Design of Emotion Analysis Model IABC-Deep Learning-based for Vocal Performance

Zhenjie Zhu[1], Xiaojie Lv[2]
College of Graduate, Sehan University, Mokpo, Republic of Korea[1]
College of Microelectronics, Xidian University, Xian, China[2]

***Abstract*—With the development of deep learning technology, and due to its potential in solving optimization problems with deep structures, deep learning technology is gradually being applied to sentiment analysis models. However, most existing deep learning-based sentiment analysis models have low accuracy issues. Therefore, this study focuses on the issue of emotional analysis in vocal performance. Firstly, based on vocal performance experts and user experience, classify the emotions expressed in vocal performance works to identify the emotional representations of music. On this basis, in order to improve the accuracy of emotion analysis models for deep learning based vocal performance, an improved artificial bee colony algorithm (IABC) was developed to optimize deep neural networks (DNN). Finally, the effectiveness of the proposed deep neural network based on improved artificial bee colony (IABC-DNN) was verified through a training set consisting of 150 vocal performance works and a testing set consisting of 30 vocal performance works. The results indicate that the accuracy of the sentiment analysis model for vocal performance based on IABC-DNN can reach 98%.**

Keywords*—Vocal performance; deep learning; Artificial Bee Colony (ABC); emotion analysis model; Deep Neural Network (DNN)

I. Introduction

Emotion analysis (sentiment analysis) is a branch of Natural Language Processing (NLP) that involves identifying and extracting emotions from raw text. The sentiment analysis model aims to play an important role in human communication. The purpose of the sentiment analysis model is to understand and analyze subjective information in human language, such as viewpoints, emotions, and so on. Recently, sentiment analysis models have been widely applied in various fields, such as brand monitoring, public sentiment tracking, and market research [1]. Artificial intelligence-based sentiment analysis models can be trained and evaluated based on standardized data features such as word frequency, word order, grammatical structure, emotional vocabulary, and phrases, and then used for sentiment analysis on social media or recommendation systems [2]. Emotional analysis models can provide automated analysis of emotional information in texts. The acquisition and analysis of emotional information can provide decision-makers with valuable insights, thereby optimizing business operations, improving user experience, and enhancing competitiveness [3]. Therefore, sentiment analysis models can help users understand the emotional tendencies and states in text, which is of great significance in the field of NLP.

Emotional analysis models include support vector machines, decision trees, random forests, and deep learning models. The methods used mainly include rule-based (dictionary) methods and learning based methods. The rule-based approach relies on pre-defined sentiment dictionaries and rules, where each word is marked as positive, negative, or neutral. By calculating the number of positive and negative vocabulary in the text, the overall sentiment of the text can be determined [4]. The advantage of such models is that they perform well on specific types of text or domains, especially when these rules are designed for specific contexts, and they do not require training datasets and can be deployed immediately. However, this method may not accurately handle texts with complex meanings or containing rhetorical devices such as satire and metaphor. In addition, rule-based methods have lower flexibility and may require a lot of manual work to maintain and update rules and dictionaries [5].

Learning-based sentiment analysis models can be divided into machine learning-based sentiment analysis models and deep learning-based sentiment analysis models. Learning based sentiment analysis models typically require a large amount of labeled data for training. A machine learning based sentiment analysis model uses labeled datasets to train the model, so that the model can learn the mapping from text features to emotions. Machine learning models typically use manually designed feature representations. Deep learning models can use techniques such as word embedding to automatically learn the distributed representation of text, better capturing semantic information [6]. Deep learning models typically consist of multiple levels of neural networks with more complex structures and parameters. By contrast, machine learning models typically have a simpler model structure. Deep learning models typically require a large amount of labeled data for training in order to effectively learn complex feature representations. However, machine learning models require relatively small amounts of data and can be trained on smaller datasets [7].

Compared to machine learning methods, deep learning methods can typically provide higher accuracy while processing more complex texts and larger scale data. Therefore, sentiment analysis models based on deep learning have the advantages of automatic learning and feature extraction, high accuracy, and high flexibility. Deep learning models are particularly adept at capturing long-range dependencies from sequence data, which is crucial for understanding the context of text [8]. However, deep learning models typically require a large amount of annotated data for training, otherwise it may lead to overfitting. In addition, training and tuning emotion analysis models based on deep learning is difficult, and the training process of deep learning models may be complex, requiring a focus on designing the network structure and tuning parameters. Therefore, sentiment analysis models based on deep learning may have an advantage in performance, but also pose challenges in adjusting network parameters [9].

