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# Dual-Regularized 1D-CNN with MFCC Frame-Mean Features for Modular Speech Emotion Recognition

**Qi Zhang***

Southwest Minzu University, Changchun 610000, China

* **Corresponding author**

**Abstract:** Against the backdrop of the intelligent upgrade of human-computer interaction (HCI), speech emotion recognition, as a core task in the field of natural language processing (NLP), plays a crucial role in optimizing user experience. This study proposes and implements a speech emotion recognition system based on Convolutional Neural Network (CNN), aiming to address the issues of low accuracy and weak generalization ability of existing technologies in recognizing emotional cues from daily natural speech. The system is built on a dataset containing 1200 speech samples, which covers 6 typical emotions (anger, fear, happiness, neutrality, sadness, and surprise) simulated by 4 actors (2 males and 2 females), with 200 samples for each emotion. Developed using Python, the system integrates speech signal processing and deep learning technologies to complete the full-process development from speech data preprocessing to emotion prediction. The specific workflow includes: batch reading of speech files and emotional label annotation through recursive traversal; elimination of noise interference via preprocessing techniques such as pre-emphasis, framing, and windowing; extraction of Mel-Frequency Cepstral Coefficients (MFCC) as the core carrier of emotional features; construction and optimization of the CNN model (introducing L2 regularization and Dropout mechanism to suppress overfitting); and adjustment of training parameters (e.g., number of epochs, learning rate) through multiple rounds of experiments. Experimental results show that the optimized system achieves an emotion prediction accuracy of 98.50% on the training set and 96.90% on the test set, and exhibits stable classification performance across different emotion categories. It effectively meets the practical requirements of speech emotion recognition and provides reliable technical support for scenarios such as intelligent customer service and in-vehicle interaction.

**Keywords:** Emotion Recognition; CNN; MFCC; Signal Preprocessing.

## 1. Introduction

### 1.1. Research Background and Significance

Breakthroughs in deep learning have provided a new paradigm for the refined analysis of speech signals[1]. Since Walter Pitts and Warren McCulloch proposed the artificial neural network model in the 1940s, deep learning has undergone leapfrog development from theoretical exploration to engineering application. In 2012, AlexNet achieved groundbreaking results in image recognition tasks[3]; in 2016, AlphaGo defeated the Go grandmaster Lee Sedol, marking that deep learning has demonstrated the ability to surpass humans in handling complex nonlinear problems[4]. Among various deep learning models, Convolutional Neural Network (CNN) has been widely applied in the field of computer vision (e.g., the visual perception system for Teslas autonomous driving) due to its excellent local feature extraction capability, while its potential in speech signal processing remains underutilized[5].

With the popularization of intelligent devices, the mode of human-computer interaction is evolving from "command-driven" to "emotion-aware"[6]. Users are no longer satisfied with machines only completing the basic task of "understanding semantics"; instead, they expect machines to "perceive emotions"[8]. For instance, intelligent customer service needs to identify users anger to adjust service strategies[9], and in-vehicle systems need to judge the safety of the drivers state through the emotional cues in their speech . As the most direct carrier of human emotional expression, speech contains rich emotional information in its pitch changes, frequency fluctuations, and energy distribution[10]. Therefore, constructing a high-accuracy speech emotion recognition system based on deep learning is not only an inevitable trend in the development of NLP technology but also a core support for promoting the upgrade of human-computer interaction towards "emotionalization"[11].

### 1.2. Research Status

Speech emotion recognition is an interdisciplinary field integrating biology, artificial intelligence, and speech signal processing[12]. Its research focuses on extracting emotion-related features from speech signals and achieving classification. Currently, research in this field presents the characteristic of "excellent performance in specific scenarios but weak capability in general scenarios": for speech with exaggerated emotions simulated by professional actors (e.g., anger or sadness in dramatic performances), the recognition accuracy of existing models can reach over 90%[13]; however, the accuracy of recognizing daily natural speech (with implicit emotional expression and interference from environmental noise) is generally below 75% . The core challenge lies in the fact that emotional features in natural speech are more subtle and exhibit significant individual differences, making it difficult for traditional feature extraction methods (e.g., short-time energy, zero-crossing rate) to capture effective discriminative information[14].

