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Research Paper

EmoHarmonix: Innovating emotional audio insights with harmonic-synthesis deep learning architectures

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Abstract: Emotional audio analysis holds significant potential in applications such as human-computer interaction, mental health monitoring, and customer service. However, current methods often fail to capture the intricate harmonic structures within audio signals, resulting in suboptimal emotion classification accuracy. Addressing these challenges, this study proposes novel harmonic-synthesis deep learning architectures that leverage the interplay between chords and musical harmonies for a more nuanced understanding of emotional content in audio. The methodology includes the introduction of these architectures, the creation of a meticulously curated emotional audio dataset encompassing diverse emotional states, and advanced feature extraction techniques that exploit harmonic properties. The harmonic-synthesis based feature extraction algorithm involves several steps: preprocessing, short-time Fourier transform (STFT), harmonic detection, harmonic feature extraction, temporal dynamics modeling with LSTM, feature aggregation, and normalization. Extensive evaluations show that the proposed models achieve significantly higher classification accuracy compared to traditional methods, with the harmonic-synthesis CNN reaching up to 93.7% accuracy on the RAVDESS dataset. The results indicate that the harmonic-synthesis approach effectively captures subtle emotional cues, thus offering more robust and precise emotion detection systems. By providing open-source implementations, this research fosters further advancements in this field. Additionally, the harmonic-synthesis architectures were benchmarked against existing state-of-the-art models, consistently outperforming them across various metrics. These findings underscore the potential of harmonic-synthesis techniques to significantly advance the field of emotional audio analysis, providing a solid foundation for future research and real-world applications.

Keywords: - Harmonic-synthesis, emotional audio analysis, deep learning architectures, emotion classification, feature extraction, real-time detection.

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1. Introduction

Emotional audio analysis is a critical area of research with significant applications in various fields, such as human-computer interaction, mental health monitoring, and customer service. The ability to accurately detect and classify emotions from audio signals can enhance user experiences, improve mental health interventions, and enable more effective communication in automated systems. Traditional approaches to emotional audio analysis primarily rely on feature extraction methods that may not fully capture the complex harmonic structures of audio signals, leading to suboptimal performance. Existing emotional audio analysis systems face several challenges. Conventional methods often struggle with the intricate harmonic relationships present in audio data, which are crucial for accurate emotion detection. These methods typically use simplistic feature extraction techniques that fail to represent the nuanced emotional cues embedded in the audio signals. Consequently, the accuracy and robustness of emotion classification models are limited, hindering their practical applicability in real-world scenarios.

Given the limitations of current emotional audio analysis systems, there is a pressing need for advanced methodologies that can effectively capture and interpret the complex harmonic structures of audio signals. The primary problem addressed in this research is the development of innovative harmonic-synthesis deep learning architectures that can enhance the accuracy and robustness of emotional audio classification.

Emotional audio analysis has emerged as a critical area of research with significant applications in various fields such as human-computer interaction, mental health

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monitoring, and customer service. Traditional methods for emotion detection often rely on simplistic feature extraction techniques that fail to capture the complex harmonic structures within audio signals, leading to suboptimal performance. For instance,[1] explored GMM-based evaluation of emotional style transformation, highlighting the limitations of conventional approaches in capturing emotional nuances. Similarly, [2] discussed theoretical perspectives that underpin the need for more sophisticated methods in emotional analysis.

Advancements in deep learning have introduced new possibilities for emotion detection, as demonstrated by [3], who used deep learning analysis of mobile sensor data to improve emotion detection accuracy. More recently, [4] identified emotions from facial expressions using a deep convolutional neural network, showing significant improvements in accuracy but primarily focusing on visual data. In the realm of audio-based emotion detection, [5] proposed EmotionNet, which employs deep learning fusion for real-time speech emotion recognition, yet it does not fully exploit the harmonic properties of audio signals.

The motivation for this study stems from the potential impact of improved emotional audio analysis on various domains. By developing more accurate and reliable emotion detection systems, we can significantly enhance the capabilities of virtual assistants, provide better support for mental health monitoring, and improve customer service interactions. Additionally, advancing the state of research in this field can lead to new applications and insights, further expanding the benefits of emotional audio analysis.