The purpose of a music sentiment analysis model is to understand and analyze the emotional content in music. This model can be used in music recommendation systems to recommend suitable music to users by analyzing their emotional state and the emotional content of music. In addition, it can also be used in music creation to help creators better express the emotions they want to convey [10]. The emotion analysis model for vocal performance refers to a system that can recognize and analyze emotional expressions in singing. This type of model not only needs to handle linguistic emotional expression, but also needs to analyze musical elements such as melody, rhythm, harmony, and the vocal characteristics of the singer [11]. A sentiment analysis model for vocal performance needs to have the ability to extract music related features from audio signals, such as fundamental frequency, timbre, loudness, rhythm, and duration. In addition, the model also needs to have the ability to analyze sound quality, accurately identify the vocal quality of the singer, including clarity, stability, and volume changes [12].

The existing artificial intelligence-based sentiment analysis models have problems such as low accuracy. Therefore, in response to the problem of artificial intelligence based vocal performance analysis, this study establishes a deep learning based emotional analysis model for vocal performance, aiming to help music researchers understand music expression more deeply. The main contributions of this study are summarized as follows: a deep neural network (IABC-DNN) based on an improved artificial bee colony algorithm is designed. The input layer of IABC-DNN includes lyrics, typification, melody, pitch, and music rhythm, while the output layer is the emotion of vocal performance works. IABC-DNN consists of a novel gradient function that takes into account the factors affecting the emotional scale of vocal performance. In IABC-DNN, the Improved Artificial Bee Colony Algorithm (IABC) is used to optimize the DNN with the aim of improving the accuracy of the DNN. Finally, the accuracy of the IABC-DNN-based sentiment analysis model for vocal performance proposed in this study can reach 98% as verified by a test set. Overall, the emotional analysis model for vocal performance established in this study not only needs to ensure that the training data of the model is diverse and comprehensive, but also can capture emotional expressions from different singers, music styles, and cultural backgrounds. In addition, the subjectivity of sentiment analysis is also taken into account by the model, which can ensure that the model can find a balance between the differences in emotional perception among different listeners.

The remaining content of this study is arranged as follows: Section II of this paper reviews the relevant work related to this article. Section III developed an improved artificial bee colony algorithm. In Section IV, a novel DNN is designed. Section V presents the results. Finally, Section VI summarizes the entire study.

II. Literature Review

A. Emotional Analysis of Vocal Performance

Building an emotional analysis model for vocal performance is an interdisciplinary task that involves fields such as audio signal processing, music theory, psychology, and computer science. Emotional analysis is an important task in natural language processing (NLP), which aims to identify and extract subjective information from text. Before the emergence of deep learning methods, sentiment analysis mainly relied on vocabulary methods and machine learning techniques, such as naive Bayes and support vector machines. These methods typically require a significant amount of feature engineering. In recent years, deep learning-based sentiment analysis models have made significant progress. Convolutional Neural Network (CNN) is a deep learning model primarily used for processing grid shaped data, such as images. However, in recent years, CNN has also been successfully applied to sentiment analysis models. Specifically, reference [13] proposed a simple CNN model for sentence classification, including sentiment analysis. This model can use one-dimensional convolution and pooling operations to directly operate on word embeddings, thereby capturing local dependencies.

In addition, Recurrent Neural Networks (RNNs) are also a type of neural network capable of processing sequential data, making them highly suitable for processing text data. RNN can capture long-term dependencies in text by passing hidden states between time steps. However, a major problem with RNNs is gradient vanishing and exploding, which makes training deep RNNs difficult. To address this issue, reference [14] proposed the Long Short-Term Memory (LSTM) model. LSTM can more effectively capture long-term dependencies by introducing gating mechanisms. In addition, Transformer is a model based on self-attention mechanism. Unlike RNN and CNN, Transformer completely abandons loops and convolutions and relies on self-attention mechanism to capture global dependencies. Transformer has achieved significant success in various NLP tasks, including sentiment analysis [15].