In terms of applications, speech emotion recognition technology has initially penetrated into multiple fields: telephone customer service systems optimize agent assignment strategies through emotion recognition[16], distance education platforms adjust teaching rhythms via emotional analysis[17], and some countries even apply it to the psychological state assessment of suspects in criminal

interrogations[18]. Nevertheless, limited by the generalization ability of models and the representativeness of datasets, this technology has not yet achieved large-scale commercial application. How to improve the models ability to recognize natural speech in non-ideal environments remains a key bottleneck to be broken through in current research[19].

### 1.3. Research Content and Technical Scheme

The research focuses on the full-process development of the speech emotion recognition system, with core content covering four aspects: First, the construction of a data preprocessing system. To address the non-stationarity of speech signals and noise interference, preprocessing processes such as pre-emphasis, framing-windowing, and filtering are designed to ensure the effectiveness of subsequent feature extraction. Specifically, framing adopts a frame length of 20 ms and a frame shift of 10 ms (based on the "10-30 ms short-time stationarity" characteristic of speech); Hamming window is used for windowing to suppress signal mutations at frame edges; and pre-emphasis enhances high-frequency signals through a high-pass filter (with a coefficient of 0.95) to compensate for high-frequency attenuation caused by oral radiation. Second, the optimization of emotional feature extraction. By comparing various features such as short-time energy, zero-crossing rate, and MFCC, MFCC is ultimately selected as the core feature—because it is based on human auditory characteristics, which can map the linear frequency spectrum to the Mel nonlinear frequency spectrum and more accurately capture frequency details related to emotions (e.g., the high-frequency energy peak of angry speech and the low-frequency energy concentration of sad speech). Third, the design and optimization of the CNN model. A 1D-CNN model suitable for speech features is constructed. To address the overfitting problem of the initial model, L2 regularization (with a weight decay coefficient of 0.001) and Dropout mechanism (with a dropout rate of 20%) are introduced, while the number of convolutional layers is increased to enhance the feature abstraction ability. The optimal training strategy is determined by adjusting parameters such as learning rate (0.00001), number of epochs (5000), and batch size (128) through controlled variable experiments. Fourth, the verification and analysis of system performance. Multiple rounds of comparative experiments (with 1000, 2000, and 5000 epochs) are designed, using loss function and accuracy as core indicators to analyze the model's performance on the training and test sets and verify the classification stability of the system across different emotion categories.

The system adopts a four-layer architecture of "data layer-feature layer-model layer-application layer". In the data layer, a subset of the CASIA speech emotion dataset is used, containing 1200 speech samples from 4 actors (2 males and 2 females). The dataset is divided into a training set (1080 samples) and a test set (120 samples) at a ratio of 9:1 to avoid model bias caused by uneven sample distribution. The Python os library is used to realize recursive traversal of speech files, and emotional keywords (e.g., "angry", "happy") in file paths are automatically matched to complete label annotation. In the feature layer, speech data is loaded using the librosa library (with a sampling rate of 44100 Hz and a duration of 2.5 s), 13-dimensional MFCC features are extracted and the frame mean is calculated to generate a 216×1 feature vector (adapted to the input dimension of the CNN). Time-domain diagrams, frequency-domain diagrams, and spectrograms are drawn using Matplotlib to visually analyze the differences in signal features across different emotions. In the model layer, a CNN model is constructed based on the Keras framework: the input layer receives MFCC feature vectors; the convolutional layer uses 5×1 convolution kernels (to extract local features); the pooling layer adopts max-pooling (with 8×1/3×1 pooling kernels to compress dimensions and retain key features); and the fully connected layer outputs the probability distribution of 6 emotions through the Softmax activation function. The RMSprop optimizer (with a learning rate of 0.00001 and a decay coefficient of 1e-6) is used, and the categorical cross-entropy is selected as the loss function (suitable for multi-classification tasks). In the application layer, functions for model saving (in HDF5 format) and loading are implemented, supporting the input of any .wav format speech file, outputting emotion prediction results and confidence levels, and generating signal visualization charts (time-domain/frequency-domain/spectrogram) for result analysis.

