Convolutional Neural Network Based Music Classification

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***Abstract*—Music classification is a vital component in music information retrieval, enabling automated categorization of musical content into genres, moods, or other classes. This paper presents a novel music classification approach using Convolutional Neural Networks (CNNs) combined with spectrogram-based feature extraction. The method leverages the LibROSA library for transforming raw audio data into Log-Mel Spectrograms, which are input into a multi-layer CNN model designed for efficient and accurate classification. Extensive experiments on the GTZAN dataset demonstrate the effectiveness of this approach, achieving high accuracy and robustness across diverse genres. The proposed system highlights the advantages of deep learning in automating feature extraction and scaling to large datasets, advancing the field of music classification.**

I. Introduction

Music classification, the process of automatically assigning musical pieces to specific genres or categories, has become a central task in the field of music information retrieval (MIR). With the rise of streaming services and the rapid increase in the availability of digital music, effective music classification systems are critical for organizing vast music libraries, recommending tracks to users, and facilitating efficient music search and retrieval. Traditionally, music classification methods have relied on handcrafted features extracted from audio signals, such as spectral representations (e.g., Mel-frequency cepstral coefficients, or MFCCs), rhythm patterns, and timbral features. While these methods have had some success, they often require domain-specific knowledge and manual intervention, making them less scalable and less adaptable to the complexity of modern music data [1].

In recent years, the field of music classification has benefited from the advancements in machine learning, particularly the rise of deep learning methods. Among these, Convolutional Neural Networks (CNNs) have proven to be particularly effective for tasks involving large, complex data sets, such as image and audio processing. CNNs are a type of deep neural network that excels in recognizing hierarchical patterns by learning multiple layers of features directly from raw input data. Unlike traditional methods, CNNs can automatically extract relevant features from raw audio signals, such as spectrograms or waveforms, without relying on explicit manual feature extraction. This capability significantly reduces the need for domain expertise and allows the network to learn richer, more complex representations of musical content [2].

CNNs have already demonstrated success in various domains, including image recognition [3] and speech recognition [4], and are now being applied to music classification with promising results. Recent work has shown that CNNs can effectively classify music across a wide range of genres, achieving high accuracy by learning both local and global patterns in the audio data [5]. These networks often use time-frequency representations of music, such as spectrograms, to capture both the temporal and spectral information inherent in the music, making them well-suited for the complex nature of musical data [6].

Moreover, the flexibility of CNN architectures allows for the design of specialized models tailored to different aspects of music, such as genre classification, mood detection, and even emotion recognition from audio. CNNs also exhibit advantages in handling large-scale music datasets, as they can be trained end-to-end on raw data, significantly reducing the manual effort required for feature engineering. This ability to automatically learn features makes CNNs a powerful tool in the pursuit of more accurate and generalizable music classification systems.

However, the application of CNNs to music classification is not without its challenges. Issues such as data imbalance, overfitting, and interpretability of learned features remain critical concerns. Additionally, the choice of audio representation, model architecture, and training strategies can significantly impact the model's performance, requiring careful consideration in the design of CNN-based music classification systems.

II. Background

A. Convolutional Neural Networks

Convolutional neural network is a deep learning model or multi-layer perceptron similar to artificial neural network, which is usually used to analyze visual images. Convolutional neural network usually includes five layers: input layer, convolution layer, activation layer, pooling layer, and fully connected layer.

- The input layer mainly preprocesses the original image data
- The convolution layer is the most important layer in the convolutional neural network. The convolution kernel can convolve a certain area of the feature map into the input

