracy (AUC=0.742) when the number of Epoch rounds is 6, and the effect becomes worse when the number of Epoch rounds continues to increase.



(a) Hidden layer



(b) Hidden number



(c) Embedding size

(d) Epoch

Figure 4: Test results of model super parameters

IV. B. Predicting Audience Behavior in Music Communication

IV. B. 1) Audience Behavior Confusion Matrix

In this section, this paper evaluates the performance of the models by randomly dividing the datasets into training and validation sets in a ratio of 7:3, and performing iterative validation and learning of the Conv3D-GRU models. In this paper, these datasets were adapted to use hyperparameters such as automatic learning rate reduction to find the optimal learning rate, a strategy to stop training early, the Adam optimizer, and L2 regularization to obtain better parametric models as well as to prevent overfitting phenomena, which leads to more accurate results. Based on the hyperparameter test results in the previous section, the optimal model environment configuration is chosen after evaluation as it has been tested to have better performance.

For the dynamic behavior of the audience in the process of music dissemination, this paper classifies and differentiates the data when performing data capture, i.e., the user's data related to the platform's liking information content and quantity, posting content and quantity, commenting content and quantity, retweeting content and quantity, favoriting content and quantity, @content and quantity, and sharing content and quantity of the platform in music dissemination, which are seven different types of behaviors (BE1~BE7). The Conv3D-GRU model designed in this paper is used to predict the dynamic behavioral characteristics of the audience in the process of music dissemination, as a way to support the innovative development of popular music in the era of integrated media.

For the audience behavior prediction effect of Conv3D-GRU model, this paper introduces the confusion matrix for evaluation, which provides an intuitive and scientific method for analyzing the performance of classification neural networks. Figure 5 shows the confusion matrix of audience dynamic behavior prediction of Conv3D-GRU model. The column edges of the matrix are labeled with the true labels, while the row edges represent the predicted labels, and the diagonal entries indicate the number of correct predictions, while the off-diagonal entries indicate instances of incorrect predictions. For example, the term located in row 4, column 3 shows a count of 4, which means that there exist 4 instances in which the predicted label of retweeted content and quantity (BE4) is misclassified as commented content and quantity (BE3). The results of the confusion matrix show that the predictions for the likes message content and count (BE1) and comments content and count (BE3) labels with larger datasets exhibit high accuracy, however, the predictions for the @content and count (BE6) labels with smaller datasets are less accurate, which suggests that the amount of available data is a key factor in the overall accuracy of the predictions. This finding implies that users' habits and behavioral activity preferences for hashtags may influence the model development and testing process, which are some of the limitations of the Conv3D-GRU-based audience dynamic behavior prediction model.

IV. B. 2) Comparative analysis of different models

After clarifying the confusion matrix of the Conv3D-GRU model for predicting audience behavior in the process of music dissemination, this paper selects a variety of different types of models to carry out comparative experiments in order to reflect the superiority of the model. On the basis of the audience behavior dataset established independently in this paper, this paper further selects the relevant dataset about music communication behavior in the UCI dataset to carry out the validation. RMSE, MAE and PCC are chosen as evaluation metrics. RMSE and MAE assess the prediction accuracy compared with the true value, while PCC measures the correlation between the predicted and true values, and the multiple metrics can ensure a robust and reliable evaluation of the results of this paper.

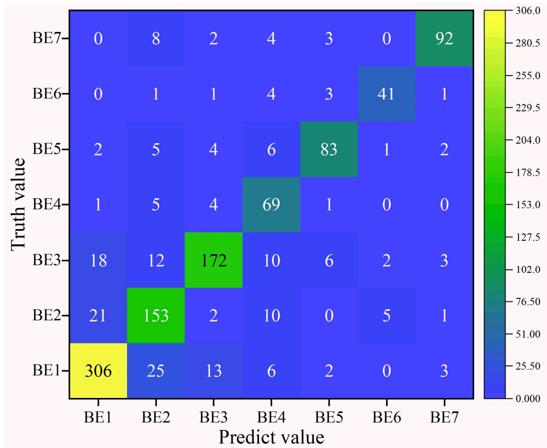


Figure 5: Audience dynamic behavior prediction confusion matrix

Table 1 shows the results of different models for predicting the dynamic behavior of the audience during music distribution. It can be found that the Conv3D-GRU model outperforms all comparative methods on all datasets in most cases, demonstrating its superior ability to capture the spatio-temporal dependence and multi-scale characteristics of audience dynamic behavior data during music dissemination. Compared with GraphTS on this paper's self-constructed dataset, the RMSE and MAE of the Conv3D-GRU model are significantly reduced by 26.19% and 29.56%, respectively; and compared with the GMSDR of the UCI dataset, the RMSE and MAE of this paper's model are significantly improved by 13.08% and 14.77%, respectively. In addition, the Conv3D-GRU model exhibited the highest PCC values of 89.68% and 97.79% on the two datasets, respectively, confirming its superior ability to capture the correlation between predicted and actual values compared to other methods.

