

## Research Article

# Designing a National Music System for a Smart Concert Hall Using Neural Network and Wireless Internet of Things

**Mingjie Zhang** 

*School of Art, Hubei Polytechnic University, Huangshi, Hubei 435000, China*

Correspondence should be addressed to Mingjie Zhang; 202072119@yangtzeu.edu.cn

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With the fast advancement of science and technology, numerous music systems have emerged. However, there are few folk music in the music industry, for example, pop music, which leads to the inability of folk music lovers to find their favorite music. For this problem, this paper develops a national system of smart concert hall based on a neural network and wireless Internet of things (IoT). It establishes the architecture model of the wireless IoT system of the concert hall by describing the neural network, neuron model, and BP neural network model in detail. Besides, this paper develops the smart music national system based on this model, completes the functional module design of the national music system, and uses the music attribute recommendation model. Finally, it analyzes the scoring performance of the national music system. The results show that when the number of recommended folk music songs is less than 20, the lowest MAE is 0.73.

## 1. Introduction

Music is a popular kind of entertainment in the digital age. It is defined as a work of human creation that uses sounds to communicate thoughts and feelings via melody, rhythm, and beat. Rock, pop, jazz, folk, and other genres of music may all be classified. Besides, background music in the digital era is made easier by smartphone capabilities that allow us to listen to music online as well as offline [1]. Access to digital music is currently more difficult than in previous times, and thus, searching through all of this digital music takes a long time and results in information overload. As a result, it is extremely beneficial to create music recommendation systems that can automatically scan music collections and recommend songs appropriated for users. Songs services like Netflix such as Spotify and Pandora include features that allow users to be recommended music. These characteristics can assist in obtaining a list of relevant music from popular artists' collections based on previously listened to music. As a result, the recommendation systems are critical to the survival of the streaming music industry [2]. Music suggestions are made by comparing one piece of music to another or by offering priority from one listener to another

[3]. The difficulty of a music recommendation system is to design a technology that can constantly locate appealing new music while also understanding the consumers' music tastes [4]. This necessitates that the music personalized recommender system accurately represents human tastes. It requires modifications to create customized suggestions for the needs of various audiences. As a result, the tailored recommender system for music is more complex than the standard recommendation systems.

Many techniques for digital music have been developed, with neural networks and wireless IoT taking center stage these days. The authors of [5] introduced the word in the context of musical instruments that were enhanced with QR codes that directed users to Internet information about the device and its cultural history. The phrase was introduced in the framework of continuous music research by the authors in [6], which includes innovative use of the Internet, portable devices, and integrated technology for continuous musical activities [7]. While the authors of [8] proposed extending the theory of IoT to the musical domain, IoMusT was defined as a subfield of IoT in which the underlying technology environment enables ecosystems of interoperable devices connecting performers and audiences to

support novel musician-musician, audience-musician, and audience interrelations. Likewise, the authors of [1] utilized the word in the context of practically complete for musical purposes, suggesting an infrastructure to address the effective use of large-scale community-generated sounds.

Although there are many online music platforms in the market, there are only few related to national music. At the same time, our country pays attention to the cultivation of national music. More and more students are learning about the knowledge and culture of national music. Therefore, more and more people urgently need to develop the national music system to meet their individual music needs [9]. In this paper, the current mainstream network technology and wireless IoT are combined and used to set up a national music system for directing concert halls. My neural network is used to gather my people's favorite types of national music, create a national music library, and disseminate national music on the network through wireless IoT so that more people may discover their favorite national music on the system.

*1.1. Contributions of the Paper.* The followings are the significant advancements in this research paper: (1) before building this system, the neural network and wireless IoT algorithm, including the neuron model and BP network model, are thoroughly discussed. Based on this, the architectural model of a wireless IoT system in a performance hall is built. (2) Designing and developing the national music system of the intelligent concert hall, introducing each function module in the national music system, and building a recommendation model based on music attributes and a weighted mixed recommendation model based on deep learning.

*1.2. Organization of the Paper.* The second section of my paper is based on the relevant work of other academics who worked in the chosen field. The third section focuses on my wireless IoT powered by a neural network. Section four goes over my proposed smart concert hall national music system. Section 5 is based on my examination of the national music system's performance. Section 6 brings this paper to a conclusion.

## 2. Related Work

With the fast development of neural network algorithms, big Internet firms at home and abroad employ artificial intelligence technology to produce more music systems to suit people's individualized music demands, attracting the attention and research of a significant number of specialists [10]. In [11], the authors proposed a method to clarify the user influence degree by using the trust relationship on social networks and then defined the similarity index of collaborative filtering based on the influence degree. In this connection, the authors of [12] pointed out that the MCRN model can accurately extract the music features on the map and use the experimental method to test the advantages of MCRN in recommendation accuracy and music

classification. In addition, the authors in [13] used the matrix decomposition technology to obtain the long-term characteristics between songs and users. They used the language processing technology to collect the music context characteristics and then called the long-term and short-term memory network model to train the real data set and to obtain the best experimental result characteristics. In [14], the authors highlighted the problems of the long music classification cycle and low accuracy, and establishing an optimized cyclic neural network model and adding an attention mechanism to the model can improve the classification accuracy. They established a fusion model based on deep learning and collaborative filtering and used the improved neural network mining algorithm and automatic encoder to capture the hidden features in music and to better integrate the collaborative filtering model with the deep learning model.