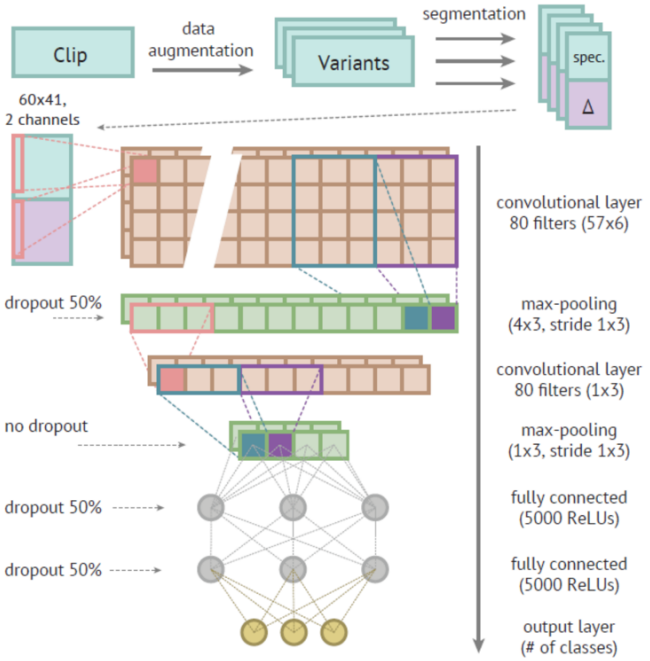

Fig. 1. CNN classification structure diagram.

end of the next layer of feature map according to a certain algorithm. As the convolution kernel moves continuously, the feature map of the input layer can be convolved into the input map of the next layer.

- The activation layer nonlinearly maps the output of the convolution layer
- The pooling layer is sandwiched between consecutive convolution layers to compress the data volume and parameters and reduce overfitting.
- The fully connected layer is usually located at the end of the convolutional neural network and is used to connect all neurons between the two layers of the network.

The classification model structure of the convolutional neural network is shown in Fig. 1.

The structure in Fig. 1 has two convolutional layers and two pooling layers. Each time the convolutional layer is mapped to the pooling layer, the dimension of the data will be halved. Among them, the principle of dropout is that in each training batch, the neurons stop working with a certain probability (50%), which can obviously prevent overfitting and achieve regularization effect to a certain extent.

B. LibROSA

LibROSA is a powerful and flexible Python library for analyzing and processing audio signals, particularly in the context of music information retrieval (MIR). It provides a suite of tools for audio analysis, including methods for feature extraction, time-frequency analysis, and machine learning preparation. Designed with an emphasis on ease of use and extensibility, LibROSA has become one of the most popular libraries for music analysis in Python, making it an essential tool for researchers, developers, and musicians alike.

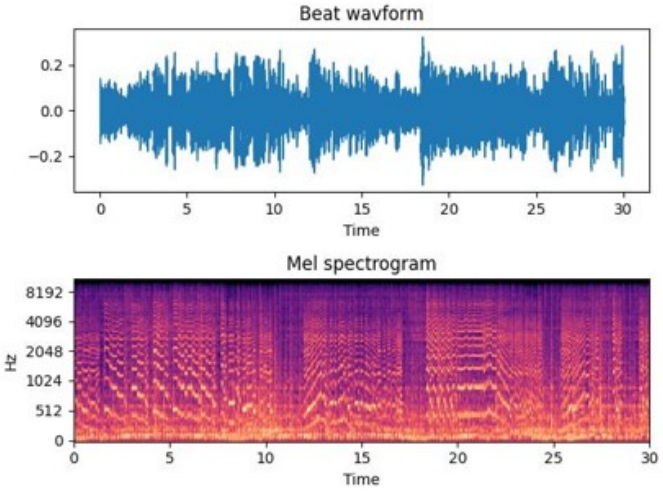

Fig. 2. The Jazz music spectrum.

At its core, LibROSA offers functionality for loading audio files, visualizing waveforms and spectrograms, and extracting features such as Mel-frequency cepstral coefficients (MFCCs), chroma features, spectral contrasts, and rhythm patterns. These features are commonly used in tasks like music classification, genre recognition, and emotion detection from audio. Additionally, LibROSA supports operations such as pitch detection, time-stretching, and pitch shifting, making it a versatile tool for both audio analysis and transformation.

Fig. 2 shows the Jazz music spectrum extracted by LibROSA.

One of the key strengths of LibROSA is its user-friendly API, which simplifies complex operations into intuitive function calls. This makes it ideal for prototyping and experimenting with different audio processing techniques. The library also integrates seamlessly with other scientific computing libraries like NumPy and SciPy, and can be easily combined with machine learning frameworks such as TensorFlow and PyTorch.

