Application of Internet of Things Technology in Vocal Music Teaching Recording Equipment Assisted by Machine Learning

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Vocal music teaching is a professional, technical, and practical subject. It is also an important part of music and art education and has certain social and educational significance. In vocal music teaching, recording equipment is an essential teaching tool. It plays a pivotal role in vocal music teaching. In recent years, with the rapid development of China’s social economy, education has also achieved great development, and it has also brought development opportunities to vocal music education. More and more advanced technologies and equipment have appeared to assist the smooth progress of vocal music teaching, especially recording equipment. This paper is aimed at studying the application of IoT technology in vocal music teaching recording equipment assisted by machine learning. Combined with machine learning and Internet of Things technology, the experiment of recognition effect of vocal music teaching recording equipment was carried out. It designs an end-to-end vocal music teaching recording device recognition model based on the Internet of Things technology assisted by machine learning. The experimental results show that the use of this model improves the recording recognition accuracy of vocal music teaching recording equipment by 20%.

1. Introduction

Vocal art is a musical art discipline with a long history and the continuous prosperity and development of human civilization, culture, and art. Vocal music teaching is an educational subject specially established for vocal music art. As a category of vocal music art, vocal music teaching also includes singing, teaching, theoretical research, and other disciplines. In vocal music teaching, teachers teach students certain theoretical knowledge through certain forms and within a certain period of time using certain teaching methods. Teachers also train students in singing skills and follow the prescribed tutorials, teaching materials, and vocal music with a serious attitude. Teachers gradually and comprehensively improve students’ cognition and practical ability of vocal art. In vocal music teaching, students are required to be good at using their hearing and voice to accurately identify and express the ideological content of vocal music songs, so as to continuously enhance their ability to express their voices. Therefore, in the vocal music teaching, it is very important to evaluate the students’ vocal music singing. And this is inseparable from the support of advanced recording equipment. Vocal music education has high requirements for recording quality. This requires the recording equipment used in the vocal music teaching process to achieve a high level of accuracy in sound recognition, and the sound preservation and processing technology must be mature enough. However, there are very few recording devices on the market that can fully meet the recording requirements of vocal music teaching in these aspects. Therefore, in order to better guarantee and promote the progress and development of vocal music teaching, some advanced science and technology are urgently needed to assist vocal music teaching recording equipment to better meet the requirements of vocal music teaching for recording quality. This paper mainly studies the application of IoT technology in vocal music teaching recording equipment assisted by machine learning.

The innovation of this paper are as follows: (1) It conducts research on the application of IoT technology in recording equipment assisted by machine learning, which lacks attention in today’s society. (2) Combined with
experimental analysis, it explores the application of IoT technology assisted by machine learning in vocal music teaching recording equipment. It designed a recognition model of vocal music teaching recording equipment based on the end-to-end model of Internet of Things technology and proved the effectiveness of the model through experiments.

2. Related Work

There is also a lot of research related to machine learning and IoT technology in academia. Among them, Wang et al. studied the multimode human-machine cooperative control algorithm assisted by machine learning. With the support of the algorithm, the car driver can flexibly turn to the auxiliary coordination mode and the differential braking coordinated control mode according to the actual situation at any time [1]. Lee et al. mainly studies haptic assisted expert driving skills assisted by neural networks and machine learning. They built a haptic driving training simulator to collect expert driving data and provide appropriate haptic feedback [2]. Lundberg et al.’s research focuses on the use of machine learning aids to predict the risk of hypoxemia during surgery. They built a system based on machine learning that can be used to predict the risk of hypoxemia. They also experimentally confirmed that the system helps to improve professionals’ clinical awareness of the risk of hypoxemia during anesthesia care [3]. Beyene et al. studied some key technologies of narrowband Internet of Things. They found that cloud radio access network is one of the pivotal technologies in NB-IoT [4]. Zhang’s research is mainly a comparative study of various IoT communication technologies. He focused on the technical characteristics of NB-IoT. He proposed an urban lighting system design scheme based on narrowband Internet of Things [5]. Wu et al.’s research designs an interactive remote care system based on IoT technology. The system enables direct communication between the patient’s medical device and the caregiver’s smartphone, thereby improving the quality of care for patients with chronic diseases [6]. Although these studies are all related to machine learning-assisted and IoT technologies, they are not sufficiently practical for the application of machine learning-assisted IoT technologies in vocal music teaching recording equipment. Moreover, the experiments are relatively complex, difficult to operate, and require a lot of time and energy.