At the same time, comprehensively analyze the user preferences and music features, to supervise the collaborative filtering process and better deal with the problem of low prediction accuracy caused by sparse matrix [15]. In this regard, the authors of [16] used a convolutional neural network to learn the audio content features of music; its essence is to transform audio into a "spectrum map" by Fourier transform. In [17], the authors proposed a model based on the perceptual characteristics of the human auditory system in music materials, and this paper studies the acoustic aesthetic evaluation method of a concert hall, defines evaluation criteria, and subjectively evaluates the objective acoustic parameters of concert hall. Similarly, the authors of [18] investigated the topic of music emotion categorization using single morphological data. Their model provides a deep confidence network-based multifeature fusion music classification method that extracts feature vectors from many viewpoints and enhances the standard deep confidence network-based music classification algorithm. Finally, the authors of [19] put forward a cross-cultural and cross-time and space national music teaching method based on education and teaching practice, build a complete music classroom teaching structure, and establish a feedback teaching system. Inspired from the work of the aforementioned scholars, this paper develops a national system of smart concert hall based on a neural network and wireless IoT (IoT). It establishes the architecture model of the wireless IoT system of the concert hall by describing the neural network, neuron model, and BP neural network model in detail.

## 3. Wireless Internet of Things Based on Neural Network

*3.1. Neuron Model.* Neural networks are simple models of how the nervous system functions. Neurons are fundamental units, which are often grouped into layers. Simple simulations of how the nervous system functions are called neural networks. Neurons are the fundamental units, which are usually grouped into layers as seen in Figure 1.

As per the above figure, the following is a brief description of the components of the neuron model.

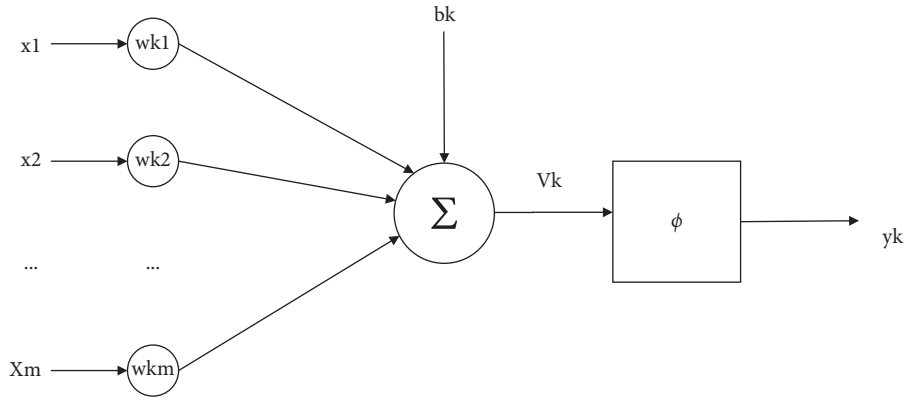


FIGURE 1: Neuron model.

**3.1.1. Connection with Authority.** This component simulates the synaptic realization of neurons in the biological nervous system. The strength is judged by the connection weights, positive for activation, and negative for inhibition.

**3.1.2. Sum Point.** After weighing all the input signals on the neuron model, the linear combination summation computes the weighted values corresponding to the summation points.

**3.1.3. Activation Function.** The function of this function is to control the output amplitude of a neuron as a controlled region, generally  $[-1, 1]$  or  $[0, 1]$ . In other words, an activation function describes how the weighting factor of the input is converted into an output from a node or endpoint in a network layer.

**3.1.4. Threshold Function.** The threshold is the function's cut-off value. So, if we adjust it to 0.5, everything below it produces a 0 result, and anything overproduces a 1. In this comparison, it is the desirable input since it influences the result. In brain neurons, 0 represents no reaction to stimuli, and 1 represents a positive response. The neuron typically fires when the stimulus strength is equal to or greater than the minimum necessary to activate it. The threshold determines the minimum needed energy. The offset and threshold can be calculated using the following equation:

$$u_k = \sum_{j=1}^p w_{kj}x_j, v_k = u_k - \theta_k, y_k = \phi(v_k). \quad (1)$$

In the above equation,  $b_k(-\theta_k)$  represents the offset, while  $\theta_k$  represents the threshold. Similarly to the above,  $x_1, x_2, x_3, \dots$  represents the input signal. The weights of the neuron  $k$  are  $w_{k1}, w_{k2}, \dots, w_{kp}$ , which means  $u_k$  is the result of a linear combination.  $\Phi(v_k)$  represents an offline activation function, and  $y_k$  represents the output of a neuron.

If you reincrease the number of bits of input data, you can add  $\theta_k$ , the following is the formula:

$$v_k = \sum_{j=0}^p w_{kj}x_j, y_k = \phi(v_k). \quad (2)$$

Add a new connection to the above equation (2),  $x_0 = -1$  or  $+1$  as input data,  $w_{k0} = \theta_k$  or  $b_k$  denotes weight.

**3.2. BP Network Model.** This paper uses the BP neural network model for the development of a national music system for a smart concert hall. BP network is one of the most commonly used neural network models. It uses the error backpropagation method to train the multilayer feed-forward network [20]. Based on the MP model, [21] suggested and enhanced the learning function, allowing the model to conduct predictive modeling. Various neural networks, including convolutional neural networks, BP neural networks, and risk assessment, involve considering neural networks and, so on, have their properties and are frequently utilized nowadays.