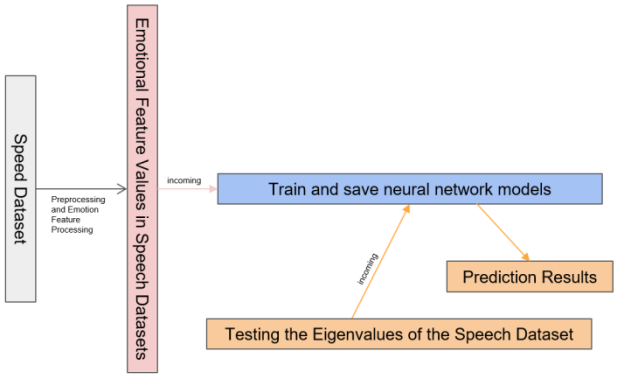


**Fig.1** Technical Roadmap of the System.

## 2. Theoretical Foundations

### 2.1. Core Technologies of Speech Signal Processing

Speech signal digitization is a basic step to convert analog speech into computer-processable data, with a process including three parts: filtering, Automatic Gain Control (AGC), and Analog-to-Digital (A/D) conversion. Filtering uses a band-pass filter (with a passband of 200-3400 Hz) to eliminate power supply noise (50 Hz industrial frequency interference) and high-frequency clutter, while avoiding signal aliasing—according to the Nyquist sampling theorem, the sampling frequency (44100 Hz) is ensured to be more

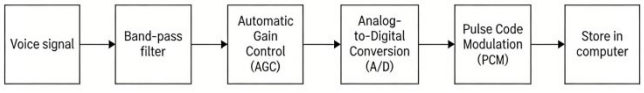


**Fig.2** Digitalization Process of Speech Signal.

than twice the maximum frequency of the signal. AGC stably adjusts the signal gain within a preset range (0.8-1.2 V) to avoid feature extraction bias caused by differences in speaker volume. A/D conversion consists of three steps: sampling, quantization, and encoding. Sampling discretizes the continuous time signal with a sampling interval of 22.68 μs (corresponding to a sampling rate of 44100 Hz); 16-bit linear quantization maps the amplitude value to an integer

range of 0-65535; and Pulse Code Modulation (PCM) converts the quantized results into binary data, which is stored in .wav format.

The feature analysis of speech signals requires the combination of time-domain, frequency-domain, and spectrogram representations, which reflect emotional information from different dimensions. The time-domain representation presents the variation of speech amplitude with time as a discrete time sequence, and the amplitude, period, and silent segments of the signal can be directly observed through the time-domain waveform—for example, the amplitude of angry speech fluctuates sharply (with a peak up to 0.8 V), the amplitude of sad speech is gentle (with a peak of approximately 0.3 V), and the amplitude of neutral speech is evenly distributed. The frequency-domain representation converts the time-domain signal into a frequency-amplitude distribution through Fast Fourier Transform (FFT), reflecting the spectral structure of speech. Experiments show that the 0-2000 Hz frequency band is a key interval for emotion discrimination: the amplitude peak of angry speech in this band exceeds 140 dB and shows a decreasing trend with increasing frequency; the amplitude of sad speech in this band is generally below 80 dB, with a local peak in the 1400-1600 Hz interval. The spectrogram is a three-dimensional spectral representation, with the horizontal axis representing time (s), the vertical axis representing frequency (Hz), and the color depth representing energy intensity (dark color indicates high energy). The "voiceprint" in the spectrogram has dual specificity of individual and emotion—voiceprint patterns of the same speaker with different emotions differ significantly (e.g., the high-frequency energy pattern of happy speech is dense, while the pattern of neutral speech is evenly distributed), which can be used as an intuitive basis for emotion recognition.