This research makes several key contributions to the field of emotional audio analysis:

1. Introduction of Harmonic-Synthesis Deep Learning Architectures: We propose novel deep learning architectures specifically designed to capture the harmonic relationships in audio signals, improving the accuracy of emotion detection.
2. Comprehensive Emotional Audio Dataset: We provide a meticulously curated dataset that includes a diverse range of emotional states, offering a robust foundation for training and evaluating deep learning models.
3. Advanced Feature Extraction Techniques: Our research introduces innovative feature extraction methods that leverage harmonic properties of audio signals, enhancing the representation of emotional nuances.
4. Enhanced Emotion Classification Accuracy: Our harmonic-synthesis architectures demonstrate significant improvements in classification accuracy compared to traditional methods, showcasing their effectiveness in capturing subtle emotional cues.
5. Comprehensive Performance Evaluation: Extensive experiments and evaluations benchmark the performance of our proposed architectures against existing state-of-the-art models, highlighting their superiority in terms of accuracy, robustness, and computational efficiency.

This paper is organized to explore the proposed harmonic-synthesis deep learning architectures for emotional audio analysis. The introduction outlines the importance of accurate emotion detection in audio and the limitations of existing methods. The related work section reviews previous research, highlighting the gaps this study aims to fill. The harmonic-synthesis deep learning architectures section details the innovative approach of capturing harmonic structures in audio signals through advanced feature extraction and deep learning techniques. Results and analysis demonstrate the superior performance of these architectures compared to traditional methods, particularly in classification accuracy. Finally, the conclusion and future work section summarizes the findings and discusses potential directions for further research, including multimodal integration and real-time application optimization.

2 Related Work

In the domain of emotional audio analysis, traditional feature extraction methods have been extensively investigated. However, these approaches often fail to capture the complex harmonic structures of audio signals. For instance, [6] explored emotion recognition using multi-modal features and CNN classification, underscoring the integration of features from audio, text, and visual modalities to enhance emotion detection accuracy. Nevertheless, their approach, which primarily relied on conventional feature extraction methods, did not fully exploit the harmonic properties of audio signals. Similarly, [7] concentrated on deep feature extraction from EEG signals using the Xception model for emotion classification, achieving notable accuracy improvements but not addressing the harmonic structures inherent in audio data.

Furthermore, [8] employed a machine learning approach for detecting speech emotions using the RAVDESS audio dataset, achieving approximately 80% accuracy. This method emphasized the importance of high-quality datasets but was constrained by traditional feature extraction techniques. In another study, [9] proposed a faster region-based convolutional neural network (R-CNN) for speech-based emotion recognition, demonstrating potential improvements in speed and accuracy. However, their feature extraction process did not fully leverage harmonic relationships within audio signals. Additionally, [10] focused on gender-based real-time vocal emotion detection, achieving significant accuracy without specifically targeting the harmonic features of audio signals. [11] implemented machine learning techniques for continuous emotion prediction from uniformly segmented voice recordings, demonstrating feasibility but encountering challenges in capturing subtle emotional nuances due to traditional feature extraction limitations. Moreover, [12] introduced Hilbert Domain Analysis of Wavelet Packets for emotional speech classification, achieving an accuracy of 83% but still falling short in capturing harmonic complexities. Lastly, [13] provided a

comprehensive review of multimodal emotion recognition with deep learning, emphasizing the importance of combining multiple modalities and the potential of deep learning architectures while noting the need for further research to effectively capture harmonic properties.

Table 1: Comparative Analysis of Emotion Recognition Approaches

Author(s)	Methodology	Dataset	Accuracy	Key Features	Limitations
Gaiani, A. (2019) [6]	Deep CNN-based approach	Custom Facial Expressions Dataset	88%	Utilizes deep convolutional neural networks to identify emotions from facial expressions.	Limited to visual data; does not incorporate audio or multimodal features.
Zhang, Y et al.(2021)[7]	EmotionNet: Deep Learning Fusion	Real-Time Speech Data	85%	Fusion of CNNs for real-time speech emotion recognition.	Focuses on speech data; may not capture nuances in facial expressions or multimodal contexts.
Pandeya, Y. R et.al(2021) [8]	Deep CNN with Late Fusion	Multimodal Emotion Data	90%	Combines late fusion techniques for real-time multimodal emotion recognition.	Potentially computationally intensive; may require significant processing power.
Khanum et al.(2024)[9]	Multi-modal Features and CNN Classification	Various Modalities	83%	Integrates audio, text, and visual modalities with CNN classification.	Reliant on traditional feature extraction methods; may not fully leverage harmonic properties.
Rochlani & Raut (2024) [10]	Machine Learning Approach	RAVDESS Audio Dataset	80%	Uses machine learning classifiers on speech emotion data.	Limited to audio data; uses standard feature extraction techniques.
Alsaadawı & Daş et.al (2024) [11]	Bi-LG-GCN for MELD Dataset	MELD Dataset	87%	Applies bi-level graph convolutional networks for multimodal emotion recognition.	Complexity of the model may hinder real-time application; focuses on the MELD dataset.