At the moment, the majority of research on the subject of innovation persistence uses regression analysis or nonlinear multiple regressions. Their benefit is the evident exposure of the link among independent factors and response variables; nevertheless, this model cannot be utilized to do more complicated processes, such as pattern classification. Despite reality, the connection among variables is frequently a complicated nonlinear model that is difficult to observe. The BP neural network is a black box technique that may do nonlinear translation without requiring the mappings connection to be determined in advance. Fundamentally, it trains the data, understands the principles, and then produces the anticipated output with the minimum mean square mistake of the actual output. It benefits from a short estimate of the parameters of time, self-learning, self-adaptation, and fault-tolerant. After decades of study and improvement, the BP neural network has emerged as one of the systems with broad application and a strong classification impact. As a result, in my study, the BP neural network is employed to recognize and evaluate patterns.

Apart from the above, the BP network can learn and understand various mapping relationships without knowing the mapping relationship between input-output modes in advance. BP neural network can reduce the error square of the network, while learning rules can adjust the threshold and weight of the network utilizing backpropagation and achieve this goal by employing the gradient descent method.

The network topology components of a neural network include the hide layer, input layer, and output layer.

Forward propagation and reverse propagation are two main components of the BP algorithm. Forward propagation is the secondary forward calculation or external data flow in the initial stage, which first propagates to the input layer, then to the hide layer, and finally to the output layer. Reverse propagation uses the error signal between the correct result and the initial result to correct the weighting process through reverse inference. The calculation process of this algorithm is that each layer of neurons in the neural network can only affect the lower layer of neurons. If the difference between the expected and initial results is considerable, the algorithm will automatically transfer the incorrect value to the reverse propagation step. When the weighted vector result is 0, the network model uses an error function gradient descent technique. During this process, overlapping loops use forward and reverse propagations to create a dynamic search for each pair of weighted vectors, minimizing the error function and performing data identification and extraction.

**3.2.1. Forward Propagation.** The input layer of the BP network model consists of three nodes, six nodes in the hide layer, and three nodes in the output layer. If  $v_{ki}$  denotes the weight between hiding and input layers,  $w_{jk}$  denotes the weight between output and hide layers. In the forward propagation process, the input layer is first passed into the recessive layer and then into the output layer. Each layer of nerve and Anu state affects only the lower neurons, and the other layers are not disturbed. Figure 2 shows the forward propagation topology of the BP network model.

According to the above figure,  $f_1()$  is the transfer function for the hide layer,  $f_2()$  is the transfer function for the output, and the value of  $k$  ranges from 1 to  $p$ . The input layer can be calculated using the following equation:

$$z_k = f_1 \left( \sum_{i=0}^n v_{ki} x_i \right). \quad (3)$$

Equation (4) calculates the output layer node output.

$$y_j = f_2 \left( \sum_{i=0}^q w_{jk} z_k \right). \quad (4)$$

The approximate mapping between  $m$ -dimensional space and  $n$ -dimensional space vector in the BP network model can be achieved by the above equations.

**3.2.2. Backpropagation.** Backpropagation is the foundation of network training. It is a way of fine-tuning neural network weights depending on the error rate achieved in the previous loop. By fine-tuning the weights, you may minimize error rates and make the design more dependable by boosting its generalization. The backpropagation (PB) network structure is a multilayered feed-forward neural network that has been developed using the error backpropagation technique. An example in a BP neural network contains  $n$  inputs,  $m$  outcomes, and multiple hidden layers between both the

input layer and the output layer. By adding the back-propagation mechanism to the neural network model, the neural network can be guaranteed to have a high recognition, strong self-correction ability, and a higher recognition and data processing ability.

**3.2.3. Architecture of Concert Hall Wireless Internet of Things System.** The IoT is a critical network design on the system network, making it more manageable, easier to run, and standardized in the future. China divides the IoT system into three levels: network layer, perception layer, and application layer [22]. The concert hall installs power equipment in the substation layer. By combining with the traditional three-tier network architecture system of the IoT, a three-tier system of wireless IoT for the virtual concert Hall is established in this paper. My proposed system consists of a data transmission layer, device monitoring layer, and application layer. Figure 3 explains the architecture of concert hall wireless IoT system.

Here are the basic roles of each layer in the architecture of the concert hall wireless IoT system.

- (i) **Monitoring layer:** The monitoring layer is responsible for constantly operating my system. This layer is the backbone of the functioning of my system. On the monitoring layer, various IoT devices such as Wi-Fi and ZigBee are installed. Wired devices provide a higher quality of service, but more wired devices will increase the difficulty of later system maintenance. Compared with this kind of wireless IoT, it is more scalable and flexible to use. Each monitoring point can control the device in real-time. After collecting data, the IoT devices will generate clusters to send to the receiver or gateway using a virtual multiantenna system. A gateway receives data, provides a path to it, and transmits it to the network layer.
- (ii) **Transport layer:** This is another critical layer that allows communication across application processes operating on multiple hosts in my model as well as other network components. The transport layer in my system takes message segments from apps and sends these into the network. It includes a wide range of wireless local area networks, including WiMAX, PLC, 4G, and others. The primary function is to provide the system with a dependable network transmission channel via which data from the monitoring layer may be transmitted and used by the application layer.
- (iii) **Application layer:** End-user applications such as Internet browser programs make use of this layer. In my approach, it offers controls for the program to send and receive data as well as show useful facts to consumers. This layer contains several monitoring systems, such as measurement equipment, monitoring management systems, gathered data information, and others. One of the main components is the application layer monitoring system, which can