In the baseline, GMSDR, MTGNN and GraphTS are the closest competitors to the Conv3D-GRU model in this paper, but they still lag behind considerably. The poor performance of classical methods such as HA, XGBoost and FC-LSTM compared to graph-based methods illustrates the importance of modeling the dynamic behavioral characteristics of the audience during music distribution on social platforms. The results also show that methods such as DCRNN and STGCN have higher PCC but higher RMSE and MAE, which suggests that they can capture the general trend of audience dynamic behavior during music dissemination but cannot accurately predict the exact values.

Table 1: Comparative analysis of different models

Method	Self-built dataset			UCI dataset		
	RMSE	MAE	PCC/%	RMSE	MAE	PCC/%
HA	5.243	3.472	16.68	29.512	16.153	63.42
XGBoost	4.051	2.481	48.51	21.193	11.628	80.75
FC-LSTM	2.827	2.315	56.42	18.075	10.232	86.32
DCRNN	3.218	1.827	72.38	14.804	8.476	91.27
STGCN	3.624	2.763	73.15	22.651	18.452	91.59
STG2Seq	3.995	2.501	51.64	18.104	9.935	86.53
GWNet	3.306	1.989	70.05	13.089	8.112	93.27
STSGCN	2.837	1.752	71.28	10.947	5.834	82.43
MTGNN	2.716	1.633	-	10.928	5.927	-
GTS	2.934	1.742	-	12.735	7.211	-
AST-GCN	-	1.885	-	-	-	-
CCRNN	2.832	1.721	79.41	9.527	5.493	96.35
ESG	2.671	1.613	-	8.931	5.048	-
GMSDR	2.735	1.668	81.05	8.649	4.983	97.14
GraphTS	2.768	1.742	81.72	9.542	5.461	97.28
Conv3D-GRU	**2.043**	**1.227**	**89.68**	**7.518**	**4.247**	**97.79**

IV. B. 3) Comparison of dynamic analysis efficiency

In the process of algorithm evaluation, the absolute and average errors directly reflect the degree of deviation between the predicted and actual values, while the precision measures the accuracy of the algorithm in processing the data. High precision and low error are signs of superior algorithm performance and can ensure the reliability and stability of prediction results. Therefore, by comprehensively analyzing these indicators, the effectiveness of the algorithm can be more comprehensively assessed, providing a scientific basis for optimizing and improving the algorithm so as to achieve higher efficiency and stability in practical applications. In this paper, linear regression, logistic regression, SVM-KNN, decision tree, random forest and LSTM are chosen as comparisons to compare the data of two types of error and accuracy of different algorithms, and their specific results are shown in Table 2.

From the table, it can be seen that the Conv3D-GRU model of this paper has the best performance in both types of errors, which are 1.79% and 2.47%, respectively, while the errors of other algorithms are higher than that of this paper's method, and the reason for the smaller errors is mainly attributed to the advantages of 3D-CNN in data feature optimization. In addition, this paper's method significantly improves the absolute error while effectively reducing the average error, thus enhancing the overall performance of the model. Meanwhile, in the comparison of algorithmic accuracy, the accuracy of this algorithm is as high as 93.25%, which shows its excellent prediction ability of audience dynamic behavior in music communication. In comparison, the highest accuracy of other algorithms is only 89.73%, while the lowest is only 81.42%. The results further emphasize the advantages of the Conv3D-GRU model, demonstrating its reliability and accuracy in processing data. Such performance indicators not only validate the effectiveness of the model, but also lay a solid foundation for its promotion and implementation in practical applications.