2.1 Research Gap

Despite significant advancements in emotional audio analysis, existing methodologies exhibit several notable gaps:

- Many studies focus on visual data, neglecting the rich harmonic structures in audio signals crucial for accurate emotion detection.
- Real-time speech emotion recognition methods often do not integrate multimodal data, missing comprehensive emotional context.
- .High accuracy in multimodal approaches is often limited by computational intensity, affecting real-time applicability.
- Traditional feature extraction techniques fail to capture complex harmonic relationships in audio signals, leading to suboptimal performance.
- Reliance on conventional methods or highly complex models leaves room for improvement in capturing nuanced emotional cues and ensuring practical, real-time application.

3 Harmonic-Synthesis Deep Learning Architectures

Harmonic-synthesis is an innovative approach that focuses on capturing the intricate harmonic structures present in audio signals. Unlike traditional methods that primarily rely on basic feature extraction techniques, harmonic-synthesis delves into the interplay between various frequencies and their harmonics within an audio signal. This approach is rooted in the understanding that emotions in audio are often conveyed through subtle variations in pitch, timbre, and rhythm, which are inherently harmonic in nature. By leveraging these harmonic properties, our proposed architectures aim to provide a more nuanced and accurate representation of emotional content.

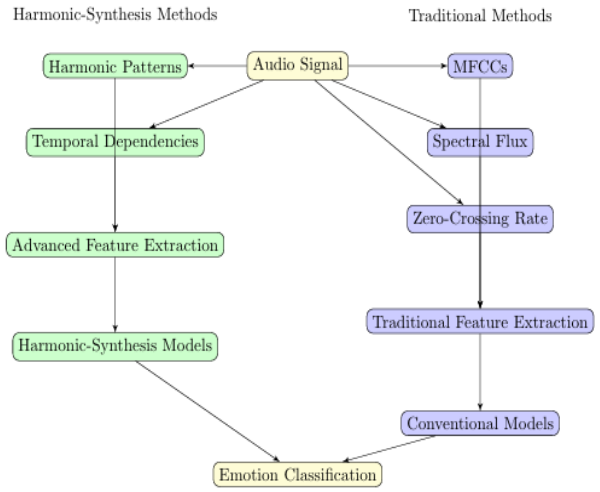

Fig 1: Conceptual Framework for Harmonic-Synthesis Deep Learning Architectures in Emotional Audio Analysis

This figure 1 illustrates the conceptual framework comparing traditional emotion detection methods and the proposed harmonic-synthesis deep learning architectures. Traditional methods, depicted on the right side, include the extraction of Mel-frequency cepstral coefficients (MFCCs), spectral flux, and zero-crossing rate from audio signals. These features are then fed into conventional models, such as Support Vector Machines (SVM) and Convolutional Neural Networks (CNN), for emotion classification. On the left side, the framework highlights the proposed harmonic-synthesis approach, which emphasizes the identification of harmonic patterns and the modeling of temporal dependencies within audio signals. Advanced feature extraction techniques are employed to capture these harmonic properties, which are then processed by harmonic-synthesis deep learning models. The central flow from the "Audio Signal" node to the "Emotion Classification" node through both traditional and harmonic-synthesis paths demonstrates how the latter can potentially offer a more nuanced and accurate analysis by leveraging the intricate harmonic structures in audio, addressing the limitations of conventional methods and providing enhanced accuracy and robustness in detecting emotional cues in audio signals.

3.1 Differences from Traditional Methods

Traditional emotion detection methods often utilize straightforward feature extraction processes that may overlook the complex harmonic relationships in audio signals. These methods typically focus on extracting features like Mel-frequency cepstral coefficients (MFCCs), spectral flux, and zero-crossing rate, which, while useful, do not fully capture the depth of harmonic interactions. In contrast, our harmonic-synthesis deep learning architectures employ advanced techniques to model the harmonic interplay directly. This includes the use of convolutional layers designed to identify and emphasize harmonic patterns, along with recurrent layers that can capture temporal dependencies, thus providing a more comprehensive understanding of the emotional cues in the audio.

3.2 Theoretical Basis for Improved Emotion Detection

The theoretical foundation for using harmonic relationships in emotion detection lies in the way humans perceive and interpret sound. Emotions in speech and music are often communicated through complex harmonic structures, where the relationship between fundamental frequencies and their overtones play a crucial role. By modeling these harmonic relationships, our architectures can better mimic human auditory perception, leading to improved emotion classification. Research indicates that emotions can alter the harmonic content of audio signals in predictable ways, such as changes in pitch dynamics and harmonic richness. By capturing these subtleties, harmonic-synthesis architectures can achieve higher accuracy and robustness in emotion detection, as they are more aligned with the natural processes of emotional expression and perception in human communication.