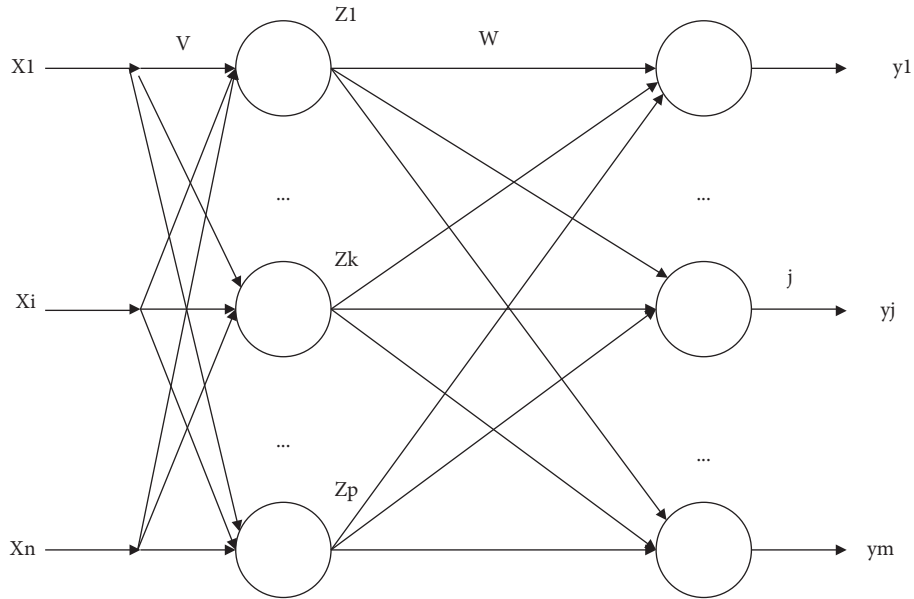


FIGURE 2: Three-layer neural network topology.

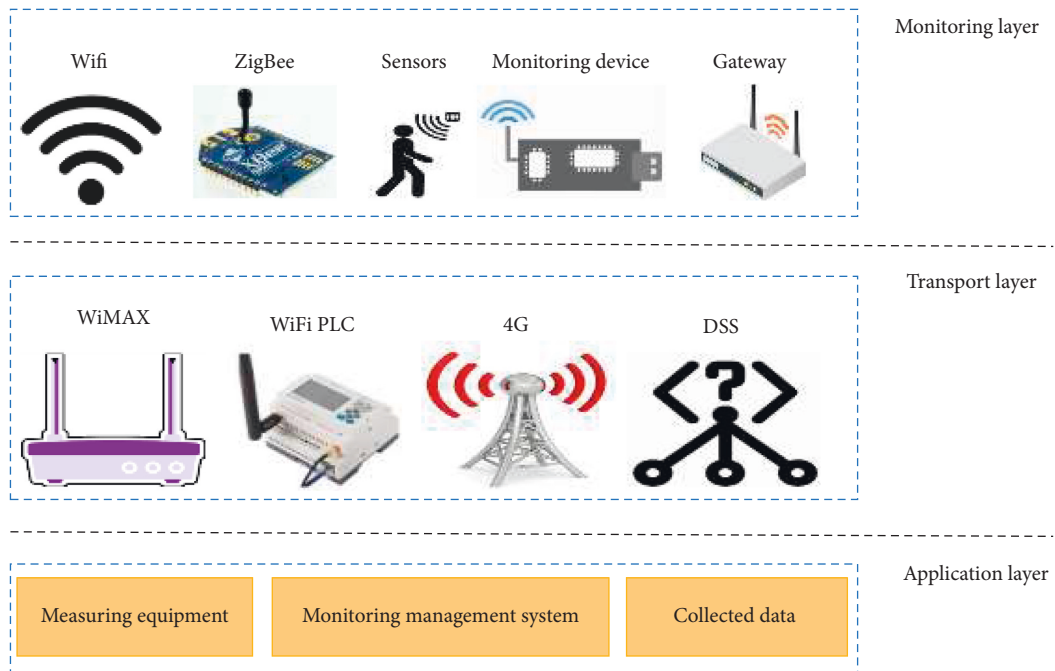


FIGURE 3: Architecture of a concert hall using wireless Internet of things system.

implement the monitoring device operation status, or send emergency commands to the device to control the device function.

#### 4. Smart Concert Hall National Music System

The concert hall is the main venue for the performance of music programs. It can be divided into types according to the purpose of the concert hall, mainly professional concert halls and multipurpose concert halls. Most of the concert halls built in the 1990s were simple to use and could only be used for indoor and symphonic performances. Today, with

the diverse growth of the market, firms from many business perspectives are constructing multipurpose concert halls, which should completely emphasize the local music peculiarities. They locate the concert hall as a national-oriented concert hall and design the concert hall's lighting system and music system. They employ lighting equipment to create a better stage environment in the concert hall. In this paper, the design of a smart concert hall starts from flexibility, switching simplicity, security, reliability, and storage, and the types of equipment configured in the system can undertake music performances of all nationalities. Reduce noise, lamp temperature, and so on to the greatest degree

possible while constructing the concert hall light system to fulfill the needs of the orchestra, symphony, chorus, and solo music, as well as to be able to record and transmit live.

*4.1. Design the National Music System Module.* This paper develops an intelligent concert hall national music system based on a neural network and wireless IoT and divides the system into two parts: front-end operation page and background operating system. The front-end page can complete the functions of charts, music management, popular recommendations, search tracks, user reviews, and my music. My music page is divided into two parts: recently played music and my music collection. There are two functions on the user review page: the latest comments and the popular comments. Figure 4 shows the function module of this system.

According to the above figure, the main function modules of the system background are comment management, song management, recommendation management, and user management. The system implicitly collects user behavior data for playing, downloading, and music collection. In addition, it uses a collaborative filtering recommendation algorithm based on neighbor users to recommend songs to users. If some national songs have different times, the similarity between songs can be analyzed by embedding network words based on heterogeneous text. According to the listening history of the national music of users, similar songs can be recommended. Furthermore, the system allows access to a user's access behavior and data records. A tag-based collaborative filtering algorithm may be used to propose music to users that are related to historical tags.