3. Recognition Method of Vocal Music Teaching Recording

3.1. Machine Learning Machine learning is an advanced intelligent technology that has developed rapidly with the advancement of science and technology in recent years. It covers the knowledge of probability theory, statistical linear algebra, etc. It is also an important branch in the field of computer intelligence [7]. In layman’s terms, machine learning is to enable computer programs to automatically improve the performance of processing problems based on the accumulation of experience, just like a human. Machine learning has high application value in many fields. It has been widely used in the fields of speech recognition and image processing [8]. The machine learning architecture is shown in Figure 1.

Machine learning is mainly divided into unsupervised and supervised learning. Unsupervised learning is a self-learning classification method. It refers to learning from training samples without conceptual labels and discovering the inner connections of the data. Supervised learning refers to a learning method with human participation. It learns from labeled training samples to make predictions as accurate as possible on the labels of samples outside the training sample set. There are three main steps in supervised learning, namely, labeling samples, training models, and estimating probabilities [9]. It is shown in Figure 2.

3.2. IoT Technology The Internet of Things (IOT) technology refers to the technology that can realize the short-range wireless transmission of communication information and the embedding of received signals into various objects that exist objectively. It can realize the interconnection between people, things and people, or things and things. This enables the Internet design structure to be built into a broader communication network system [10]. In the application field of Internet of Things technology, there are various communication technologies such as sensor technology, radiofrequency identification technology, and wireless network information transmission technology. The communication layer of the Internet of Things is based on modern

Machine Learning Architecture

![Figure 1: Machine learning architecture.](Image)

Historical data ➔ Training ➔ Model ➔ Predict

New data ➔ Enter ➔ Model ➔ Unknown property

Machine learning

Historical data

Training

Model

Predict

Unknown property

Figure 1: Machine learning architecture.
communication technology. It is the bridge for the flow of information in the entire IoT architecture. The Internet of Things relies on technologies such as wireless networks, wired networks, and the Internet to enable people to transmit and share information anytime, anywhere [11]. The IoT architecture is shown in Figure 3.

The IoT architecture shown in Figure 3 is mainly composed of the application layer, network layer, and perception layer, which is the infrastructure of IoT [12]. What makes the Internet of Things realize powerful communication functions is its unique communication mode. The communication patterns of IoT are as follows:

$$\mu_k = \sum_{j=1}^{p} w_{kj} x_j.$$  \text{(1)}

The training steps of the IoT communication mode are to generate sample data, determine the network type and structure, and train and test. The first step is to determine the input quantities, that is, to test the correlation between the input quantities. If more nodes are set at the beginning, the error cost function needs to be used after the network training is [13]

$$J_f = \frac{1}{2} \sum_{p=1}^{N_x} \sum_{i=1}^{n} (t_{pi} - x_{pi})^2.$$  \text{(2)}

In the formula, $J_f$ is the sum of squares of the error output. In the second item, in order to minimize the connection weight coefficient after training, the learning algorithm is obtained by calculating the gradient of to. The role of the learning algorithm is to attenuate unnecessary or less influence connection weights to zero and remove the corresponding nodes to make the resulting overall neural network scale appropriately [14]. Its gradient is as follows:

$$\frac{\partial J_f}{\partial w_{ij}^{(q)}} = \frac{\partial J_f}{\partial w_{ij}^{(q)}} + \varepsilon \text{sgn}(w_{ij}^{(q)}).$$ \text{(3)}

The performance of a network is mainly measured by its generalization ability, which is tested and verified with a set of independent data. For the MISO (multiple input single output) structure, a set of $m$ fuzzy rules can be used to represent its discrete time model. The $j$th fuzzy rule [15] is as follows:

$$R^j : \text{if } x_m \text{ is } A^j_m \text{ then } y^j = p^j m x_m.$$ \text{(4)}