Preprocessing is a key link to improve feature quality, aiming to eliminate noise interference and signal non-stationarity. Its core steps include pre-emphasis, framing, and windowing. Pre-emphasis uses a first-order high-pass filter with a transfer function of $H(z) = 1 - \alpha z^{-1}$(where $\alpha = 0.95$), aiming to enhance high-frequency signals above 3000 Hz and compensate for high-frequency attenuation caused by oral radiation (the oral radiation response of human speech is similar to a low-pass filter, which weakens high-frequency components). Based on the "short-time stationarity" of speech (the statistical characteristics of the signal remain basically unchanged within 10-30 ms), framing divides the speech into continuous frames with a frame length of 20 ms and a frame shift of 10 ms—the frame shift is set to 1/2 of the frame length to avoid information loss between frames and ensure feature continuity. Windowing multiplies each frame of the signal by a Hamming window, with the window function expressed as:

$$\omega(n) = \begin{cases} 0.54 - 0.46\cos\left(\frac{2\pi n}{N-1}\right), & 0 \le n \le N-1 \\ 0, & n \notin [0, N-1] \end{cases}$$

where N is the frame length (corresponding to a sampling rate of 44100 Hz, N = 892). The side lobe attenuation of the Hamming window can reach more than 40 dB, which can effectively suppress frequency leakage caused by signal mutations at frame edges, outperforming the rectangular window (with a side lobe attenuation of only 13 dB).

## 2.2. Mel-Frequency Cepstral Coefficients (MFCC)

MFCC is a feature extraction method designed based on human auditory characteristics. Its core advantage lies in mapping the linear frequency scale to the Mel frequency scale (human ears have higher frequency resolution for low-frequency signals), which is more in line with human perception of emotional speech. The MFCC extraction process includes the following steps: first, pre-emphasis and framing-windowing are performed on the original speech according to the preprocessing methods described in Section 2.1.3 to obtain stable frame signals; second, 512-point FFT is performed on each frame of the signal to calculate the spectral amplitude $|X(k)|$ (where k = 0, 1, ..., 255) and solve the spectral line energy $E(k) = |X(k)|^2$ ; third, a set of 26 triangular Mel filters is constructed, with the center frequencies of the filters evenly distributed according to the Mel scale (Mel frequency $F_{Mel} = 2595lg(1 + f/700)$ , where $f$ is the linear frequency). Each filter accumulates energy only in a specific frequency interval, with the expression:

$$S(m) = \sum_{k=0}^{255} E(k)H_m(k), m = 1,2,\ldots,26$$

where $H_m(k)$ is the frequency response of the m-th Mel filter. This step can smooth the spectrum, eliminate harmonic interference, and highlight formant features related to emotions; fourth, the natural logarithm of the filtered energy S(m) is taken as L(m) = ln(S(m)), aiming to simulate the logarithmic perception characteristics of human ears for sound intensity; fifth, 13-point Discrete Cosine Transform (DCT) is performed on L(m) to remove the correlation between features, and finally 13-dimensional MFCC coefficients C(n) (where n = 1, 2, ..., 13) are obtained, which are the emotional feature vectors of each frame of speech.