In recent years, pre trained models have achieved significant success in various NLP tasks. These models are first pre trained on large-scale corpora and then fine-tuned on specific tasks. Pre trained models can capture rich language knowledge, significantly improving the performance of various NLP tasks, including sentiment analysis [16]. Meanwhile, knowledge graphs are also a structured way of representing knowledge, which can be used to represent entities and their relationships. In recent years, some studies have begun to explore how to use knowledge graphs for sentiment analysis. For example, reference [17] proposed a sentiment analysis model based on knowledge graphs, which can utilize the information in the knowledge graph to improve the performance of sentiment analysis.

However, the above artificial intelligence-based sentiment analysis models also have some challenges and limitations. Firstly, the above sentiment analysis models ignore the fine-grained issues in sentiment analysis, such as sentiment intensity detection, multi-dimensional sentiment analysis, etc. In addition, the above sentiment analysis models face significant challenges when dealing with texts with satire and metaphor.

B. Deep Neural Network

Deep Neural Network (DNN) is a machine learning model that simulates the structure of human brain neural networks. It consists of multiple hidden layers, each of which is composed of multiple neurons. DNN has a wide range of applications in fields such as image recognition, speech recognition, and natural language processing [18]-[19]. In [18], a random DNN for image processing was designed, which has fewer neurons and higher accuracy compared to traditional DNNs. In [20], a deep neural network for signal processing was designed, which has better generalization ability against noise compared to traditional DNNs. In study [21], a DNN for image classification was designed using a two-stage algorithm, which can improve the accuracy of image classification during the DNN process. In study [22], several deep learning methods were combined and heuristic optimization methods were introduced to optimize the relevant parameters in the combination process, providing ideas for the design of new DNNs. In study [23], a DNN based risk model was developed to design the risk assessment process as an optimization problem.

Although DNN has achieved significant results in many fields, it still faces many challenges. Firstly, the training of DNN requires a large amount of computing resources and data, which is not feasible for many practical applications. Secondly, DNN has poor interpretability and it is difficult to understand its internal working mechanism. In addition, DNN is also susceptible to adversarial attacks, which is a problem for applications with high security requirements. In the future, research on DNN will focus more on improving its efficiency, interpretability, and security to meet the needs of more practical applications.

III. IABC-Deep Learning Framework

The basic principle of DNN is to map input data to output space through multi-layer nonlinear transformations. Each layer is composed of multiple neurons, each with an activation function used to convert input data into output data [24]-[27]. DNN is trained through backpropagation algorithm, optimizing weights and biases through gradient descent to minimize the difference between predicted and true values. Deep learning models may encounter difficulties when dealing with long texts, as long texts may contain a large amount of information, making it difficult for the model to capture key information. Therefore, similar to [22], in order to improve the accuracy of DNN, researchers have begun to attempt to combine meta heuristic algorithms with DNN algorithms to design DNN with better performance. Fig. 1 shows how to conduct sentiment analysis on vocal performance works based on DNN.

A. Collection of Sound Signals in Vocal Performance Works

Before designing the DNN framework, it is necessary to first sample and preprocess the speech of vocal performance works. Fig. 2 shows the short-term energy map of a vocal performance. In the specific sampling process, it is first necessary to frame the sound signal according to the time scale. Among them, the length of each audio segment is L_{audio} . Divide the entire audio into Num_{audio} segments. Without considering overlapping frames, the total number of sampling points for the sound signal is calculated as shown in Eq. (1).

$$Num_{total} = L_{audio} \times Num_{audio} \tag{1}$$

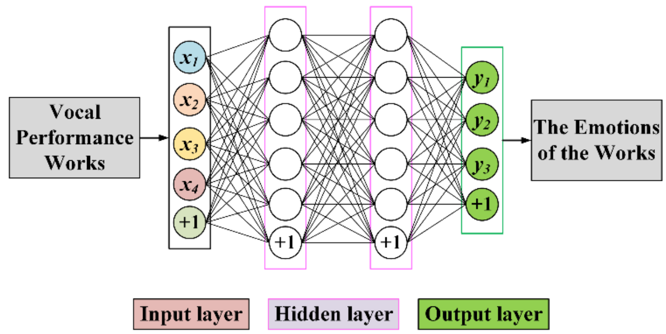

Fig. 1. The DNN schematic diagram for emotional analysis of vocal performance works.