Among them, becomes the generalized input variable of the model, and the membership function of the fuzzy subset is a convex set composed of pieces. Given a generalized input variable $(x_{i1}, x_{i2}, \ldots, x_{im})$, the output can be obtained by the weighted average of the outputs $(i = 1, 2, \ldots, n)$ of the rules:

$$\tilde{y} = \frac{\sum_{i=1}^{n} G^i y^j}{\sum_{i=1}^{n} G^i},$$ \text{(5)}

where $n$ is the number of fuzzy rules and $y$ is obtained from the conclusion formula of the $i$th rule. Weight represents the truth value of the $i$th rule corresponding to this generalized input vector [16], which is determined by

$$G^i = \prod_{j=1}^{m} A^j_i(x_{ji}).$$ \text{(6)}

Here, $\Pi$ is a fuzzy operator, usually using a small operation or a product operation. The MIMO system structure is a further derivation of the MISO system principle relative to the MISO structure principle. Each node of the first layer of the antecedent network is connected to each component 2 of the input vector, that is,
\[ \mu_j^l = e^{(x - c_j)/\sigma_j}, \]  

(7)

where and are the center and width of the function, respectively.

\[ \alpha_j = \mu_1^j \mu_2^j \cdots \mu_n^j, \]  

(8)

where \( i_1 \in \{1, 2, \ldots\}, i_2 \in \{1, 2, \ldots\}, \ldots, i_n \in \{1, 2, \ldots\}, j = 1, 2, \ldots, m, \) and \( m = \prod_{i=1}^n m_i. \) The role of the fourth layer is to normalize the calculation, that is,

\[ \bar{\alpha}_j = \frac{\alpha_i}{\sum_{i=1}^d \alpha_i}. \]  

(9)

The first layer of the postware network is also the input layer. Its zeroth node mainly provides the constant term of the network, so its value is 1. The second layer deals with the consequent of each rule [17, 18], namely,

\[ y_{ij} = \sum_{i=0}^n \tilde{\alpha}_j x_i. \]  

(10)

The computational output of this network is implemented in the third layer. When calculating the output, the output of the antecedent network is used as the weighting coefficient, and the output value is the weighted sum. At this point, the MIMO system structure model is realized, namely,

\[ y_i = \sum_{j=1}^m \bar{\alpha}_j y_{ij}. \]  

(11)

It then uses the MapMinMax function to normalize the training data according to the coefficients and parameters required for training [19], such as

\[ y = (y_{\max} - y_{\min}) \times \frac{(x - x_{\min})}{(x_{\max} - x_{\min})} + y_{\min}. \]  

(12)

In the formula, is generally 1, is -1, and and are the maximum and minimum values of the input. It takes the error cost function as \( E =, \) and represents the expected output and the actual output, respectively. The following is the learning algorithm for parameter \( p_i^j: \)

\[ \frac{\partial E}{\partial p_i^j} = \frac{\partial E}{\partial y_i} \frac{\partial y_i}{\partial y_{ij}} \frac{\partial y_{ij}}{\partial p_i^j} = -(t_i - y_i)\bar{\alpha}_ix_i, \]  

(13)

\[ p_i^j(k + 1) = p_i^j(k) - \beta \frac{\partial E}{\partial p_i^j} = p_i^j(k) + \beta(t_i - y_i)\bar{\alpha}_ix_i. \]  

(14)

For the learning problems of and, the simplified structure is similar to the neural network. Even if \( y_{ij} = w_{ij}, \) with the help of the above results, that is,

\[ \sigma_i^* = t_i - y_i, \]  

(15)

\[ \sigma_i^* = \sum_{i=1}^r y_{ij}. \]  

(16)

which is

\[ \sigma_i^* = \frac{\sigma_i^*}{(\sum_{i=1}^m \alpha_i)}. \]  

(17)

At the same time,

\[ \sigma_i^* = \sum_{k=1}^m \rho s_{ij}. \]  

(18)

It finally obtained

\[ c_i(k + 1) = c_i(k) - \beta \frac{\partial E}{\partial c_i}. \]  

(19)

In the formula, \( \beta \) is the obtained final learning rate.