*4.2. Recommendation Model Based on Music Attributes.* There are many attributes of national music, which are usually used to define a better distinction between different music. The internal attributes mainly refer to the information of music beat, lyrics, sound quality, instruments, and sound quality. The external attributes include language, singer, style, and emotion. Music attributes have some objective attributes and some subjective attributes. Music genres and feelings can differ depending on who is listening, and user perceptions and preferences cannot be homogenized. The label, which comprises music emotion, style, and language, is another important outward aspect of music.

Here, five external attributes are selected to find out user attribute preferences, namely style, language, scene, theme, and emotion. These external attributes correlate to the dataset's music classification standards, and category information on different criteria may be acquired by utilizing the CURNN model to learn classification. By looking at the user's history of playing national music, we can see that each user's sensitivity to songs in different languages varies greatly, some prefer Mongolian music, and others prefer folk classics. For this feature, each user's preference for different music languages is calculated by the following equation:

$$MLP_{ij} = \frac{\text{musicLanguage}(U_i, L_j)}{\text{musicCount}(U_i)}, \quad (5)$$

where  $MLP(U_i, L_j)$  refers to  $U_i$  users' preference for  $L_j$  language music,  $\text{musicLanguage}(U_i, L_j)$  refers to users' listening to music in  $L_j$  language in  $U_i$  history music, and  $\text{musicCount}(U_i, L_j)$  refers to the number of music played.

According to this method, the user's scene preference (MNP), music style preference (MSP), theme preference (MTP), and emotion preference (MMP) can be calculated. The preference degree of music attribute is calculated through weighted calculation. It can be calculated by the following equation:

$$P_{i,j} = l * MLP_{i,j} + s * MSP_{i,j} + n * MNP_{i,j} + mMMP_{i,j} + t * MTP_{i,j}. \quad (6)$$

In the above equation, we can calculate it as  $l + s + n + m + t = 1$ .

*4.3. Weighted Hybrid Recommendation Model Based on Deep Learning.* The hybrid recommendation method used in this paper needs to weigh two different models. Users often use the system to listen to songs, which will increase the weight of collaborative filtering. Less times of users' historical listening to songs will increase the weight of music attributes [23]. The recommendation degree of the weighted mixed music recommendation model is calculated by equation (7), and  $\alpha$  represents the weight.

$$\text{Rec} = \alpha \text{sim} + (1 - \alpha)P_{i,j}. \quad (7)$$

The basic process of weighted mixed recommendation is shown in Figure 5. The more the music labels, the better the recommendation effect. However, in most music libraries, the lack of music labels in varying degrees. The recommendation effect can be strengthened only after the missing music classification labels are supplemented. This paper uses the current neural network model to extract music features, label music types, and classification and to improve the music label classification on the music collection. Calculate the user's music attribute preference based on the music attribute recommendation model, and calculate the user similarity based on the collaborative filtering recommendation model. After completion, the top  $n$  recommendation list can be generated according to the preference and similarity of music attributes.

## 5. Performance Analysis of National Music System

*5.1. Analysis of the Results of Recommendation Score of National Music System.* In this paper, the national music system of the smart concert hall is developed based on a neural network and wireless IoT, and the national music system is applied in the concert hall. To better verify the effect of the music system, this paper uses the implicit scoring method to judge [24]. The selected data mainly come from the public

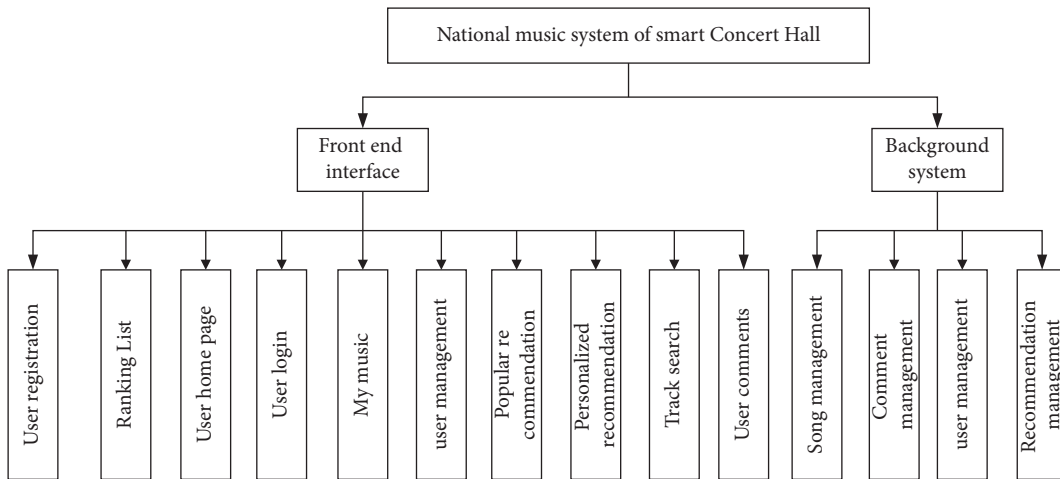


FIGURE 4: System function modules.

