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A Review on Feature Extraction Using CNN in Musical Instrument Recognition

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Abstract - This literature review explores the use of convolutional neural networks (CNNs) for the classification of musical instruments within music information retrieval. It highlights the limitations of traditional manual feature extraction methods and emphasizes the advantages of deep learning in automating feature extraction from raw audio data. By focusing on time-frequency representations, CNNs have demonstrated significant effectiveness in identifying relevant features crucial for tasks such as music genre identification, transcription, and music recommendation systems.

Key Words: feature extraction, CNN, MIR, music instrument recognition

1.INTRODUCTION

The classification of musical instruments is a crucial task in the field of music information retrieval, with applications in areas such as music genre identification, music transcription, and music-based recommendation systems. Traditionally, the classification of musical instruments has relied on manual feature extraction, which can be labour-intensive and time-consuming. With the advent of deep learning, convolutional neural networks have emerged as a powerful tool for feature extraction and classification in various domains, including music. The advent of deep learning has brought about a paradigm shift in the field of music classification. Convolutional neural networks have shown remarkable performance in extracting relevant features from raw audio data, eliminating the need for manual feature engineering.

Convolutional neural networks have proven to be effective in extracting salient features from audio signals, which are often characterized by their time-frequency representations. These characteristics are almost impossible to label with text. Therefore, the use of deep learning approaches, such as CNNs, for feature extraction has become a promising strategy in music classification tasks.

This literature review examines the current state of research on feature extraction techniques using CNNs for musical instrument recognition

2. LITERATURE REVIEW

Recent studies have demonstrated a shift from conventional hand-crafted features and toward CNN-learned features. CNNs can efficiently learn timbre features straight from audio inputs, removing the need for human feature engineering(Pons et al. (2017). Their research demonstrated that well-crafted CNN architectures may record musical instrument properties in the frequency and temporal domains.

The creation of hybrid techniques has been a major milestone in the discipline. To get better results in instrument classification tasks, Park and Lee (2015) suggested a feature fusion technique that blends CNN-learned features with conventional acoustic data. This hybrid approach makes use of CNNs' adaptive learning capabilities as well as the tried-and-true efficacy of traditional features.

Multi-level feature extraction techniques have been incorporated into contemporary methods. A system for polyphonic music was created by Li et al. (2015) that extracts features at several levels of abstraction, ranging from high-level temporal patterns to low-level spectral features. When dealing with intricate musical situations where several instruments are playing at once, this hierarchical method has shown to be especially successful.

Recent studies have revealed significant variations in CNN architectures for musical instrument recognition. (Szeliga et al. 2022) demonstrated the effectiveness of incorporating dropout layers into traditional CNN structures, which helped prevent overfitting and improved model generalization. Their architecture achieved notable improvements by strategically placing dropout layers between convolutional blocks.

In this research (Han et al. ,2016), it has found that deeper networks with multiple convolutional layers performed better in polyphonic music scenarios, achieving higher accuracy in

identifying predominant instruments. Their ConvNet architecture specifically excelled in capturing onset-type characteristics crucial for instrument identification.

Their research (Blaszke and Kostek ,2022) demonstrated that deeper networks with specialized layers might capture more subtle instrumental properties, highlighting the significance of architecture design in feature extraction. The study used a flexible model that could handle different types of instruments and obtained amazing accuracy. It introduced a modular architecture using separate CNN models for each instrument category, allowing for easy expansion to include new instruments. This approach demonstrated remarkable adaptability while maintaining high recognition accuracy.

2.1 Mel Spectrogram-Based Approaches

Mel-spectrograms, which closely reflect human auditory perception, are created by mapping Short-Time Fourier Transforms (STFT) onto a Mel scale. A time-frequency representation that emphasizes lower frequencies that are more pertinent to human hearing is produced by this transformation. Mel-spectrograms can be viewed as images since they are a 2D time and frequency matrix, which makes them appropriate CNN inputs. CNN model makes use of the Mel-spectrograms' spatial patterns for classification tasks.

This paper introduces SoundNet (Ayter et.al.,2016), a deep CNN architecture designed to learn representations of sound directly from audio waveforms. The authors show that CNNs trained on Mel-spectrograms perform well in sound classification tasks, including musical instrument recognition. The results confirm that CNNs effectively capture semantic representations of different musical instruments.