4. Experiment on Sound Recognition Effect of Vocal Music Teaching Recording Equipment

4.1. Recording Device Source Identification Based on IoT Spatial and Temporal Feature Fusion. Most IoT device source recognition-based methods only use representation learning based on a single spatial feature and cannot fully utilize device source information. Therefore, in this section, in order to fully explore the spatial and temporal information representation of device sources, this section proposes a machine learning-assisted recording device source identification method based on the fusion of spatial feature information and temporal feature information of the Internet of Things. It is shown in Figure 4.

From a representation learning perspective, this section designs a specific network to characterize the spatial and temporal information of device sources. After that, an attention mechanism is used to adaptively assign the weights of spatial information and temporal information. From a model perspective, the models in this section use frameworks. The framework learns deep representations directly from two different device source features. It is also trained with a deep loss and a shallow loss to jointly optimize the network.

4.2. Parallel Spatial and Temporal Feature Extraction Networks. The parallel spatial and temporal feature extraction network model is divided into two parts. One is the spatial information extraction network, and the other is the time series information extraction network, as shown in Figure 5.

To extract timing information from device source features, this section designs an LSTM+DNN network. Among them, the LSTM network can solve the long-term dependence of temporal information and improve the adaptability of the network. The LSTM network can perform the
The structure of each cell and delete or add information through the gate structure. It does essentially transfer useful device source information to the next frame. The structure diagram of LSTM+DNN designed in this section is shown in Figure 6.

The structure of the end-to-end recognition method proposed in this section consists of three modules: a parallel dimensionality reduction network module, an attention mechanism module, and a back-end classification module. When the parameter structure of each module is fixed, the end-to-end recognition method is similar to a black box. At this point, the device source information will be mapped to a low-dimensional space. In this low-dimensional space, the interclass distance will be enlarged and the intraclass distance will be reduced.

The deep learning-based end-to-end device source recognition method consists of three stages: training, registration, and testing. During the training phase, the deep network learns device-source deep representations from device-source features. The deep network parameter learning includes three module parameter learning: parallel dimension reduction network parameter learning module, attention mechanism network parameter learning module, and back-end classification network parameter learning module. These three modules train all network parameters using a joint optimization function. During the registration phase, test data is fed into the trained network to obtain a deep representation of the device-source features learned by freezing the network layers. A model for each category in a device source is obtained by averaging each device source feature. During the testing phase, the model in this section compares the distance between the model for each class and each test data supervector. It determines whether each test data supervector matches each class model by setting a threshold.

4.3. Experimental Setup and Result Analysis. In this section, the proposed dataset, baseline system, and end-to-end device source identification method are evaluated. The Adam optimization method is used to optimize all network parameters.
parameters. The exponential decay rates for the first and second moment estimates are set to 0.9 and 0.999, respectively. All network model experiments in this chapter are built using Tensorflow and Keras software packages, and the hardware information GPU is RTX TAITAN X.

The dataset used in this section is the CCNU_Mobile dataset. It includes 45 devices; each device contains 642 records. The length of each record is 6-8 s. When extracting the temporal feature MFCC in the experiment, it will extract the MFCC for each signal frame (30 ms length, 15 ms overlap) windowed by the Hamming window. In order to make the features better reflect the temporal continuity, the dimension of the frame information before and after the frame is added to the feature dimension, in which commonly used are first-order difference and second-order difference. Therefore, 39-dimensional MFCCs are used in this section. It was trained on 64 Gaussian UBMs using 40,000 speech files from the TIMIM database. The spatial feature Gaussian hypervector uses 64 Gaussian 39-dimensional parameters. The baseline system uses the GMM-UBM model, the I-vector (SVM) model, and the baseband differential feature (SVM) model.

In order to verify the validity of the work in this section, four groups of experiments are designed to verify the model of this chapter: network selection comparison experiments based on parallel spatial and temporal feature extraction networks. A comparison experiment based on the weight setting of the deep and shallow loss functions and a single loss function. Experiments based on comparison of shallow and deep loss with multiple common loss functions and comparison of end-to-end models with baseband differential features (SVM) and the work in Section 3. Among them, the Internet of Things spatial feature extraction network and time series extraction network parameters and structures are shown in Table 1.

