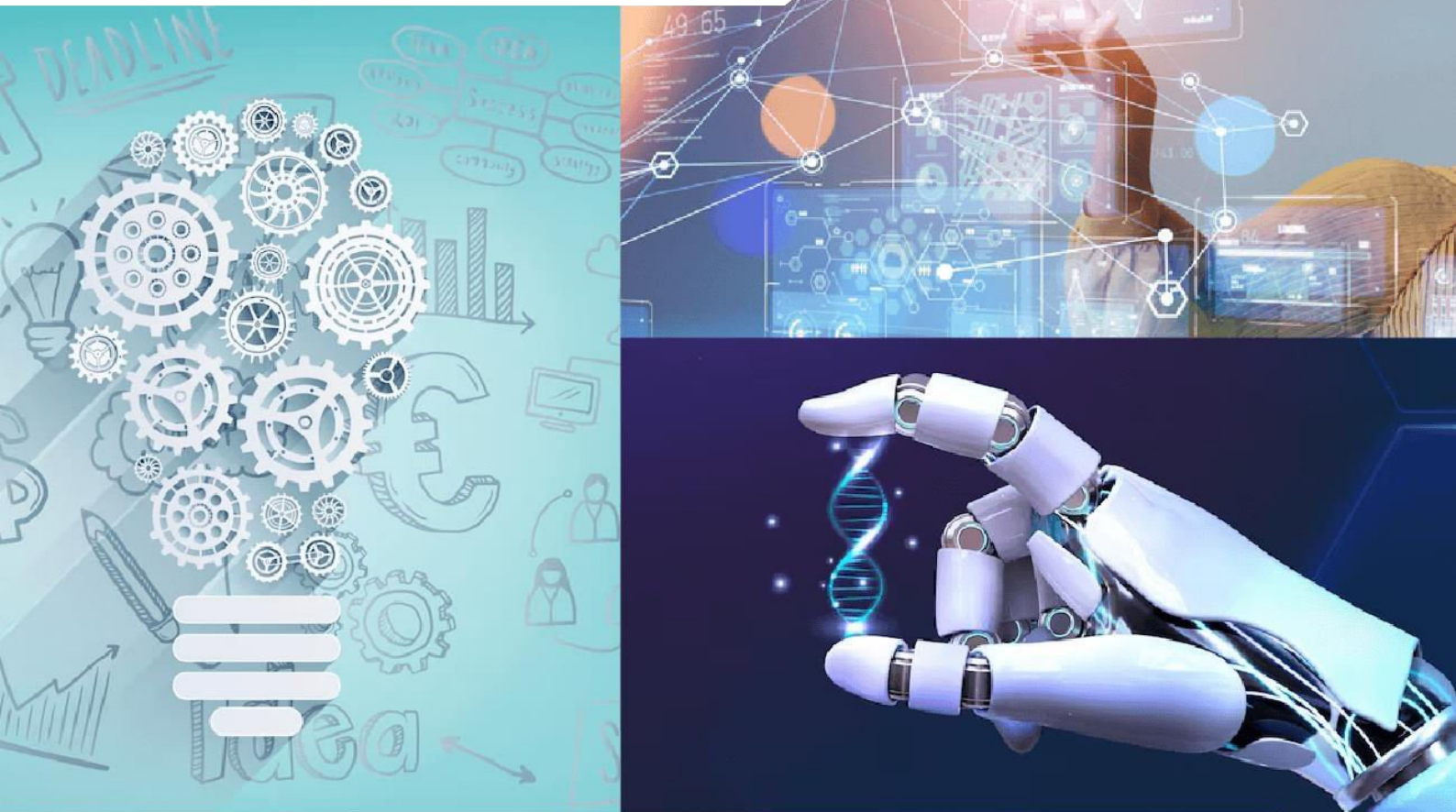




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Music Emotion Classification with Neural Network Architecture and LIBROSA