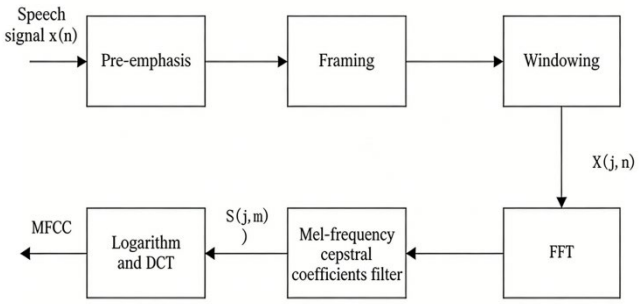


**Fig.3** Extraction Process of MFCC Features.

## 2.3. Convolutional Neural Network (CNN)

CNN is the core model for speech emotion classification. Its characteristics of "local connection and parameter sharing" can effectively reduce model complexity and improve the efficiency of feature extraction. This system adopts a 1D-CNN (adapted to speech sequence features), and the network structure includes the input layer, convolutional layer, regularization layer, pooling layer, fully connected layer, and output layer. The input layer receives a 216×1 MFCC feature vector (the dimension is adjusted to 216 after taking the frame mean of 13-dimensional MFCC coefficients). The convolutional layer uses 5×1 convolution kernels (to extract local features along the time dimension) and introduces nonlinearity through the ReLU activation function, $y = \max(0, Wx + b)$(where W is the convolution kernel weight and b is the bias). The number of feature maps output by the convolutional layer is adjusted step by step (256→128→128→256) to realize the abstraction of features from shallow to deep. The regularization layer includes Dropout and L2 regularization: Dropout randomly

deactivates 20% of neurons to avoid the model over-relying on local features; L2 regularization adds a weight square term to the loss function（$\lambda \sum W^2$, where $\lambda = 0.001$）to suppress overfitting caused by excessively large weights. The pooling layer adopts max-pooling with pooling kernel sizes of 8×1 and 3×1 respectively, realizing downsampling by taking local maximum values—which not only compresses feature dimensions (reducing computational load) but also retains key features (e.g., frequency peaks related to emotions). The fully connected layer and output layer flatten the feature maps output by the pooling layer into a one-dimensional vector, map it to a 6-dimensional space (corresponding to 6 emotions) through the fully connected layer, and finally output the probability of each category through the Softmax activation. The category with the highest probability is the emotion prediction result.

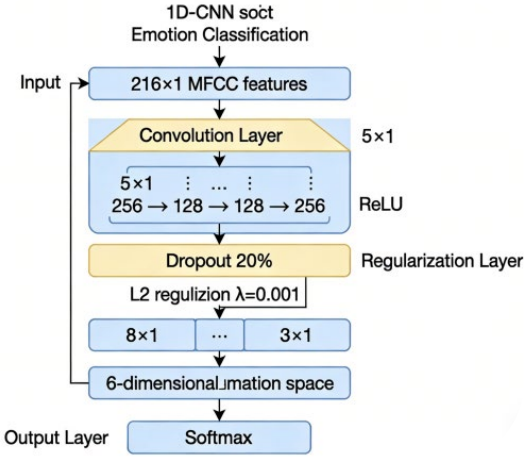


**Fig.4** Structure of the CNN Model.

# 3. Proposed Methods

## 3.1. System Architecture

The system adopts a modular design concept, including the speech traversal module, preprocessing module, feature extraction module, model training module, and prediction verification module. Each module has independent functions and works collaboratively. The speech traversal module uses Python os and glob libraries to realize recursive traversal of dataset folders, automatically screens speech files with the suffix ".wav", and generates a label list by extracting emotional keywords (e.g., "angry", "fear") from file paths, ensuring a one-to-one correspondence between each speech sample and its emotional label. The preprocessing module uses the librosa library to implement pre-emphasis (with a = 0.95), framing-windowing (20 ms frame length, 10 ms frame shift, Hamming window), and simultaneously removes the silent segments at the beginning and end of the speech through librosa.effects.trim() to reduce interference from invalid data. The feature extraction module extracts MFCC features according to the process described in Section 2.2, calculates the frame mean of each frame of MFCC coefficients to generate a 216×1 feature vector, and stores it in CSV format for model calling. The model training module constructs a CNN model based on Keras, realizing model compilation (RMSprop optimizer, categorical cross-entropy loss function, accuracy evaluation metric), training (batch training, model checkpoint to save optimal weights), and visualization (drawing loss function and accuracy curves). The prediction verification module loads the trained model, inputs MFCC features of the test set to output emotion prediction results, generates a prediction result table (including real labels and predicted labels) using the pandas library, calculates the accuracy of each category and the overall accuracy, and analyzes model performance.