Table 2: Data of both errors and accuracy (%)

Method	Average error	Absolute error	Accuracy
Ours	1.79	2.47	93.25
LR	4.65	3.69	89.73
Logistic	6.73	5.38	85.64
SVM	6.18	5.52	82.29
DT	4.24	4.51	87.31
RF	3.95	3.62	81.42
LSTM	4.61	4.79	88.56
CNN	4.59	4.68	89.07

In order to further verify the superiority of the Conv3D-GRU model, the experiment also compares the dynamic analysis efficiency of different algorithms, and its specific results are shown in Fig. 6. As can be seen from the figure, in the comparison of dynamic analysis efficiency, the Conv3D-GRU model designed in this paper significantly outperforms other algorithms, which is mainly due to the recursive process adopted in the GRU module of the model, which makes the processing and analysis of the data more efficient.The GRU is able to flexibly capture the time-dependent and sequential characteristics of the audience's dynamic behaviors in the data during the process of music dissemination by memorizing the previous input information, so as to analyze the data in the process of analysis. By memorizing the previous input information, GRU can flexibly capture the time-dependent and sequential characteristics of the audience's dynamic behavior data during the music dissemination process, thus eliminating redundant calculations during the analysis. The efficient dynamic analysis capability not only improves the adaptability of the Conv3D-GRU model in real-world applications, but also ensures that it can quickly produce results when faced with complex data.

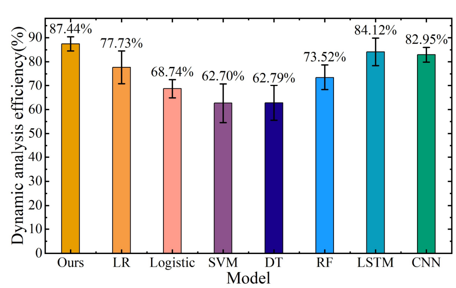


Figure 6: Dynamic analysis efficiency comparison

V. Conclusion

The article proposes a Conv3D-GRU model based on recurrent neural network, which is applied to the prediction of audience behavior in music communication. The simulation results show that compared with GraphTS, the RMSE and MAE of the Conv3D-GRU model are significantly reduced by 26.19% and 29.56%, respectively, and the PCC value of the model can reach up to 97.79%.Compared with the related machine learning algorithms, the Conv3D-GRU model has a better two-type error and accuracy, and the overall dynamic analysis efficiency reaches 87.44%. Under the background of the era of integrated media, the introduction of recurrent neural networks to deeply analyze the changes of audience dynamic behavior in the process of music dissemination can provide guidance for the innovation of music dissemination channels and the expansion of audience scope.

References

[1] Eiriz, V., & Leite, F. P. (2017). The digital distribution of music and its impact on the business models of independent musicians. The Service Industries Journal, 37(13-14), 875-895.

[2] Arbatani, T. R., Asadi, H., & Omidi, A. (2018). Media innovations in digital music distribution: the case of Beeptunes. com. Competitiveness in Emerging Markets: Market Dynamics in the Age of Disruptive Technologies, 93-108.

[3] Ruthmann, S. A., & Hebert, D. G. (2018). Music learning and new media in virtual and online environments. Creativities, technologies and media in music learning and teaching: an Oxford handbook of music education, 254-272.

[4] Siles, I., Valerio-Alfaro, L., & Arriagada, A. (2024). "Music Is Just Right There on Social Media!": Discovering, Exploring, and Incorporating Songs Across Platforms. International Journal of Communication, 18, 21.

[5] Jidong, L. (2023). Music Communication Strategies in the Era of Digital Culture Industry: An Examination Centered on QQ Music Platform. Media and Communication Research, 4(7), 35-41.

[6] CUI, Y. M. (2024). RESEARCH ON THE ADVANTAGES OF USING NEW MEDIA TO SPREAD CHINESE MINORITY MUSIC. Quantum Journal of Social Sciences and Humanities, 5(2), 13-23.

[7] Flexer, A., Lallai, T., & Rašl, K. (2021). On evaluation of inter-and intra-rater agreement in music recommendation. Transactions of the International Society for Music Information Retrieval, 4(1).

[8] Schedl, M., Zamani, H., Chen, C. W., Deldjoo, Y., & Elahi, M. (2018). Current challenges and visions in music recommender systems research. International Journal of Multimedia Information Retrieval, 7, 95-116.

[9] Bauer, C., & Schedl, M. (2019). Global and country-specific mainstreaminess measures: Definitions, analysis, and usage for improving personalized music recommendation systems. PloS one, 14(6), e0217389.

[10] Chakrabarty, S., Islam, R., & Sarma, H. K. D. (2023). Music recommendation system based on users' rating as a cloud-based healthcare information system. In IoT and Cloud Computing-Based Healthcare Information Systems (pp. 201-210). Apple Academic Press.

[11] Gunawan, A. A., & Suhartono, D. (2019). Music recommender system based on genre using convolutional recurrent neural networks. Procedia Computer Science, 157, 99-109.

[12] Schedl, M. (2019). Deep learning in music recommendation systems. Frontiers in Applied Mathematics and Statistics, 5, 44.