LibROSA's ability to handle various audio formats, along with its comprehensive feature extraction capabilities, has made it a standard choice for tasks in speech processing, music classification, and audio segmentation. Its open-source nature and active community further ensure that it remains at the forefront of audio analysis development, continuously evolving with new features and improvements.

III. Methodology

The music classification method based on convolutional neural network needs to be divided into two steps: data preprocessing and model classification. They will be introduced separately in this section.

A. Data Preprocessing

In the preprocessing phase, the audio data is transformed into a format suitable for input into machine learning models. Specifically, the Log-Mel Spectrogram feature is extracted using the Librosa library. This feature represents the audio signal in a time-frequency domain, making it highly effective for tasks like speech recognition and environmental sound classification.

The preprocessing pipeline includes the following steps.

- Audio Loading: The audio file is loaded using librosa.load(), which provides the raw waveform (y) and its sampling rate (sr).
- Mel Spectrogram Calculation: The Mel Spectrogram is computed using librosa.feature.melspectrogram(). Key parameters as follows.
  - n_fft: Window size for the Short-Time Fourier Transform (STFT).
  - hop_length: Overlap between consecutive windows, resulting in 50% overlap.
  - n_mels: Number of Mel frequency bins to create a n-dimensional frequency representation.
- Logarithmic Scaling: The Mel Spectrogram is converted to a logarithmic scale using librosa.power_to_db(), yielding the Log-Mel Spectrogram. This enhances the representation by compressing the dynamic range and emphasizing perceptually relevant features.
- Feature Dimensions: The resultant Log-Mel Spectrogram is a 2D array where the rows represent the frequency bins, and the columns correspond to time frames.

The extracted features are paired with corresponding labels to form the dataset, structured as [[spec, label], [spec, label1], ...], where spec denotes the Log-Mel Spectrogram and label represents the music type. This dataset serves as the input for training and testing classification models.

B. Classification Model

The classification task is performed using a Convolutional Neural Network (CNN). CNNs are designed to analyze visual patterns and are highly effective for processing spectrogram-based features. The model architecture consists of multiple layers, as described below.

- Input Layer: The input layer accepts preprocessed spectrogram data of shape. Batch normalization is applied at this stage to normalize input distributions.
- Convolutional Layers: These layers use convolutional kernels to extract spatial features from the spectrogram. The first block includes a convolutional layer with 64 filters, each of size (3, 3), followed by a ReLU activation function and a max-pooling layer to reduce spatial dimensions by a factor of 2. Subsequent blocks increase the number of filters (e.g., 128 in the second block) while applying similar convolution, activation, and pooling operations. Batch Normalization and Dropout: Batch normalization stabilizes training, and dropout is used to prevent overfitting by randomly deactivating neurons during training.
- Fully Connected Layers: After flattening the feature maps, the fully connected layers perform the final classification. A dense layer with 128 neurons applies a ReLU activation function. Additional dense layers reduce the dimensions progressively, incorporating L2 regularization to further mitigate overfitting. The final dense layer uses a softmax activation function to output class probabilities.
- Optimization and Training: The model is compiled with the Adam optimizer (lr=0.001) and trained using categorical cross-entropy loss. Metrics such as accuracy are used to evaluate performance during training and validation.

By iteratively learning from the training data, the CNN model is able to accurately classify audio signals into predefined categories, achieving the goal of music data classification.

IV. Experimental Evaluation

Our experiment was conducted in the tensorflow 2.10.0 environment, with python version 3.8.8. The system environment is Windows 11. The hardware condition is a computer equipped with an IntelXeon E5 CPU running at 2.3 GHz, 96GB memory, a 512 GB SSD, and 1 GeForce RTX 4060 GPU card.