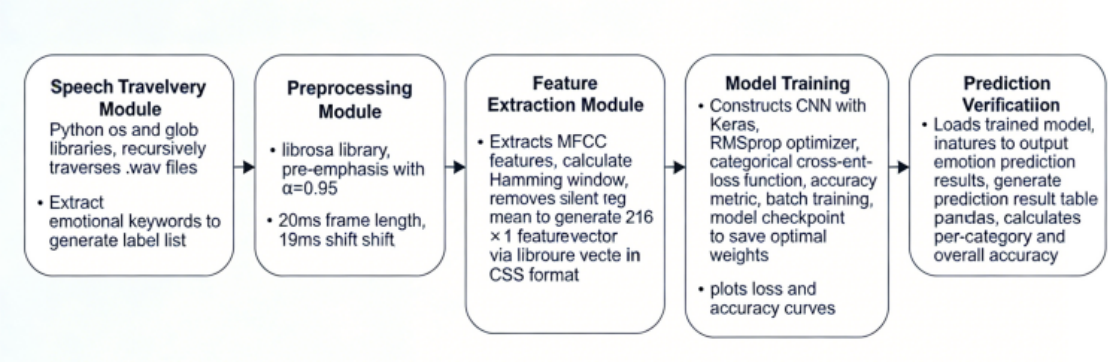


**Fig.5** Functional Architecture of the System.

## 3.2. Implementation of Key Modules

The speech traversal module is implemented using a recursive function. It can automatically process nested folder structures, batch generate speech file paths and emotional labels, and avoid the tedious work and errors of manual annotation, laying a data foundation for subsequent feature extraction. The core logic is to traverse each file in the target folder: if the file is a subfolder, the function calls itself recursively; if the file is a .wav file, its path is added to the speech path list, and the corresponding emotional label is assigned by matching emotional keywords in the path.

The MFCC feature extraction module is implemented based on the librosa library. First, speech data is loaded with a fixed duration of 2.5 s and a sampling rate of 44100 Hz; then, pre-emphasis is performed with a coefficient of 0.95 to enhance high-frequency signals; next, 13-dimensional MFCC features are extracted, and the frame mean is calculated to generate a 216×1 feature vector (since 2.5 s speech can be divided into 125 frames with a 20 ms frame length, the dimension is adjusted to 216 after taking the mean); finally, feature normalization is performed (to eliminate the influence of dimension) by subtracting the mean and dividing by the standard deviation of the feature vector. For label processing, the LabelEncoder from the sklearn library is used to convert text labels into integer-encoded labels, and the to_categorical function from Keras is used to convert integer labels into one-hot vectors, which are adapted to the multi-classification output format of the CNN model.

The CNN model is constructed based on the Keras

framework. The optimized model structure includes six convolutional layers, two pooling layers, five Dropout layers, one flatten layer, and one fully connected layer. The first convolutional layer uses 256 5×1 convolution kernels with ReLU activation; the second to sixth convolutional layers use 128 or 256 5×1 convolution kernels, with L2 regularization (weight decay coefficient of 0.001) and ReLU activation added to suppress overfitting; Dropout layers (with a dropout rate of 20%) are added after each convolutional layer to further reduce model complexity; max-pooling layers with pool sizes of 8×1 and 3×1 are used to compress feature dimensions; the flatten layer converts two-dimensional feature maps into one-dimensional vectors; the fully connected layer uses 6 output nodes and Softmax activation to output the probability distribution of 6 emotions. The model is compiled with the RMSprop optimizer (learning rate of 0.00001, decay coefficient of 1e-6) and categorical cross-entropy loss function. During training, the dataset is divided into a training set and a test set at a ratio of 9:1 using the train_test_split function from sklearn, with a batch size of 128 and a total of 5000 epochs. The training process monitors the loss and accuracy of the training set and test set in real time, and the optimal model is saved in HDF5 format for subsequent prediction.