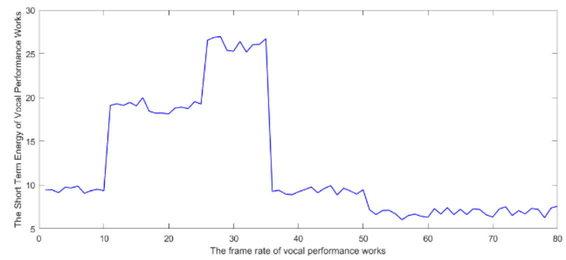

Fig. 2. The short-term energy map of a vocal performance work.

In audio processing, root mean square energy is often used for feature extraction of signals such as music and speech. For example, in tasks such as music emotion classification, speech activity detection, and speech recognition, root mean square energy is one of the important features. Meanwhile, as root mean square energy can reflect the loudness of audio signals, it is often used in applications such as music dynamic range compression and volume adjustment. Fig. 3 shows the mean square energy root of the audio signal in a certain vocal performance. Mean square energy root is a commonly used feature in audio processing, mainly used to describe the energy magnitude of audio signals. It is obtained by calculating the square of each sample of the audio signal, then taking the average value, and finally taking the square root. This value can reflect the loudness of audio signals and can also be used for audio segmentation classification.

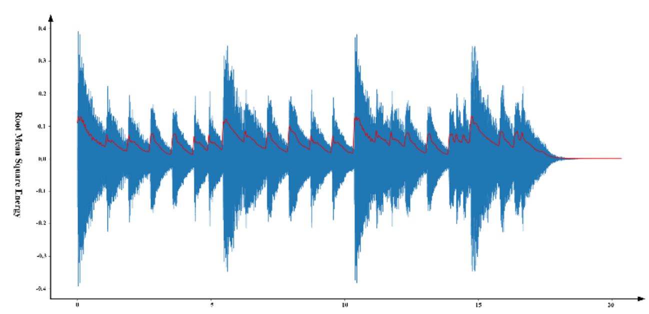

Fig. 3. The root mean square energy of a certain vocal performance.

B. Overview of Emotional Analysis Framework for Vocal Performance Works

After extracting language and speech from the audio of vocal performance works, Fig. 4. shows the sentiment analysis framework for vocal performance works based on IABC-DNN constructed in this study. The framework shown in Fig. 4. mainly consists of three parts: language prompts, knowledge-based encoding and decoding, and joint inference based on weighted first-order logic rules. In this study, propositional logic was constructed as a formal reasoning system. However, the minimum unit of propositional logic language is propositional symbols, which makes it impossible to conduct a more in-depth analysis of individual propositional symbols. Therefore, we used weighted first-order logic rules.

The framework shown in Fig. 4 which encodes the output of DNN using the following rules:

$$\square(k): DNN\_P\_issu(t,k) \rightarrow BoolP(t) \tag{2}$$

Among them, $BoolP(t)$ is Boolean variables, t indicates polarity, and $\square(k)$ represents weight. The rule weights are defined in Eq. (3):