[13] Chang, J. W., Chiou, C. Y., Liao, J. Y., Hung, Y. K., Huang, C. C., Lin, K. C., & Pu, Y. H. (2021). Music recommender using deep embedding-based features and behavior-based reinforcement learning. Multimedia Tools and Applications, 1-28.

[14] Xu, D. (2020). Research on music culture personalized recommendation based on factor decomposition machine. Personal and Ubiquitous Computing, 24(2), 247-257.

[15] Zheng, H. T., Chen, J. Y., Liang, N., Sangaiah, A. K., Jiang, Y., & Zhao, C. Z. (2019). A deep temporal neural music recommendation model utilizing music and user metadata. Applied Sciences, 9(4), 703.

[16] Vamosi, S., Reutterer, T., & Platzer, M. (2022). A deep recurrent neural network approach to learn sequence similarities for user-identification. Decision Support Systems, 155, 113718.

[17] Grekow, J. (2021). Music emotion recognition using recurrent neural networks and pretrained models. Journal of Intelligent Information Systems, 57(3), 531-546.

[18] Hou, R. (2024). Music content personalized recommendation system based on a convolutional neural network. Soft Computing, 28(2), 1785-1802.

[19] Zhang, J., Ma, C., Mu, X., Zhao, P., Zhong, C., & Ruhan, A. (2021). Recurrent convolutional neural network for session-based recommendation. Neurocomputing, 437, 157-167.

[20] Song, G., & Wang, Z. (2022). An efficient hidden markov model with periodic recurrent neural network observer for music beat tracking. Electronics, 11(24), 4186.

[21] De Boom, C., Agrawal, R., Hansen, S., Kumar, E., Yon, R., Chen, C. W., ... & Dhoedt, B. (2018). Large-scale user modeling with recurrent neural networks for music discovery on multiple time scales. Multimedia Tools and Applications, 77, 15385-15407.

[22] Donkers, T., Loepp, B., & Ziegler, J. (2017, August). Sequential user-based recurrent neural network recommendations. In Proceedings of the eleventh ACM conference on recommender systems (pp. 152-160).

[23] Lin, Q., Niu, Y., Zhu, Y., Lu, H., Mushonga, K. Z., & Niu, Z. (2018). Heterogeneous knowledge-based attentive neural networks for short-term music recommendations. IEEE Access, 6, 58990-59000.

[24] Santana, I. A. P., & Domingues, M. A. (2022). Context-Aware Music Recommendation with Metadata Awareness and Recurrent Neural Networks. Computing and Informatics, 41(3), 834-860.

[25] Kumar, C., Kumar, M., & Jindal, A. (2023, May). Session-based song recommendation using recurrent neural network. In Machine Intelligence Techniques for Data Analysis and Signal Processing: Proceedings of the 4th International Conference MISP 2022, Volume 1 (pp. 719-728). Singapore: Springer Nature Singapore.

[26] Kim, H. G., Kim, G. Y., & Kim, J. Y. (2019). Music recommendation system using human activity recognition from accelerometer data. IEEE Transactions on Consumer Electronics, 65(3), 349-358.

[27] He, X. (2022). Improved music recommendation algorithm for deep neural network based on attention mechanism. Mobile Information Systems, 2022(1), 4112575.

[28] Yufeng Wang. (2025). Network Analysis and Audience Behavior Modeling of Popular Music Communication Paths in the Information Age. Applied Mathematics and Nonlinear Sciences,10(1).

[29] Rúben Teimas & José Saias. (2023). Detecting Persuasion Attempts on Social Networks: Unearthing the Potential of Loss Functions and Text Pre-Processing in Imbalanced Data Settings. Electronics,12(21).

[30] Nasiri Elahe,Berahmand Kamal,Samei Zeynab & Li Yuefeng. (2022). Impact of Centrality Measures on the Common Neighbors in Link Prediction for Multiplex Networks. Big data,10(2).

[31] Aron Mohammadi,Jonathan Tsang,Xiao Huang & Richard Kearsey. (2025). Convolutional neural network based methodology for flexible phase prediction of high entropy alloys. Canadian Metallurgical Quarterly,64(2),431-443.

[32] Xun Chen,Chengqi Wang,Chao Hu & Qin Wang. (2025). Correction: Chen et al. Mandarin Recognition Based on Self-Attention Mechanism with Deep Convolutional Neural Network (DCNN)-Gated Recurrent Unit (GRU). Big Data Cogn. Comput. 2024, 8, 195. Big Data and Cognitive Computing, 9(3),60-60.