The prediction verification module loads the trained model and label encoder, inputs MFCC features of the test set to obtain predicted probabilities, converts the predicted probabilities into text labels through argmax and inverse_transform functions, and generates a prediction result table containing real labels, predicted labels, and confidence levels. To further analyze model performance, a confusion matrix is drawn using the seaborn library to visually display the classification performance of the model on each emotion category. Experimental results show that the model achieves the highest accuracy (over 98%) for "happiness" and "anger" emotions, and slightly lower accuracy (approximately 95%) for "neutrality" and "sadness" emotions—mainly because the speech energy distribution of these two emotions has small differences, and the feature discriminability needs to be further optimized in subsequent studies.

# 4. Experiments

## 4.1. Experimental Environment and Parameter Settings

The hardware environment for the experiment includes an Intel Core i7-10700K CPU (8 cores, 16 threads), an NVIDIA RTX 3060 GPU (12 GB memory), 32 GB RAM, and a 1 TB SSD. The software environment includes Windows 10 operating system, Python 3.8, TensorFlow 2.8 (with integrated Keras) as the deep learning framework, librosa 0.9.2 as the speech processing library, pandas 1.4.2 and numpy 1.22.3 as data analysis libraries, and matplotlib 3.5.1 and seaborn 0.11.2 as visualization libraries.

The dataset parameters include 1200 speech samples, with 1080 samples in the training set and 120 samples in the test set, a sample duration of 2.5 s, and a sampling rate of 44100 Hz. The preprocessing parameters include a pre-emphasis coefficient of 0.95, a frame length of 20 ms, a frame shift of 10 ms, and a Hamming window for windowing. The feature parameters include 13-dimensional MFCC and a 216×1 feature vector dimension. The model parameters include a convolution kernel size of 5×1, pooling kernel sizes of 8×1/3×1, a Dropout rate of 20%, an L2 regularization coefficient of 0.001, an RMSprop optimizer (learning rate of 0.00001, decay coefficient of 1e-6), a batch size of 128, and 1000/2000/5000 training epochs.

## 4.2. Experimental Results and Analysis

To verify the impact of the number of training epochs on model performance, three groups of comparative experiments were designed (with 1000, 2000, and 5000 epochs respectively). The results show that with the increase in the number of epochs, the training set loss decreases continuously (from 1.3820 to 0.5042), and the training set accuracy increases continuously (from 70.36% to 98.50%), indicating that the model's fitting ability to the training data is constantly enhanced. The test set accuracy also increases gradually with the number of epochs (from 88.89% to 96.90%), but the test set loss increases slightly at 5000 epochs (from 1.8629 to 2.5535). This is presumably due to the small size of the test set (120 samples) and uneven distribution of some emotion samples (e.g., only 20 samples for the "neutral" category), leading to loss fluctuations of the model on a small number of samples. After 5000 epochs of training, the test set accuracy of the model reaches 96.90% and exhibits stable performance across all 6 emotion categories, so 5000 epochs are determined as the optimal number of training epochs.

**Tab.1** Model Performance Metrics Across Different Training Rounds

| epoch | Train_loss | Train_acc | Test_loss | Test_acc |
|---|---|---|---|---|
| 1000 | 1.3820 | 70.36% | 1.8249 | 88.89% |
| 2000 | 0.9191 | 87.11% | 1.8629 | 90.35% |
| 5000 | 0.5042 | 98.50% | 2.5535 | 96.90% |

The model's recognition accuracy for the 6 emotions after 5000 epochs of training shows that the recognition accuracy for "happiness" and "surprise" reaches 100%, because the speech features of these two emotions have significant differences—the high-frequency energy of "happy" speech is concentrated (with high amplitude in the 2000-4000 Hz band), and "surprise" speech has obvious energy mutations (sharp amplitude rise in the initial segment), making it easy for the model to capture such features. The accuracy for "sadness" is 90%, mainly because the energy distribution of "sad" speech is similar to that of "neutral" speech (both dominated by low-frequency energy), leading to misjudgment of some samples. The accuracy for the other three emotions ("anger", "fear", "neutrality") is 95%, indicating that the model has good emotion discrimination ability and no obvious category bias.