$$\square(k) = ln\left(\frac{k}{1-k}\right) \tag{3}$$

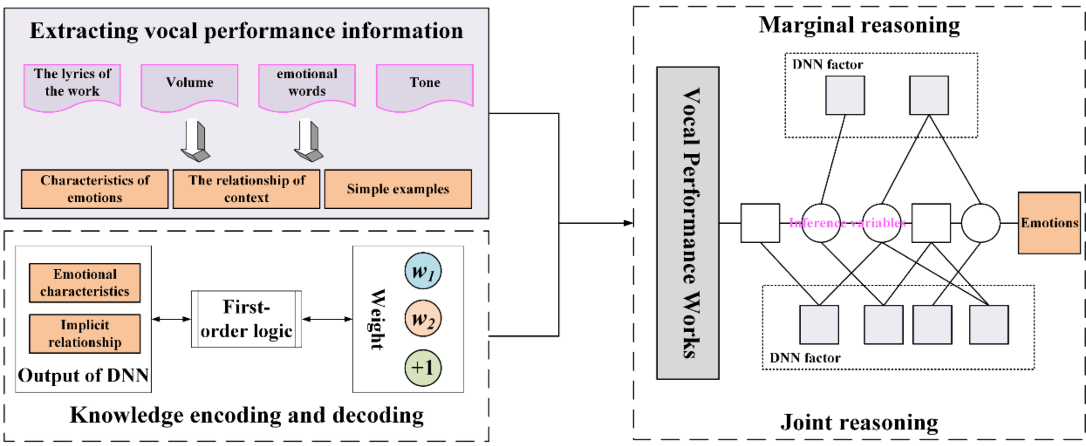

Fig. 4. The overall framework of vocal emotion analysis based on IABC-DNN.

IV. Design of IABC-DNN Algorithm

The swarm intelligence optimization algorithm is an optimization algorithm that simulates the behavior of groups in nature, such as bird flocks searching for food, ants finding their way, and so on. This algorithm has global search capability and can find the optimal solution over a large range, avoiding getting stuck in local optima. Therefore, it can be used to optimize the parameters of DNN. DNN is a complex machine learning model with numerous parameters and high optimization difficulty. Traditional optimization methods such as gradient descent may fall into local optima, while swarm intelligence optimization algorithms can avoid this problem. Specifically, the parameters of deep neural networks can be regarded as "individuals" in swarm intelligence optimization algorithms, each with a fitness value, that is, the performance of the deep neural network under this parameter setting. The swarm intelligence optimization algorithm continuously updates individuals by simulating group behavior, such as bird foraging and ant pathfinding, to optimize the parameters of deep neural networks and improve their performance.

A. IABC Algorithm

The Artificial Bee Colony (ABC) algorithm, as a novel swarm intelligence algorithm, is used in this paper to optimize the weights of DNN networks. The ABC algorithm is inspired by the honey gathering process of bees. In the optimization process, the ABC algorithm consists of two parts: feasible solutions (food sources) and solution positions (hired bees and non-hired bees). Among them, in any optimization problem, the feasible solution of the problem is given in a certain form. In the ABC algorithm, the food source is the feasible solution to the problem and is the basic object to be processed in the artificial bee colony algorithm. The quality of the food source can be evaluated by the value of the fitness function. Hiring bees refers to leading bees (collecting bees) that correspond to the position of their food source, with one food source corresponding to one leading bee. The steps and process of the improved Artificial Bee Colony (IABC) algorithm designed in this article are as follows. The algorithm flowchart of IABC is shown in Fig. 5.

1) Step 1: Initialization. Generate initial solutions based on the weights w_d of each neuron in DNN, and form a set of initial solution positions based on $I\max$ initial solutions. Specifically, as follows:

$$W_I = \left[w_1, w_2, \cdots, w_{d\max}\right] \tag{4}$$

$$abc\_Swarm_I = \left[W_1, W_2, \cdots, W_{I\max}\right]^T \tag{5}$$

2) Step 2: Calculate the fitness function value. Calculate the fitness function value for each honey source in the bee population. In Eq. (6), the objective function f_RMSE used in this study is given.

$$f\_RMSE = \sqrt{\tfrac{1}{n} \times \sum\left(V_{pre} - V_{ture}\right)^2} \tag{6}$$

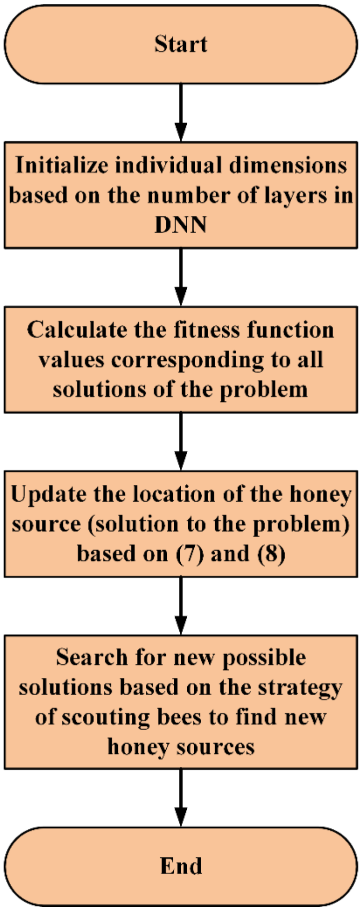

Fig. 5. The flowchart of IABC algorithm.

where, V_{pre} is the predicted value, and V_{ture} is the true value.