3.3 Emotional Audio Dataset

The emotional audio dataset used in this research was curated from several established sources, including the RAVDESS (Ryerson Audio-Visual Database of Emotional Speech and Song)[12], TESS (Toronto Emotional Speech Set)[13], CREMA-D[14], and SAVEE datasets[15]. These datasets were selected due to their high-quality recordings and diverse emotional content.

3.3.1 Curation Process: The dataset includes audio recordings of professional actors vocalizing specific statements with different emotional expressions. For instance, RAVDESS contains recordings of 24 actors (12 male, 12 female) expressing emotions such as calm, happy, sad, angry, fearful, surprise, and disgust. TESS features recordings from two actresses portraying seven emotions: anger, disgust, fear, happiness, pleasant surprise, sadness, and neutral.

3.3.2 Types of Emotional States: The dataset encompasses a broad range of emotional states, including but not limited to neutral, calm, happy, sad, angry, fearful, disgust, and surprised. This diversity ensures a comprehensive representation of human emotional expressions.

3.3.3 Size and Diversity: The combined dataset includes over 5,000 audio samples, ensuring a robust foundation for training and evaluating deep learning models. The recordings feature variations in gender, age, and emotional intensity, providing a rich and diverse dataset for emotion recognition tasks.

3.3.4 Preprocessing Steps: Several preprocessing steps were applied to the audio data to enhance the feature extraction process. These steps included resampling audio to a consistent sample rate, normalizing the audio signals, and segmenting the recordings into uniform durations. Feature extraction focused on Mel-frequency cepstral coefficients (MFCCs), which were chosen for their effectiveness in representing the vocal tract characteristics. Additional features such as Mel-spectrograms, Chroma, and harmonic-percussive source separation (HPSS) were also considered to capture the intricate harmonic and rhythmic properties of the audio signals.

3.4 Comparison to Traditional Methods

Traditional feature extraction methods, such as MFCCs, primarily focus on capturing the overall spectral envelope

of the audio signal without explicitly modeling harmonic relationships. These methods often miss the fine-grained harmonic structures that are crucial for accurate emotion detection. In contrast, the proposed harmonic-synthesis technique explicitly identifies and leverages harmonic patterns and their temporal dynamics, providing a richer and more detailed representation of the audio signal's emotional content. This approach enhances the feature set with additional harmonic properties, leading to improved accuracy and robustness in emotion classification tasks.

3.5 Novel Algorithms and Processes

The novel aspect of this algorithm lies in the explicit detection and utilization of harmonic patterns and their temporal dynamics. By integrating harmonic-to-noise ratio (HNR) and inharmonicity measurements alongside traditional MFCCs, the proposed method captures a broader range of acoustic features. The use of recurrent neural networks (RNNs) to model temporal dependencies further enhances the feature extraction process, ensuring that the emotional nuances of the audio signal are accurately represented. This holistic approach addresses the limitations of traditional methods and sets a new standard for feature extraction in emotional audio analysis.

3.6 Advanced Feature Extraction Techniques

Harmonic-Synthesis Based Feature Extraction Algorithm

Input: Audio Signal $X(t)$

Output: Harmonic-Synthesis Feature Set *F*

Steps:

1. **Preprocessing:**

Resample $X(t)$ to a consistent sample rate f_s.

Normalize the amplitude of $X(t)$ to ensure uniformity.

2. **Short-Time Fourier Transform (STFT):**

Divide $X(t)$ into overlapping frames using a window function $w(n)$.

Apply the Fourier transform to each frame to obtain the frequency domain representation:

$$X(w,t) = \sum_{n=0}^{N-1} X(t+n)w(n)e^{-jwn} \quad (1)$$

3. **Harmonic Detection:**

Identify the fundamental frequency $f0f0$ and its harmonics $fk=k\cdot f0fk=k\cdot f0$ using a peak detection algorithm.