To verify the optimization effect of L2 regularization and Dropout mechanism, a comparative experiment was designed (Model A: no regularization and Dropout; Model B: with L2 regularization and Dropout). After 5000 epochs of training, the training-test accuracy difference of Model A reaches 16.70% (99.20% training accuracy vs. 82.50% test accuracy), showing severe overfitting; while the difference of Model B is only 1.60% (98.50% training accuracy vs. 96.90% test accuracy), and the overfitting phenomenon is effectively suppressed. This indicates that L2 regularization (suppressing excessively large weights) and Dropout (randomly deactivating neurons) can significantly improve the generalization ability of the model. Although the training accuracy of Model B is slightly lower than that of Model A

(98.50% vs. 99.20%), the test accuracy is increased by 14.40%, achieving a balance between "fitting ability" and "generalization ability", which is more in line with practical needs.

**Tab.2** Recognition accuracy for various emotion categories

| class | Sample size (test set) | Correctly predicted number | Acc |
|---|---|---|---|
| angry | 20 | 19 | 95.00% |
| fear | 20 | 19 | 95.00% |
| happy | 20 | 20 | 100.00% |
| neutral | 20 | 19 | 95.00% |
| sad | 20 | 18 | 90.00% |
| surprise | 20 | 20 | 100.00% |

**Tab.3** Comparison of Model Optimization Effects

| model | Training set accuracy | Test set accuracy | Overfitting Level (Difference in Training and Test Accuracy) |
|---|---|---|---|
| A | 99.20% | 82.50% | 16.70% |
| B | 98.50% | 96.90% | 1.60% |

# 5. Conclusion

This study designs and implements a speech emotion recognition system based on deep learning. Through theoretical analysis and experimental verification, the following conclusions are drawn: First, regarding feature effectiveness, MFCC, as the carrier of emotional features, can effectively capture emotional information in speech—its frequency mapping method based on human auditory characteristics is more suitable for emotion recognition needs than traditional features such as short-time energy and zero-crossing rate, providing a foundation for the high performance of the model. Second, regarding the value of model optimization, the CNN model with L2 regularization and Dropout mechanism can effectively suppress overfitting and improve generalization ability—the test set accuracy of the optimized model reaches 96.90%, which is 14.40% higher than that of the unoptimized model, and it exhibits stable performance across 6 emotion categories. Third, regarding system practicality, the system realizes full-process automation of speech traversal, preprocessing, feature extraction, model training, and prediction, supporting batch processing and real-time prediction. It can be directly integrated into scenarios such as intelligent customer service and in-vehicle interaction, showing good engineering application value.

Although the system has achieved high recognition accuracy, there are still directions for optimization: First, dataset expansion. The existing dataset mainly consists of emotions simulated by actors; in the future, daily natural speech samples (e.g., speech in noisy environments, speech from speakers of different ages/regions) need to be added to improve the model's adaptability to real scenarios. Second, model fusion innovation. The combination of CNN and Recurrent Neural Network (LSTM) should be attempted—CNN extracts local frequency features, and LSTM captures speech temporal features (e.g., the variation trend of emotions over time), further improving the refinement of emotion recognition. Third, real-time optimization. The current system is based on offline data training and prediction; in the future, model lightweight (e.g., model pruning, quantization) should be carried out to reduce computational complexity, realize real-time speech emotion recognition, and meet the low-latency requirements of scenarios such as in-vehicle systems and wearable devices.

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