3) Step 3: Honey source update operation. In this study. DNN has $d\max$ weight coefficients that need to be optimized, and the number of bees collected or observed is equal to the number of solutions. Therefore, the number of bees collected or observed is $Imax$. Before updating the honey source, first generate a random number Q in the [0,1] interval. In Eq. (7) and Eq. (8), the way honey source updates are displayed.

If $Q \le 0.5$, then

$$w_{d,x}(new) = w_{d,x}(old) + \alpha \times \left(w_{d,x}(old) - w_{d,y}\right) \tag{7}$$

If $Q > 0.5$, then

$$w_{d,x}(new) = w_{d,x}(old) + F \times \left(w_{d,y} - w_{d,z}\right) \tag{8}$$

where, α is a random number on the interval [-1,1]. F is the variation factor, and its value range is generally within the range of [0.4, 0.95].

In Eq. (9) and Eq. (10), individuals before and after the honey source update operation are displayed, respectively.

$$W_I(old) = \left[w_1(old), w_2(old), \cdots, w_{d\max}(old)\right] \tag{9}$$

$$W_I(new) = \left[w_1(new), w_2(new), \cdots, w_{d\max}(new)\right] \tag{10}$$

After completing the honey source update operation, use a greedy selection strategy to retain better honey sources. Each observed bee selects a honey source based on probability, and the probability formula is shown in Eq. (11).

$$P = \frac{f\_RMSE(i)}{\sum f\_RMSE(k)} \tag{11}$$

4) Step 4: Generate feasible solutions based on reconnaissance bees. If, after the honey source update operation, the fitness value of a honey source is not further optimized within the given steps, the honey source is discarded, and the corresponding honey collecting bee becomes a reconnaissance bee. The reconnaissance bee searches for new possible solutions using the following:

$$w_{d,x}(new) = w_{d,x}(\min) + ramd(0,1) \times \left[w_{d,x}(\max) - w_{d,x}(\min)\right] \tag{12}$$

5) Step 5: End. Record the optimal solution and determine if the termination condition is met. If so, output the optimal solution.

V. Results Display

For the dataset, we selected a dataset consisting of 180 vocal performance works. The specific experiment is set up according to the following steps. Firstly, based on three different academic groups of students majoring in vocal performance, judges specializing in vocal performance, and experts in vocal performance, 180 vocal performance works were scored and their emotional expressions were given using a back-to-back scoring method. This study focuses on analyzing vocal performance works with five emotions: sadness, tenderness, anger, joy, and pride. In DNN, the five emotions are represented by 1, 2, 3, 4, and 5, respectively. Secondly, swarm intelligence algorithms are used in the structure of English DNNs. On this basis, the IABC-DNN algorithm was compared with DNN based on improved group search algorithm (IGSO-DNN), DNN based on ABC algorithm (ABC-DNN), and DNN based on improved genetic algorithm (IGA-DNN). The results showed that the proposed method is superior to the above three algorithms.

A. Dataset Settings

Table I shows the audio features and descriptions of vocal performance works, and the DNN algorithm conducts sentiment analysis based on these features and descriptions. Furthermore, 180 vocal performance works were divided into three sets of data to fully validate the model's generalization ability, as shown in Table II. In Table II, dataset WD-1 includes a training set consisting of 50 vocal performance works and a testing set consisting of 10 vocal performance works. The dataset WD-2 includes a training set consisting of 100 vocal performance works and a testing set consisting of 20 vocal performance works. The dataset WD-3 includes a training set consisting of 100 vocal performance works and a testing set consisting of 20 vocal performance works.