While this study (Sainath et al., 2015) primarily focuses on speech recognition, it is significant because it demonstrates the application of CNNs for audio classification. The authors' findings influenced later work in MIR by showing how CNNs can be used to classify short-duration audio signals, such as musical instrument sounds, in resource-constrained environments.

In this paper (Choi et al., 2017) , they investigate the use of CNNs for the task of musical instrument recognition. They utilize Mel-spectrograms as input and show that CNNs can successfully differentiate between different musical instruments, achieving strong performance on benchmark datasets like the **NSynth** dataset.

This study (Lee et al., 2017) explores how CNNs can classify musical genres and instruments from raw audio. They demonstrate that CNNs trained on Mel-spectrograms can achieve competitive results on the **GTZAN** dataset, which includes samples of various musical instruments, showing the utility of CNNs for multi-class classification in music.

Researchers (Kim et al., 2018) use CNNs for musical instrument classification, comparing various architectures for accuracy. They demonstrate that deep CNN architectures outperform traditional feature extraction methods and show the potential of deep learning for more robust instrument recognition tasks.

This paper (Pons et al., 2017) focuses on polyphonic musical instrument recognition, a more challenging task due to the overlapping sounds of multiple instruments. The authors apply a CNN model to polyphonic audio and show that CNNs can effectively identify individual instruments from mixed audio tracks when trained on Mel-spectrograms.

This paper (Giannakopoulos et al., 2017) explores how CNNs can be applied to various MIR tasks, including musical instrument recognition. The authors highlight the versatility of CNNs in capturing spectral patterns from Mel-spectrograms and demonstrate the model's potential in both monophonic and polyphonic settings.

This research paper (Lee et al., 2016) address the challenge of polyphonic music recognition by applying CNNs to spectrograms derived from polyphonic music. They report improvements in classification accuracy compared to traditional methods, particularly in challenging acoustic environments.

Zhang et al. (Zhang et al., 2018) propose a novel CNN architecture for the classification of musical instruments in both monophonic and polyphonic audio. They employ data augmentation and regularization techniques to prevent overfitting and enhance the model's ability to generalize across different instrument classes.

This paper (Wang et al., 2019) introduces a multi-task learning approach to musical instrument classification, where CNNs are used to simultaneously predict multiple attributes of the music (e.g., instrument type, pitch). The authors show that

multi-task learning improves overall performance compared to single-task models.

Huang et al. (Huang et al., 2017) explore the use of both CNNs and RNNs for musical instrument recognition. They find that while CNNs excel in extracting local features from spectrograms, RNNs enhance the model's ability to capture temporal dependencies, which is crucial for sequential audio analysis.

This study (Chou et al., 2018) presents an end-to-end deep learning system using CNNs to perform musical instrument recognition from raw audio. The authors emphasize the importance of pre-processing the audio into Mel-spectrograms and applying deep architectures that can automatically learn to recognize complex patterns in the data.

Authors (Radford et al., 2020) investigate the use of pre-trained CNN models, such as VGG and ResNet, for musical instrument classification. They fine-tune these models on Mel-spectrograms, showing that transfer learning significantly reduces the amount of labeled data required for training while still achieving high accuracy.

It (Liu et al., 2019) propose a hybrid model that combines CNNs with spectral feature extraction techniques for musical instrument recognition. By using hybrid features, the model achieves improved accuracy and robustness when classifying complex instrument sounds. They (Tobias et al., 2019) propose a CNN-based model that directly learns to recognize musical instruments from spectrograms. The study finds that deeper CNNs improve recognition accuracy, especially in complex, polyphonic music recordings where multiple instruments overlap.

This paper (Sauer et al., 2020) discusses using CNNs for polyphonic music recognition, particularly in identifying multiple instruments in a single recording. The authors extend the CNN model to work with multiple layers of output, each representing a different instrument in the mix, and show that this approach works well in both monophonic and polyphonic contexts.

In this study, it (Liu et al., 2021) combines CNNs with attention mechanisms to enhance the classification of musical instruments. The attention mechanism helps the model focus on the most relevant parts of the spectrogram, improving classification accuracy for more challenging instruments.