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ABSTRACT: The classification of musical emotions plays a vital role in organizing, searching, and recommending music on modern digital platforms. This study proposes an effective approach for music emotion recognition using a Convolutional Neural Network (CNN) combined with Librosa-based feature extraction. The primary objective is to bridge the gap between raw audio signals and human emotional perception by extracting meaningful audio features such as Mel-Frequency Cepstral Coefficients (MFCCs), chroma features, spectral contrast, and tonnetz representations. These features capture the timbral, harmonic, and rhythmic characteristics of music in a compact and informative form. The extracted features are then processed using a CNN model, where convolutional layers identify local patterns and pooling layers reduce dimensionality while emphasizing dominant emotional cues. The model is trained and evaluated on labeled datasets to classify emotions such as happiness, sadness, calmness, and energy. The results demonstrate that the proposed method achieves improved accuracy and generalization compared to traditional approaches. This framework provides a scalable and efficient solution for automated music emotion classification, with applications in music recommendation systems, playlist generation, and music analytics. how many words

I. INTRODUCTION

Music is a universal language that conveys a wide range of emotions, influencing human mood, behavior, and cognitive processes. Recognizing these emotions in music has become increasingly important for applications such as personalized recommendation systems, playlist generation, and music analytics. Traditional approaches for musical emotion classification often rely on raw audio signals or textual metadata, which may fail to capture the intricate emotional nuances embedded within the music. Additionally, handcrafted features can be time-consuming to extract and may not generalize well across diverse music genres. With the advancement of machine learning and deep learning techniques, automated approaches have emerged to address these challenges effectively. In this study, we propose a hybrid framework that combines Librosa-based feature extraction with Convolutional Neural Networks (CNN) to classify musical emotions. Librosa, a powerful audio processing library, is used to extract meaningful audio representations such as Mel-frequency cepstral coefficients (MFCCs), chroma features, spectral contrast, and tonnetz features. These features capture the timbral, harmonic, and rhythmic characteristics of music, providing a compact yet informative input for emotion recognition. The CNN model is then applied to learn hierarchical patterns from these features, automatically detecting correlations that indicate emotional content. Convolutional layers in CNN efficiently capture local dependencies, while pooling layers reduce dimensionality and emphasize dominant patterns relevant to emotions. This deep learning approach eliminates the need for manual feature engineering, allowing the model to generalize across various musical styles and genres. By integrating Librosa's feature extraction with CNN's pattern learning capability, the proposed system effectively models complex relationships between audio characteristics and perceived emotions. The framework supports scalable and automated classification, making it suitable for real-world music platforms. Furthermore, this approach enhances the accuracy and robustness of music emotion recognition systems, providing valuable insights for listeners, content creators, and streaming platforms. By leveraging deep learning, the system can adapt to large and diverse music datasets, improving recommendation quality and user satisfaction. Ultimately, this project contributes to intelligent music management and analytics, enabling emotionally aware applications in digital music platforms.

II. LITERATURE REVIEW

Music Emotion Recognition (MER) has emerged as an important area of research due to its applications in music recommendation systems, playlist generation, and human-computer interaction. Early research in this domain relied on traditional machine learning algorithms such as Support Vector Machines (SVM) and k-Nearest Neighbors (k-NN), which used handcrafted features like pitch, tempo, and energy. However, these methods were limited in capturing the complex and hierarchical nature of musical signals [10].

With the advancement of deep learning, Convolutional Neural Networks (CNNs) have become widely used for music emotion classification. CNNs can automatically extract deep features from audio representations such as spectrograms and Mel-Frequency Cepstral Coefficients (MFCCs). Jia [1] proposed an improved CNN model that enhances classification accuracy by learning meaningful patterns from audio data. Similarly, Chaudhary

Relevance to current Research

In this paper, the authors Kang J and Dorien Herremans proposed a unified multitask learning framework to address the problem of heterogeneous emotion representations in Music Emotion Recognition (MER). The basic idea behind this work was to combine categorical emotions (such as happy and sad) with dimensional models (such as valence-arousal) into a single framework, allowing training across multiple datasets. The model used a combination of musical features like key and chords along with MERT embeddings to improve input representation. Additionally, knowledge distillation was applied to transfer knowledge from multiple teacher models into a single student model, improving generalization and performance. The framework was evaluated on multiple datasets such as MTG-Jamendo, DEAM, PMemo, and EmoMusic, where it outperformed existing state-of-the-art models. This work is relevant to the proposed research as it highlights the importance of combining multiple feature representations and improving generalization, which can further enhance CNN-based music emotion classification systems.