TABLE I. AUDIO FEATURES AND DESCRIPTIONS OF VOCAL PERFORMANCE WORKS

Characteristic	Describe
Sound quality characteristics	Very rough, very smooth, medium
Irregularity	Anger, fear, and sadness
Variability	More unpleasant (valence), awake or tired (awakening energy), and more tense (awakening tension)

TABLE II. DESIGN OF DATASETS

Data	Work types	Train	Test
WD-1	Vocal performance	50	10
WD-2	Vocal performance	100	20
WD-3	Vocal performance	150	30

B. Result Comparison

This study uses ABC algorithm, IABC algorithm, IGA algorithm, and IGSO algorithm to optimize the weights between neurons in DNN. The optimization results are shown below.

To demonstrate the robustness of swarm intelligence algorithms, ABC algorithm, IABC algorithm, IGA algorithm, and IGSO algorithm were run 50 times each. Fig. 6, 7, and 8 respectively show the optimal fitness function curve, worst fitness function curve, and average fitness function curve of the 50 run results of the four algorithms in optimizing the weights of the DNN network. From Fig. 6, 7, and 8, it can be concluded that the IABC algorithm designed in this study converges faster and has higher accuracy in optimizing the weight coefficients of DNN compared to the IGSO, IGA, and ABC algorithms.

Furthermore, this study compared three algorithms, DNN, IGWO-DNN, and IGA-DNN, with the proposed IABC-DNN algorithm. The comparison indicators included Accuracy, Precision, Sensitivity, Specification, and F-1 score. Tables III, IV, and V respectively show the various indicators of dataset WD-1, WD-2, and WD-3 when using the four models. In three datasets, regardless of which indicator, the IABC-DNN algorithm performed the best, fully demonstrating the effectiveness of the algorithm designed in this study.

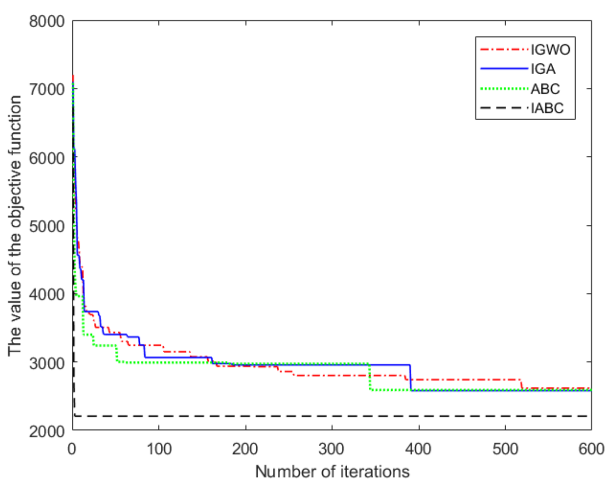

Fig. 6. The optimal fitness function curve during 50 runs of four algorithms.

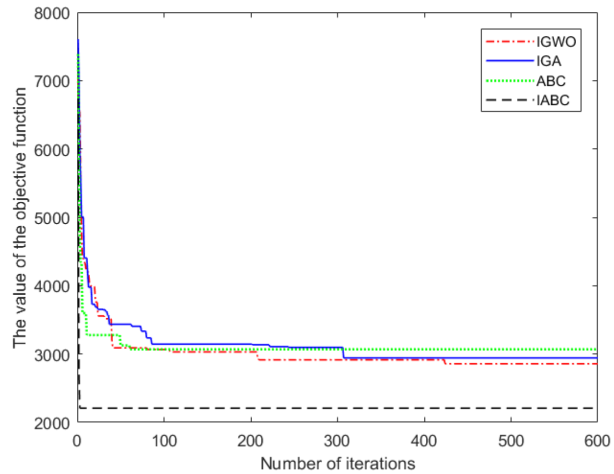

Fig. 7. The worst fitness function curve during 50 runs of four algorithms.