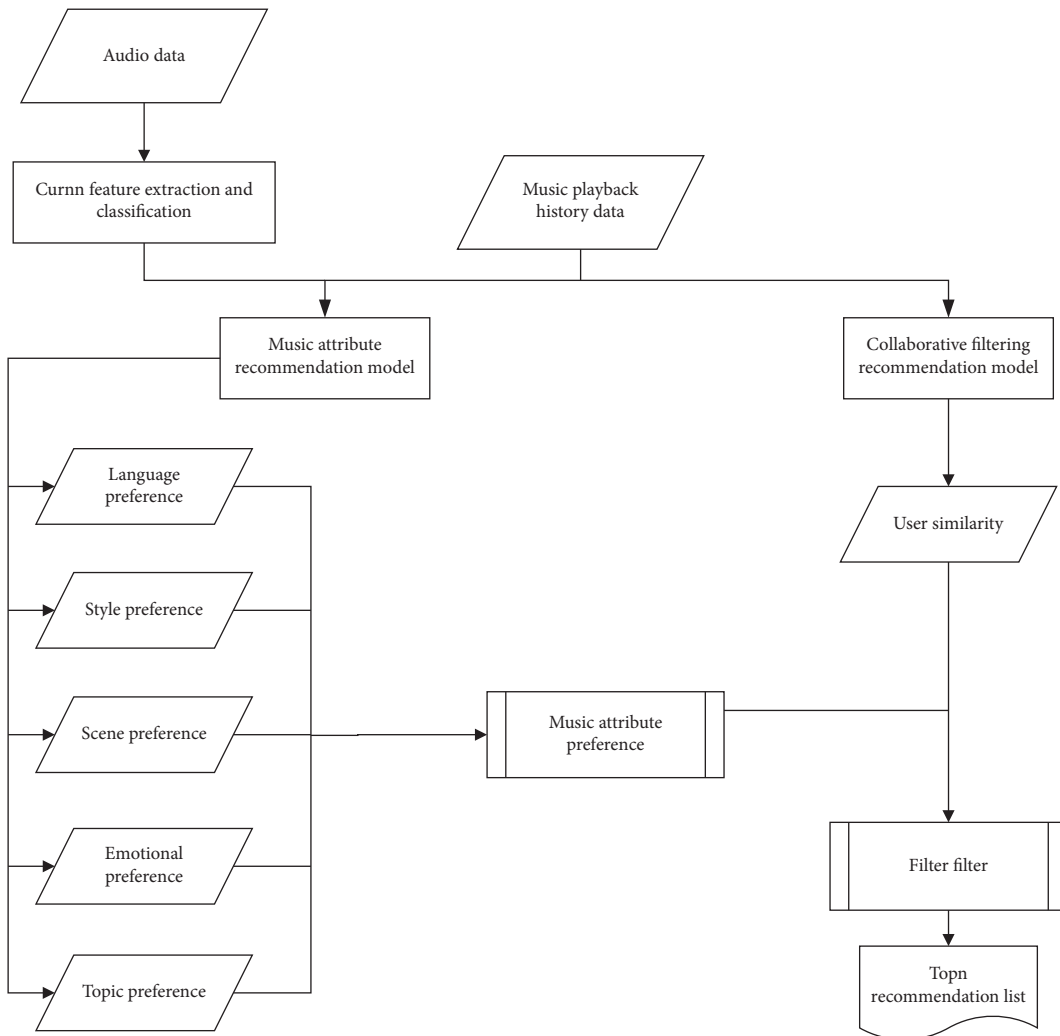


FIGURE 5: Hybrid recommendation process.

TABLE 1: Captured music data.

Data item	Quantity	Remarks
Music	245209	Music basic information and audio link
Music label	754683	Number of tags per music
User	798	User information
User label	2849	Different labels available to each user
Singer	11702	Singer information
Singer label	35698	Each singer's corresponding label
Song sheet	962	Song list information
Song list label	27954	Label corresponding to each song list
History of listening to songs	10000	The history of listening to folk music and songs repeatedly listened to by users

TABLE 2: Music classification in dataset.

Classification label	Classification details
Languages	Chinese, European and American, Arabic, French, Japanese, Cantonese
Style	Pop, dance music, light music, grassland, jazz, country, nationality, England
Scene	Morning, night, study, playing football, subway, driving
Emotion	Fresh, nostalgic, romantic, lonely, happy, missing and excited
Theme	Children, Internet songs, Internet, classics, variety show

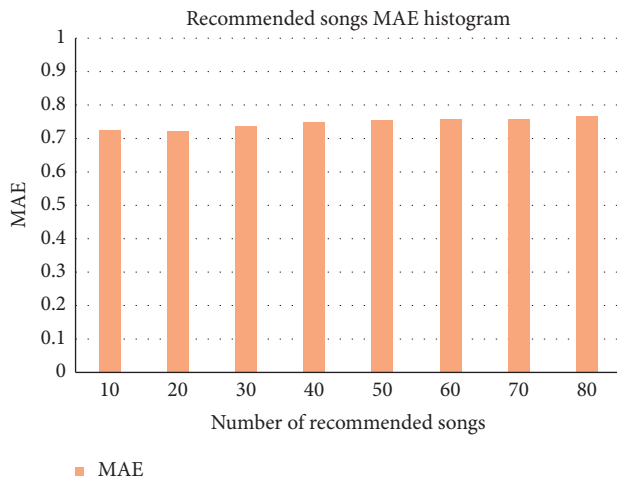


FIGURE 6: Recommended songs MAE histogram.

data on the Netease cloud. The national music data on the interface are captured through python data capture program, as shown in Table 1.

The classification standards of music labels in the data set mainly include style, language, scene, and language. The detailed classification contents of different classification indicators are listed in Table 2.

The system actively plays music once, downloads music, and collects a piece of music for 5 points. Combined with the data in Tables 1 and 2, the experimental results shown in Figure 6 are obtained.