(1) Comparison experiment of spatial and temporal feature extraction network selection

In the experiments in this section, the weight ratio of the joint optimization loss is 0.25:0.5:0.25. In order to optimize the network structure of this section, this section designs a network comparison experiment based on parallel spatial and temporal feature extraction. This experiment compares networks that extract spatial and temporal features. The spatial feature extraction networks designed in this chapter include DNN, CNN, and ResNet. DNN contains three hidden layers. The CNN network contains three layers of convolution, three layers of pooling, and two layers of fully connected. The residual blocks in the residual network are shown in the table. The residual network consists of four segments of the residual block. Temporal feature extraction networks include LSTM and BiLSTM. The specific network structure and parameters are shown in Table 2.

From the longitudinal comparison in Table 2, when the training period is 100 epochs, the best result is to use DNN as the spatial extraction network, and the accuracy rate reaches 96.6%. Followed by the ResNet network, the accuracy rate reached 94.6%. Finally there is the CNN model with an accuracy of 94.5%. In the temporal feature extraction network, LSTM slightly outperforms BiLSTM. This has changed when the training epoch is 200 epochs, and the effect of using BiLSTM exceeds that of LSTM. This proves that BiLSTM requires longer training time than LSTM network to achieve convergence and balance. Through the horizontal comparison, for the single-network model, the DNN is used to extract the device source spatial information, and the best result of 96.6% is obtained. For the fusion network model, the network combination of DNN and BiLSTM achieved the best result with 97.5% accuracy. Compared with other fusion network models, the maximum increase is 1.4%. Each fusion network outperforms a single network. All in all, the combination of DNN and BiLSTM achieves the best fit. It outperforms the worst single network model by 27%. The reason for this result is that the model in this section incorporates spatiotemporal information in the process of device source identification and further proves that the method in this section is effective.

(2) Comparison experiment of deep and shallow loss weight settings and single loss function

In order to explore the effectiveness of the deep and shallow loss, by controlling the weight of the deep and shallow
loss, this section designs several sets of comparative experiments to optimize the deep and shallow loss function. Furthermore, to verify the effectiveness of deep and shallow losses, this section compares deep and shallow losses with using a single cross-entropy loss function. The parallel spatial and temporal feature extraction networks used a combination of DNN and BiLSTM and a combination of DNN and LSTM and were trained for 200 epochs. The learning rate baseline is set to 0.001 and reduced to 1/10 every 20 epochs.

When optimizing the system with shallow and deep loss functions, all results are above 97.1%, regardless of the weight of the loss. Compared with the network model using a single loss, the deep and shallow loss function loss is significantly better than the single-loss network model, and the maximum effect is improved by about 1%. The results show that by jointly optimizing the shallow loss and the deep loss, the network can converge better and the fitness of the network can be improved. It establishes a comparison experiment of deep and shallow loss functions with different weights. When the weight distributions are 0.25:0.5:0.25 and 0.25:0.25:0.5, the network model in this section can achieve the best results, reaching 97.5%. The results show that better results can be obtained by assigning appropriate weights to the network. It may be because BiLSTM is more difficult to train and adapt than DNN and CNN networks and thus needs to directly or indirectly increase the weight of the training loss.

(3) Comparison experiment between end-to-end model and benchmark model

In order to verify that the end-to-end model in this section outperforms the traditional model and the work in Section 3, a set of experiments are designed in this section. It compares the end-to-end model in this section with baseline models and the work in Section 3. The parallel spatial and temporal feature extraction network in the end-to-end network in this section adopts a combination of DNN and BiLSTM with the same parameters as those in Table 2.

The experimental results of the comparison between the experimental model and the benchmark model in this section are shown in Figure 7.

The results in Figure 7 show that the end-to-end model based on machine learning-assisted IoT technology in this experiment has better performance than traditional methods. This also indirectly proves that the end-to-end model in this chapter can better exert the performance of the entire model by jointly optimizing the model weights.