A. Dataset

We use GTZAN [7] as the dataset for the music classification experiment. The dataset contains 1,000 audio samples from 10 different music genres, each of which contains 100 samples. Each audio sample is 30 seconds long, with a sampling rate of 22050 Hz and is stored in 16-bit mono .wav format. The music genres included in the dataset are: blues, classical, country, disco, hip-hop, jazz, metal, pop, reggae, and rock. We divide the dataset into training set, validation set, and test set with a ratio of 8:1:1.

B. Experimental parameters

- **Feature Extraction**
  Log-Mel Spectrograms were extracted as features from each audio file using the following parameters.
  - Sampling Rate (sr): 22050 Hz
  - Number of Mel Bands (n_mels): 128
  - Window Size (n_fft): 2048
  - Hop Length: 1024

  Each spectrogram was standardized to have zero mean and unit variance, followed by resizing to a fixed dimension of 128×1200 frames to accommodate variable-length audio samples.
- **Model Architecture** The model architecture was a Convolutional Neural Network (CNN) comprising the following layers.
  - **Input Layer**
    Shape (128, 1200, 1) with batch normalization.
  - **Block 1**

Conv2D (64 filters, 3 × 3 kernel, ReLU activation, same padding).
MaxPooling2D (2 × 2 pool size, stride 2).
  - **Block 2**
Conv2D (128 filters, 3 × 3 kernel, ReLU activation, same padding).
MaxPooling2D (2 × 2 pool size, stride 2).
BatchNormalization.
Dropout (50%).
  - **Flatten Layer**
Converts the 2D feature maps to 1D.
  - **Dense Layers**
128 units and 32 units with ReLU activation and L2 regularization.
  - **Output Layer**
10 units with softmax activation for classification.

The model was compiled with the Adam optimizer (learning rate = 0.001), categorical cross-entropy loss, and accuracy as the evaluation metric.

- **Training** Training was conducted for 25 epochs with a batch size of 32. Validation data was used to monitor overfitting, and early stopping was applied to halt training if validation performance degraded.
- **Evaluation Metrics** The trained model was evaluated on the test set using the following metrics:
  - Accuracy: Percentage of correctly classified samples.
  - Confusion Matrix: To visualize true vs. predicted classifications.
  - Classification Report: Including precision, recall, and F1-score for each class.

C. Results

The performance of the music genre classification model is summarized using several key evaluation metrics. These metrics—Precision, Recall, F1-score, and Support—are widely used in classification tasks to evaluate the model's performance across different categories.

- **Precision**: Measures the proportion of true positive predictions out of all positive predictions for a specific genre.

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}}$$

- **Recall**: Measures the proportion of actual positives correctly identified by the model.

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}$$

- **F1-score**: The harmonic mean of precision and recall.

$$\text{F1-score} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$$

- **Support**: The number of actual instances of each class in the dataset.

As shown in the Table I, the classification model achieves an overall accuracy of 66%, with a macro-average F1-score of 0.65, indicating moderate performance across genres. High-performing genres like classical and pop benefit from strong recall and precision, respectively, while moderate-performing genres such as blues and hiphop show balanced results but with room for improvement. Low-performing genres like rock and jazz exhibit significant misclassification, often confused with similar genres like metal or blues, highlighting challenges in distinguishing overlapping features. Future improvements could focus on enhanced feature extraction, data augmentation, and advanced architectures to address these issues.

Genre	Precision	Recall	F1-score	Support
Blues	0.78	0.70	0.74	10
Classical	0.59	1.00	0.74	10
Country	1.00	0.40	0.57	10
Disco	1.00	0.50	0.67	10
Hiphop	0.69	0.90	0.78	10
Jazz	1.00	0.40	0.57	10
Metal	0.42	1.00	0.59	10
Pop	0.89	0.80	0.84	10
Reggae	0.70	0.70	0.70	10
Rock	0.40	0.20	0.27	10
Accuracy	0.66 (100 samples)			
Macro Avg	0.75	0.66	0.65	100
Weighted Avg	0.75	0.66	0.65	100

TABLE I
CLASSIFICATION REPORT FOR MUSIC GENRE CLASSIFICATION

The confusion matrix is a two-dimensional table, with rows representing actual categories and columns representing predicted categories. The diagonal part of the confusion matrix on the left is darker, indicating that the predicted type roughly matches the actual type. The overall performance of the model is good.