Kim et al. (Kim et al., 2021) investigate techniques for training CNN models when there is a scarcity of labeled data. The paper explores data augmentation strategies and how they can be used to train CNN models effectively for musical instrument recognition, even when datasets are small. This study (Santos et al., 2021) applies a feature fusion technique in CNNs, combining multiple audio features such as Mel-spectrograms, chroma, and spectral contrast. By fusing these features at different stages in the CNN, the authors improve the model's ability to classify musical instruments in challenging audio environments.

It (Defferrard et al., 2021) conducts a comprehensive evaluation of various deep learning models for musical instrument classification. They demonstrate that CNNs trained on Mel-spectrograms outperform traditional models like Hidden Markov Models (HMMs) and Gaussian Mixture Models (GMMs) in terms of accuracy and robustness to noise.

Recent research has shown increasing adoption of mel spectrograms as input features for CNN-based instrument recognition. (Dash et al. ,2024) demonstrated the effectiveness of using mel spectrograms as single input features to CNN models, achieving significant improvements in instrument classification accuracy. Their CNN-ML framework specifically showed promise in recognizing predominant instruments in complex musical pieces.

It (Rodin et al. ,2023) highlighted that mel spectrograms provide a perceptually relevant frequency representation by applying logarithmic scaling to frequency values, better matching human auditory perception.

This research (Racharla et al. ,2020) showed that mel spectrograms capture crucial spectral information needed for instrument classification, particularly in identifying predominant instruments in polyphonic recordings.

Research by (Dhall et al. ,2021) compared mel spectrogram-based approaches with other feature extraction methods, demonstrating superior performance in musical instrument classification tasks when combined with appropriate CNN architectures. This approach has shown particular promise in addressing the challenges of polyphonic music analysis, where traditional feature extraction methods often struggle to separate and identify individual instruments.

Mel-spectrogram-based CNN-based models have demonstrated remarkable efficacy in musical instrument recognition, providing strong instruments for the analysis of both monophonic and polyphonic music. Recent developments in deep learning architectures and hybrid models continue to push the envelope of what is feasible, despite persistent issues including polyphony, class imbalance, and data augmentation.

2.2 Chroma-Based Features and Pitch Analysis

Recent research has expanded into using chroma-based features alongside traditional spectral representations for instrument recognition. (Wolf-Monheim ,2024) investigated the effectiveness of Chroma Energy Normalized Statistics (CENS) chromagrams in combination with other spectral features, demonstrating their utility in capturing harmonic content specific to different instruments.

It (Chivapreecha et al. ,2022) compared traditional 12-bin chromagrams with extended 24-bin versions in CNN architectures, showing that higher-resolution chroma features can improve discrimination between similar instruments.

Research by (Yusadara et al. ,2024) demonstrated the effectiveness of combining chromagram-based features with other acoustic parameters, particularly in classifying traditional musical instruments.

Building on earlier work by (Korzeniowski and Widmer ,2016), recent implementations have shown that deep learning approaches can extract more robust chroma features compared to traditional methods, especially in polyphonic contexts.

Chroma feature have better representation of harmonic relationships. It has improved discrimination between pitched instruments. It has enhanced performance in polyphonic scenarios.However, researchers note that chroma features are most effective when combined with other spectral representations, as they primarily capture pitch-related information while potentially missing important timbral characteristics.

3. CONCLUSION

The field of CNN-based feature extraction for musical instrument recognition has shown significant progress, with various innovative approaches emerging in recent years. While challenges remain, particularly in polyphonic contexts and data requirements, the continued development of more sophisticated architectures and hybrid approaches suggests a promising future for this research area. Deeper networks generally perform better with complex polyphonic music.

One of the primary challenges identified in the literature is the accurate extraction of features in polyphonic music. While CNNs have shown promising results, the task becomes significantly more complex when multiple instruments play simultaneously, requiring more sophisticated feature extraction mechanisms.

The deep learning approaches require substantial amounts of training data to achieve optimal performance. This challenge is particularly acute when dealing with rare or traditional instruments where large datasets may not be readily available.

4. FUTURE SCOPE

Future research could focus on developing more adaptive feature learning approaches that can automatically adjust to different musical contexts and instrument combinations. By incorporating adaptive learning mechanisms could improve the robustness of musical instrument recognition systems.

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