According to the experimental results in the above figure, the average absolute error of MAE first decreases and then increases after increasing the number of recommended national music songs. When the number of recommended national music songs is 20, the lowest Mae value is 0.73. When the number of recommended national music songs exceeds 20, the MAE value increases rapidly. As the number

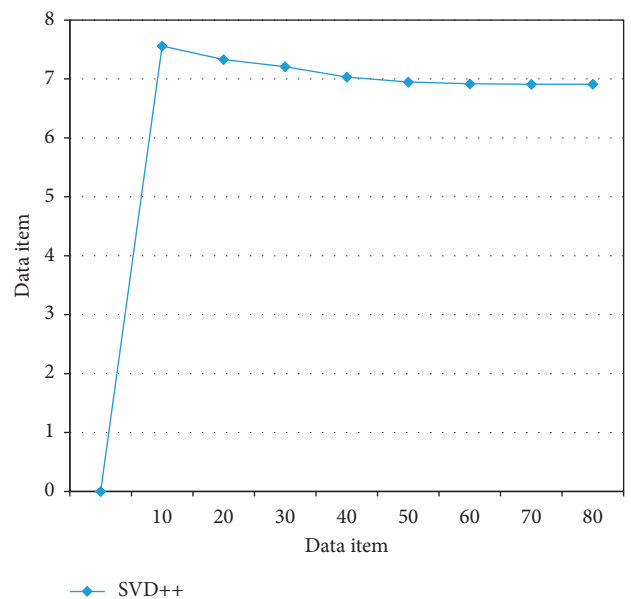


FIGURE 7: Comparison of 9 data items.

of suggested folk music songs grows, so does the number of needed scores. Furthermore, the results produced in this experiment are consistent with people's fundamental cognition when the system error rate increases.

**5.2. Analysis of Recommendation Results of National Music System.** This paper develops an intelligent concert hall ethnic system based on a neural network and wireless IoT. The music attribute model, collaborative filtering model, mixed model, K-means model, SVD++ model, MAE (average absolute deviation), and RMSE evaluation models are created to examine the efficacy of this system [25]. Using this index to evaluate the effect of music physical examination, RMSE is



TABLE 3: Comparison results of recommended models.

Number of music	SVD++ (MAE)	SVD++ (RMSE)	K-means (MAE)	M-means (MAE)	Hybrid model (MAE)	Hybrid model (RMSE)
10	7.56	10.69	8.37	10.45	7.25	9.76
20	7.33	10.32	8.02	10.12	6.91	9.65
30	7.21	10.24	7.61	10.05	6.85	9.49
40	7.03	10.12	7.35	10.04	6.78	9.35
50	6.95	10.03	7.12	10.01	6.76	9.29
60	6.92	6.95	7.06	9.88	6.74	9.18
70	6.91	9.93	6.99	9.74	6.73	9.13
80	6.91	9.81	6.91	9.71	6.69	9.09
90	6.85	9.58	6.85	9.67	6.66	9.04
100	6.81	9.44	6.81	9.25	6.65	8.97

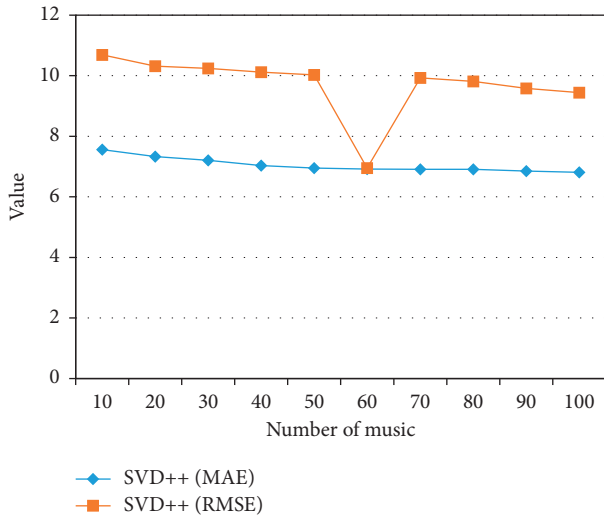


FIGURE 8: Comparison between SVD++(MAE) and SVD++(RMSE).

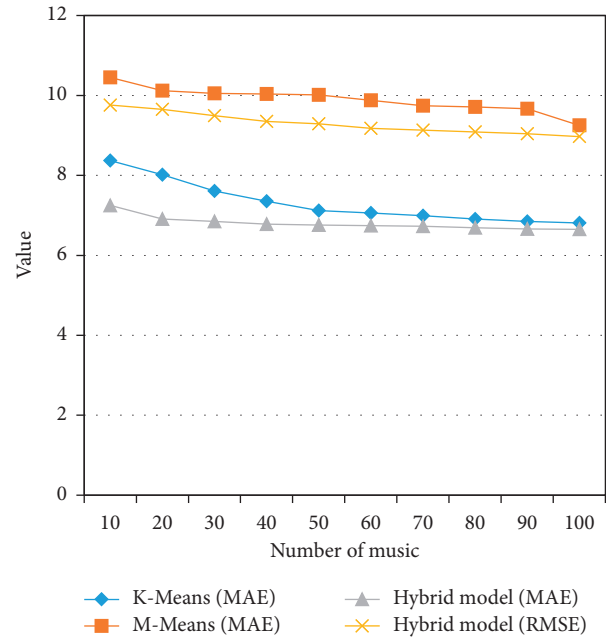


FIGURE 9: Comparison among 4 models.

the root mean square error. By using this index, we can evaluate the dispersion of music recommendation results.