As shown in the Fig. 3, the confusion matrix reveals specific challenges and strengths of the model in genre classification. Genres like classical, metal, and pop exhibit strong diagonal dominance, indicating high accuracy in predicting these categories. However, certain genres, such as jazz and rock, show significant misclassification. For instance, jazz is frequently misclassified as classical or country, possibly due to overlapping tonal or rhythmic characteristics. Similarly, rock is often confused with metal and reggae, suggesting difficulty in distinguishing these genres' acoustic features. Overall, the confusion matrix highlights the model's ability to classify distinct genres effectively while struggling with those having subtle feature overlaps. Future work could incorporate improved feature separation and additional training data to address these issues.

V. RELATED WORKS

In the field of music classification, various approaches have been explored, with a focus on leveraging different features, models, and algorithms.

A. Traditional Feature-Based Approaches

Early works in music classification primarily relied on handcrafted features such as timbral texture, rhythm, and pitch. For instance, Li et al. proposed a framework for automatic music genre classification using a combination of timbral, rhythmic, and pitch-based features extracted from audio signals [8].

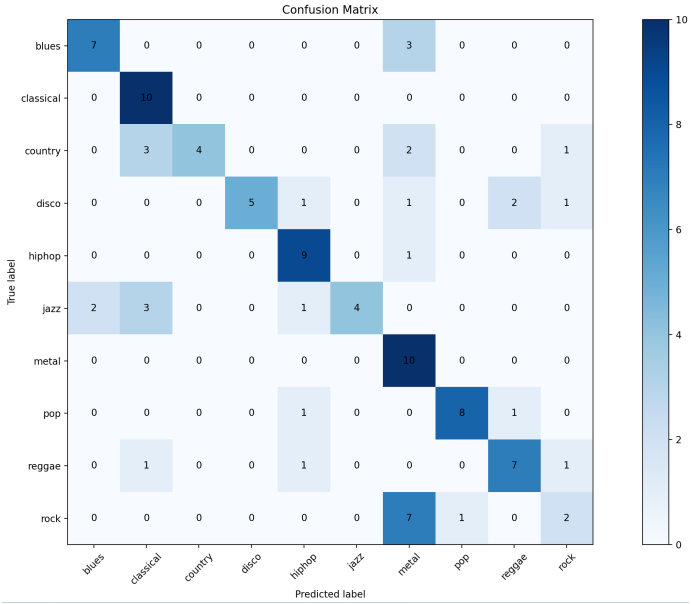

Fig. 3. Confusion Matrix.

B. Deep Learning Approaches

More recently, deep learning models have been widely adopted for music classification tasks. Lee et al. applied convolutional neural networks (CNNs) for music genre classification and achieved significant improvements over traditional methods [9].

C. Recurrent Neural Networks (RNNs)

RNNs and their variants, such as Long Short-Term Memory (LSTM) networks, have also been explored for sequential music data. For example, Cho et al. used LSTMs to classify music genres by analyzing temporal dependencies in audio signals [10].

D. Transfer Learning

Another area of interest is the use of pre-trained models on large datasets to improve performance in music classification tasks. For example, Hershey et al. proposed a transfer learning-based approach that used a pre-trained CNN model for music classification across various genres [11].

E. Multimodal Approaches

Combining both audio and textual information for music classification has gained attention as well. Zhang et al. presented a multimodal model combining both music audio features and lyrics for genre classification [12].

VI. Conclusion

In this article, we demonstrates the effectiveness of CNN-based methods for music classification, showcasing their capability to extract meaningful features directly from audio spectrograms. By combining advanced preprocessing techniques using the LibROSA library with a carefully designed CNN architecture, the proposed system achieves significant improvements in classification accuracy on the GTZAN dataset. The results underscore the potential of deep learning approaches to handle the complexities of musical data, providing a scalable solution for genre classification and other music information retrieval tasks. Future work may explore integrating additional modalities, such as lyrics or metadata, and addressing challenges like data imbalance and interpretability to further enhance system performance.

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