### Table 1: Spatial feature extraction network and time series extraction network parameters and structure.

| Spatial feature extraction network | Time series feature extraction network |
|-----------------------------------|----------------------------------------|
| DNN                              | LSTM                                   |
| Input layer (2496)               | Input layer                            |
| Fully connected layer (1024)     | Batch normalization layer              |
| Fully connected layer (1024)     | LSTM (39)                              |
| Fully connected layer (1024)     | BiLSTM (39)                            |
| DNN                              | Fully connected layer (1024)           |
| Pooling layer (16 * 10 * 16)     | Convolutional layer (16 * 3 * 3)       |
| Convolutional layer (16 * 3 * 3) | BiLSTM (78)                            |
| Pooling layer (8 * 5 * 40)       | Fully connected layer (1024)           |

### Table 2: Comparative experimental results based on parallel spatial and temporal feature extraction networks.

| End-to-end model | Spatial feature extraction network | Time series feature extraction network | Epoch |
|------------------|-----------------------------------|----------------------------------------|-------|
|                  | DNN | CNN | ResNet | LSTM | BiLSTM | 100 | 200 |
| Experiment 1     | √   |     |        |      |        | 96.5% | 96.6% |
| Experiment 2     |     | √   |        |      |        | 94.5% | 94.6% |
| Experiment 3     |     |     | √      |      |        | 94.6% | 94.5% |
| Experiment 4     |     |     |        | √    |        | 68.8% | 69.4% |
| Experiment 5     |     |     |        |      | √      | 70.9% | 70.7% |
| Experiment 6     | √   |     |        |      |        | 97.3% | 97.3% |
| Experiment 7     |     | √   |        |      |        | 96.2% | 96.1% |
| Experiment 8     |     |     | √      |      |        | 96.2% | 96.2% |
Figure 8 shows the recognition accuracy in the two voice recognition experiments of vocal music teaching recording equipment using this model.

Combining the above experimental process and Figure 8, it can be concluded that the sound recognition accuracy of the vocal music teaching recording equipment using the experimental design model is increased by 20%. This shows that the use of the recording equipment recognition model based on the Internet of Things technology has a certain effect on the improvement of the sound recognition effect of the vocal music teaching recording equipment.

5. Discussion

Vocal music teaching is an important part of music art education. The sound development of vocal music teaching is conducive to promoting the development of vocal music art education and the acceleration of the overall music education development process. Vocal music teaching has certain specific requirements for teaching equipment, that is, in the process of vocal music teaching, a good recording equipment is essential [20].

In order to ensure the accurate and specific evaluation of students’ singing voice in the process of vocal music teaching, vocal music teaching has higher requirements on the recording quality of the recording equipment. This also means that the composition technology of the recording equipment is also demanding. Machine learning and Internet of Things technology are two advanced technologies that have emerged with the improvement of social science and technology. Since its birth, it has been widely used in many fields. Based on the powerful technologies and functions of machine learning and the Internet of Things, this paper explores the application of the Internet of Things technology assisted by machine learning in vocal music teaching recording equipment [21].

The effect experiment of vocal music teaching recording equipment designed in this paper is carried out by combining the recording equipment source identification method based on the fusion of spatial feature information and time series feature information of Internet of Things technology assisted by machine learning. It also designs an end-to-end vocal music teaching recording device recognition model based on the Internet of Things technology assisted by
machine learning. The experimental results show that the voice recognition accuracy of the vocal music teaching recording equipment using this model is improved by 20%. This conclusion shows that the model has a certain effect on improving the recognition accuracy of vocal music teaching recording equipment [22].

6. Conclusions

This paper mainly studies the application of IoT technology assisted by machine learning in vocal music teaching recording equipment. This article begins with a detailed introduction to machine learning and IoT technologies. It then combined machine learning and Internet of Things technology to conduct an experiment on the sound recognition effect of vocal music teaching recording equipment. The conclusion drawn from the experiment proves that the application of the Internet of Things technology assisted by machine learning in the vocal music teaching recording equipment has improved the sound recognition accuracy of the recording equipment by 20% in total. The conclusion of this paper has certain reference significance for promoting the technical development and updating of vocal music teaching recording equipment. However, the research of this paper also has some shortcomings, such as the research method being not innovative enough, and the research angle is not comprehensive enough. The author hopes to do better in the future and make more contributions to the development of vocal music teaching.

Data Availability

This article does not cover data research. No data were used to support this study.

Conflicts of Interest

The author declares that he/she has no conflicts of interest.

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