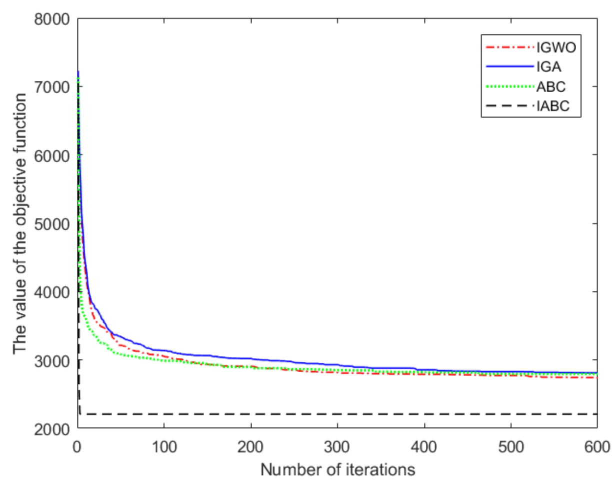

Fig. 8. The average fitness function curve during 50 runs of four algorithms.

TABLE III. EVALUATION OF PERFORMANCE METRICS FOR DATASET WD-1

Algorithm	Accuracy	Precision	Sensitivity	Specificity	F-1 score
DNN	0.812	0.865	0.821	0.920	0.855
IGWO-DNN	0.966	0.897	0.899	0.931	0.945
IGA-DNN	0.892	0.913	0.920	0.982	0.928
IABC-DNN	**0.975**	**0.987**	**0.999**	**0.987**	**0.991**

TABLE IV. EVALUATION OF PERFORMANCE METRICS FOR DATASET WD-2

Algorithm	Accuracy	Precision	Sensitivity	Specificity	F-1 score
DNN	0.889	0.863	0.901	0.902	0.890
IGWO-DNN	0.904	0.900	0.895	0.911	0.881
IGA-DNN	0.948	0.925	0.916	0.958	0.916
IABC-DNN	**0.981**	**0.988**	**0.990**	**0.946**	**0.970**

TABLE V. EVALUATION OF PERFORMANCE METRICS FOR DATASET WD-3

Algorithm	Accuracy	Precision	Sensitivity	Specificity	F-1 score
DNN	0.829	0.885	0.856	0.916	0.885
IGWO-DNN	0.876	0.839	0.853	0.901	0.916
IGA-DNN	0.925	0.900	0.895	0.970	0.924
IABC-DNN	**0.984**	**0.978**	**0.928**	**0.976**	**0.993**

Furthermore, Fig. 9 shows the accuracy of DNN, ABC-DNN, and IABC-DNN in predicting the emotions of 30 vocal performance works when using 150 vocal performance works as the test set.

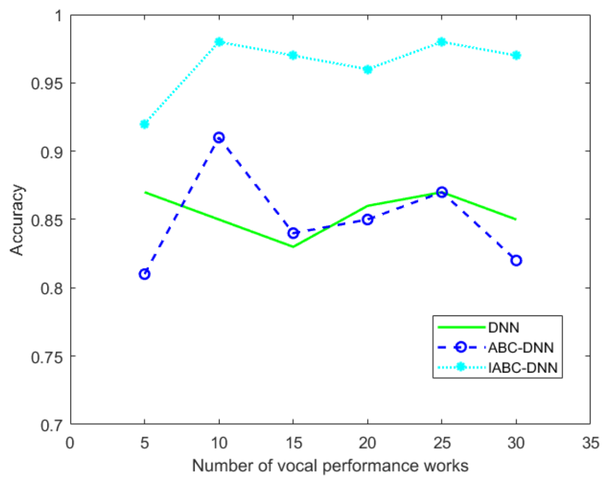

Fig. 9. The accuracy of different sentiment analysis models.

From Fig. 9, it can be seen that the IABC-DNN algorithm designed in this study has the highest accuracy, at 98%, which is higher than 87% of DNN and 91% of ABC-DNN algorithm. Compared with DNN algorithm and ABC-DNN algorithm, the accuracy of IABC-DNN algorithm has improved by an average of 9%.

VI. CONCLUSION

This study designed corresponding algorithms and models for the emotional analysis of vocal performance works. Especially, an improved ABC algorithm was designed and applied to the optimization process of weight coefficients in DNN networks. The effectiveness of the IABC-DNN algorithm has been fully demonstrated through three datasets. Compared with DNN and ABC-DNN algorithms, the accuracy of IABC-CNN algorithm has improved by 9%. In addition, compared with IGA, IGSO, and ABC, the IABC algorithm has the fastest convergence speed and highest convergence accuracy in optimizing the weight coefficients of DNN networks.

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