Relevance to current Research

In this paper, the authors Pedro L. Louro, Hugo Redinho, Ricardo Malheiro, Rui P. Paiva, and Ricardo Panda presented a comparative study of classical machine learning and deep learning methodologies for Music Emotion Recognition (MER). The basic idea behind this work was to analyze the limitations of traditional approaches that rely on handcrafted audio features and compare them with deep learning techniques that can automatically learn features from spectral representations. The authors highlighted that while deep learning models eliminate the need for manual feature engineering, they require large amounts of labeled data. To address this, they evaluated multiple models and proposed an ensemble approach combining a Dense Neural Network and a Convolutional Neural Network (CNN), which achieved improved performance over baseline methods. This work is relevant to the proposed research as it supports the effectiveness of CNN-based models and emphasizes the importance of combining handcrafted features with deep learning, which aligns with the use of Librosa feature extraction and CNN in this study to achieve better accuracy and generalization.

Relevance to current Research

In this paper, the authors Sihan Ma and Ruohua Zhou proposed a music emotion recognition approach specifically focused on violin music, addressing the challenge of limited specialized datasets in this domain. The basic idea behind this work was to develop a dedicated dataset called VioMusic to better capture the emotional characteristics of violin performances. The authors implemented a CNN-BiGRU model combined with an attention mechanism to effectively learn both spatial and temporal emotional patterns from the audio data. The CNN component captures local feature patterns, while the BiGRU models sequential dependencies, and the attention mechanism highlights the most relevant emotional cues. The model demonstrated strong performance in capturing emotional nuances, achieving low mean absolute error values. This work is relevant to the proposed research as it highlights the effectiveness of CNN-based architectures and the importance of combining feature extraction with sequential modeling and attention mechanisms, which can further enhance the performance of Librosa and CNN-based music emotion classification systems.

Relevance to current Research

In this paper, the authors Sheetal Patil, Rudragoud Patil, Shweta Goudar, Sangeeta Sangani, and R. H. Goudar presented a comprehensive review of music emotion analysis using machine learning techniques. The basic idea behind this work was to study the evolution of music emotion recognition and analyze various approaches including machine learning, deep learning, and ensemble methods, along with the datasets used in these systems. The authors also discussed key challenges such as feature extraction complexity, dataset limitations, and the difficulty of accurately capturing human emotions from music. Additionally, the study explored emerging technologies like EEG-based

emotion detection and highlighted future research directions in the field. This work is relevant to the proposed research as it provides a broad understanding of existing methodologies and challenges, supporting the use of deep learning approaches like CNN and feature extraction techniques such as Librosa to improve accuracy and efficiency in music emotion recognition systems.

Relevance to current Research

In this paper, the author Jing Chen proposed an interactive system for music emotion recognition based on deep learning techniques. The basic idea behind this work was to address the complexity and subjectivity of emotion recognition by combining spectrogram analysis, convolutional neural networks (CNN), and wavelet analysis. The system first converts audio signals into spectrograms to capture time-frequency characteristics, and then uses a CNN to automatically extract emotion-related features. Additionally, the Mallat algorithm for wavelet decomposition is applied to enhance local audio details, improving feature extraction accuracy. The system also supports real-time interaction, allowing users to adjust emotional labels and personalize their experience. Experimental results showed improved accuracy compared to traditional methods. This work is relevant to the proposed research as it highlights the effectiveness of CNN-based feature learning and advanced signal processing techniques, supporting the use of Librosa feature extraction and CNN models to improve performance and enable more interactive and scalable music emotion recognition systems.

III. METHODOLOGY

3.1 Methodology:

The methodology employed in this project is designed to establish a structured, scientifically sound workflow for building an effective music emotion classification system. This section outlines in detail the processes used for data acquisition, preprocessing, feature extraction, neural network design, training and validation, and evaluation. Each stage in the methodology is carefully constructed to ensure that the system achieves high accuracy, generalizability, and robustness in identifying emotional characteristics from audio signals. The following subsections present a comprehensive explanation of the methodologies and techniques used throughout the project.