If the predicted user's score set for  $n$  music is  $P = \{P_1, P_2, P_3, \dots, P_n\}$ , the user's true score set for  $n$  national music is  $R = \{R_1, R_2, R_3, \dots, R_n\}$ , and the MAE is calculated using the following equation:

$$\text{MAE} = \frac{\sum_{i=1}^n |P_i - R_i|}{n} \quad (8)$$

Calculate RMSE from the following formula:

$$\text{MAE} = \sqrt{\frac{\sum_{i=1}^n (P_i - R_i)^2}{n}} \quad (9)$$

The EaseSong dataset built in this paper has a total of 800 users and stores up to 25,000 pieces of music. It divides all music into three subsets for  $i$  users, represented by  $D_{1i}$ ,  $D_{2i}$ , and  $D_{3i}$ . Here,  $D_{3i}$  is the national music collection that  $i$  users have not heard, the mutually exclusive collection of national music that users have heard is represented by  $D_{1i}$  and  $D_{2i}$ ,  $D_{1i}$  is the training set,  $D_{2i}$  is the testing set, and the number of national music stored in  $D_{1i}$  is about twice as large as that in  $D_{2i}$ .

Figure 7 shows the data comparison of 9 data items. According to this figure, the highest quality among these data items is the music label, which is 754683 (no. of tags per music). On other hand, the smallest quantity is the user (only 798 user information).

The experimental results show that the MAE and RMSE values of the mixed model are lower than those of other models, and the recommended results are satisfactory. The RMSE and MAE values decreased significantly after continuously increasing the number of prediction scores. Only the results between the three music models are listed in Table 3, which fully demonstrates that the model recommendation works well.

The analysis of the experimental results in Table 1 shows that the MAE predicted by the hybrid model is lower than that of the other two models, so it can be concluded that the recommended effect of the hybrid model is more ideal [26].

The mean absolute error (MAE) is a linear rating, which indicates that all individual variances in the average are weighted proportionally. The root-mean-square mistake

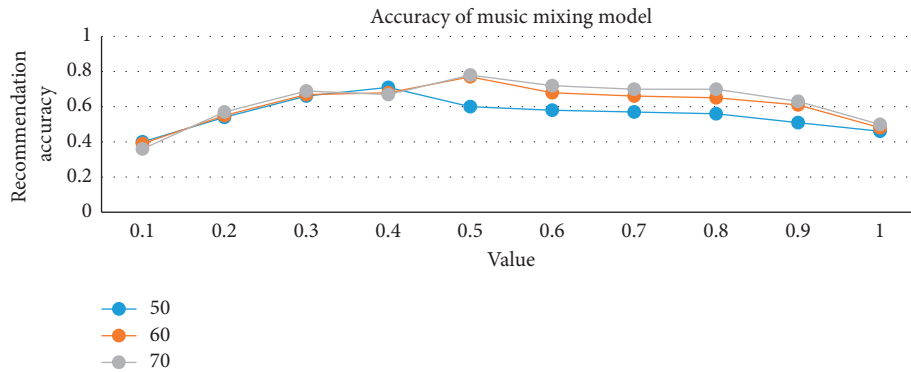


FIGURE 10: Variation of the accuracy of music mixing model with  $\alpha$  value.

(RMSE) is a quadratic scoring mechanism that calculates the average size of an error. Figure 8 shows the comparison between SVD++(MAE) and SVD++(RMSE) for the number of music. According to this figure, the MAE for 10 music is the greatest (such as 7.56), and the MAE for 100 music is the lowest (such as 6.81).

Figure 9 compares K-means (MAE), M-means (MAE), hybrid model (MAE), and hybrid model (MAE) (RMSE). According to this figure, the outcome of my suggested model is good, demonstrating the model's correctness.

The national music system of the smart concert hall developed in this paper has great changes in the accuracy of the model according to different weight values, as shown in Figure 10. In this paper, by processing the EaseSong data crawled by the system, the processing results show that 60 songs heard by users are the median. Therefore, 50, 60, and 70 songs heard by users are selected for experiments to judge the impact of value difference on accuracy. The experimental results show that after the number of songs continues to increase, the accuracy of the model also continues to increase. If it is 50 songs and the value of  $\alpha$  is 0.4, the recommended accuracy is the highest. If the number of songs is 60 and  $\alpha$  is 0.5, the recommendation accuracy is the highest. If the number of songs is 70 and  $\alpha$  is 0.6, the recommendation accuracy is the highest. Therefore, the validity of the music recommendation model of the system is tested. When users listen to a large number of folk music songs, they can improve the weight of the collaborative filtering model. When the number of songs is small, the weight of the music attribute model is low, so they can get a better recommendation effect.

## 6. Conclusions

With the rapid development of science and technology, all fields are moving towards intelligence. The single music mode of a traditional concert hall cannot meet people's basic needs. More and more people expect to build a smart concert hall, which can perform national music. For this demand, this paper adopts the most advanced neural network algorithm and combines it with the wireless IoT to develop and establish the national music system of the smart concert hall. By constructing the architecture model of the wireless IoT system in the concert hall, complete the development of the

intelligent music ethnic system, and introduce the functional modules of the system. Combined with the music attribute recommendation model and the weighted hybrid recommendation model based on deep learning, realize the recommendation function of the ethnic music system. To verify the application effect of the system, the scoring analysis of the system shows that when the number of folk music songs recommended by the system is less than 20, the minimum MAE is 0.73, and the MAE value continues to rise after the number of folk music recommended exceeds 20.

## Data Availability

All the data are available in this paper as part of the publication.

## Conflicts of Interest

The authors declare that there are no conflicts of interest.

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