3.1.1 Data Collection and Preprocessing

The research work on Music Emotion Classification with Neural Network Architecture and Librosa begins with the collection of emotionally labeled music datasets such as the DEAM dataset, along with other datasets like EMO-Music or self-curated collections to improve diversity and generalization. After data acquisition, preprocessing steps are applied to ensure consistency across all audio inputs, including resampling audio to a standard rate (22,050 Hz), converting stereo signals into mono, normalizing amplitude levels, and applying trimming and padding to maintain uniform length. Optional noise reduction techniques such as spectral gating are also used to remove background disturbances, ensuring that the model receives clean, standardized, and reliable input data for effective training.

3.1.2 Feature Extraction using Librosa

Feature extraction is performed using the Librosa library, which transforms raw audio signals into structured numerical representations suitable for machine learning. Important features extracted include MFCCs for capturing timbral characteristics, chroma features for representing harmonic and pitch-related information, spectral contrast for distinguishing frequency bands, and tonnetz features for capturing tonal relationships and harmonic structures. These features together provide a compact yet informative representation of music, enabling the system to effectively capture emotional characteristics and prepare the data for input into the CNN model.

3.1.3 CNN-Based Model Architecture

The extracted feature matrices are provided as input to a Convolutional Neural Network (CNN), which is designed to learn hierarchical patterns associated with musical emotions. The model consists of multiple convolutional layers that identify local patterns such as timbral textures and harmonic variations, followed by pooling layers that reduce dimensionality while preserving important information. Activation functions like ReLU introduce non-linearity to enhance learning, and the processed features are passed through fully connected layers to perform classification. Finally, a softmax output layer generates probability scores for emotional categories such as happy, sad, calm, and energetic, enabling accurate emotion prediction.

3.1.4 Model Training and Validation

The model is trained using a structured dataset split into training, validation, and testing sets to ensure proper evaluation and avoid overfitting. The training set is used to learn patterns, the validation set helps in tuning model

parameters, and the testing set evaluates the final performance of the system. Regularization techniques such as dropout, L2 regularization, and early stopping are applied to improve generalization and prevent overfitting, ensuring that the model performs effectively not only on training data but also on unseen data.

3.1.5 Performance Analysis and Evaluation

The performance of the proposed system is analyzed using evaluation metrics such as accuracy, precision, recall, and F1-score, along with confusion matrix analysis to understand class-wise prediction performance and identify misclassifications. Additionally, generalization testing is conducted on unseen music samples from different genres and styles to evaluate real-world applicability. The results demonstrate that the combination of Librosa-based feature extraction and CNN-based learning effectively captures complex emotional patterns in music, leading to reliable and robust classification performance.

IV. CONCLUSION AND FUTURE WORK

The integration of Librosa-based feature extraction with a Convolutional Neural Network (CNN) architecture presents a powerful and innovative approach to music emotion classification, where diverse audio descriptors such as MFCCs, chroma features, spectral contrast, and tonnetz effectively capture the harmonic, rhythmic, and timbral nuances that convey emotion in music. These compact yet information-rich representations enable the CNN to learn hierarchical emotional patterns, with convolutional layers identifying subtle local variations and pooling operations emphasizing the most relevant emotional cues, thereby reducing noise and eliminating the need for manual feature engineering. This results in improved accuracy, robustness, and adaptability across different musical genres and structures. Building on this strong foundation, future enhancements can further elevate the system by incorporating multimodal inputs like lyrics, metadata, and user feedback, as well as leveraging advanced models such as CNN-LSTM hybrids or Transformers to better capture temporal and contextual dynamics. Expanding datasets to include diverse cultures and languages will improve generalization, while real-time streaming analysis can enable live emotion detection. Techniques like transfer learning can boost performance with limited data, and the inclusion of explainable AI can enhance interpretability by revealing key contributing features. Additionally, deployment through mobile and cloud platforms, integration with music streaming services, and the ability to detect complex or mixed emotions can transform the system into a fully personalized, emotion-aware music assistant, advancing the field of intelligent music information retrieval.

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