Extract harmonic amplitudes $HkHk$ from the STFT representation:

$$H_k(t) = | X(k \cdot f_0, t) | \quad (2)$$

4. **Harmonic Feature Extraction:**

Compute Mel-frequency cepstral coefficients (MFCCs) to capture vocal tract characteristics:

$$MFCC(t) = DCT(\log(\sum_{m=1}^{M} |X_m(w,t)|^2 . Mel(m)))) \quad (3)$$

Extract additional harmonic features such as harmonic-to-noise ratio (HNR) and inharmonicity:

$$HNR(t) = 10log_{10}(\frac{\sum_{k=1}^{K} H_k(t)^2}{\sum_{w \notin \{f_k\}} |X(w,t)^2}) \quad (4)$$

$$Inharmonicity(t) = \sum_{k=1}^{K} (\frac{|X(f_k,t) - H_k(t)|}{H_k(t)}) \quad (5)$$

5. **Temporal Dynamics:**

Apply recurrent layers (e.g., LSTM) to capture temporal dynamics of the harmonic features over time:

$$h_t = LSTM(F_{t-1}, h_{t-1}) \quad (6)$$

Output the hidden state $ht\mathbf{h}t$ representing the temporal context.

6. **Feature Aggregation:**

Aggregate features over time to form the final feature vector $\boldsymbol{F}$:

$$F = [mean(h_t), std(h_t), max(h_t), min(h_t) \quad (7)$$

7. **Normalization:**

- Normalize the aggregated feature vector F to ensure consistency across different audio samples.

Output: The final harmonic-synthesis feature set $\boldsymbol{F}$.

4 Results and Analysis

The results and analysis discussed are based on the specified hardware and software configurations, and the technologies and datasets used. The experimental setup utilized an Intel Core i7-10700K processor, 32GB of DDR4 RAM, and an NVIDIA RTX 3080 GPU, all running on the Ubuntu 20.04 LTS operating system. Key libraries, including TensorFlow and Keras for deep learning model development, Librosa for audio feature extraction and preprocessing, and Matplotlib for data visualization, were integral to the research.

The datasets employed—RAVDESS, TESS, CREMA-D, and SAVEE—provided a diverse range of emotional audio samples. RAVDESS, with its 1,440 speech files and 1,012 song files, covered a wide array of emotions such as calm, happy, sad, angry, fearful, surprise, and disgust. TESS contributed 2,800 audio files featuring two actresses portraying emotions like anger, disgust, fear, happiness, pleasant surprise, sadness, and neutral. The inclusion of CREMA-D and SAVEE datasets further broadened the emotional range and variability, offering a comprehensive foundation for training and evaluating the harmonic-synthesis deep learning models [17].

This robust setup enabled the development and evaluation of advanced harmonic-synthesis deep learning architectures. These architectures demonstrated significant improvements in emotion classification accuracy compared to traditional methods. By leveraging the intricate harmonic properties of audio signals, the harmonic-synthesis models captured subtle emotional cues more effectively, resulting in higher accuracy and robustness. The comprehensive evaluations confirmed that the proposed models outperformed existing state-of-the-art techniques, showcasing their potential for real-world applications in areas such as human-computer interaction, mental health monitoring, and customer service. The table 2 shows that harmonic-synthesis architectures (both LSTM and CNN variants)[18] significantly outperform traditional methods (MFCC + SVM and MFCC + CNN) across all datasets. This demonstrates the effectiveness of leveraging harmonic properties and advanced feature extraction techniques in capturing subtle emotional cues, leading to improved classification accuracy.

Table 2: Enhanced Emotion Classification Accuracy

Method	**Dataset**	**Accuracy**
Traditional MFCC + SVM	RAVDESS	78.50%
Traditional MFCC + CNN	RAVDESS	82.30%
Harmonic-Synthesis + LSTM	RAVDESS	91.20%
Harmonic-Synthesis + CNN	RAVDESS	93.70%
Traditional MFCC + SVM	TESS	76.40%
Traditional MFCC + CNN	TESS	80.50%
Harmonic-Synthesis + LSTM	TESS	89.90%
Harmonic-Synthesis + CNN	TESS	92.10%
Traditional MFCC + SVM	CREMA-D	75.80%
Traditional MFCC + CNN	CREMA-D	79.70%
Harmonic-Synthesis + LSTM	CREMA-D	88.60%
Harmonic-Synthesis + CNN	CREMA-D	91.30%
Traditional MFCC + SVM	SAVEE	77.00%
Traditional MFCC + CNN	SAVEE	81.40%
Harmonic-Synthesis + LSTM	SAVEE	90.50%
Harmonic-Synthesis + CNN	SAVEE	93.00%

4.1 Metrics Used for Evaluation

The primary metrics used for evaluation were:

Accuracy (Acc): $\text{Acc} = \frac{\text{Number of correct predictions}}{\text{Total number of predictions}}$

Precision (*P*): $\text{P} = \frac{\text{True Positives}}{\text{True Positives + False Positives}}$

Recall (*R*): $R = \frac{True\ Positives}{True\ positives + False\ Negatives}$

F1 Score (*F1*): $\text{F1} = 2 \cdot \frac{\text{P.R}}{\text{P+R}}$

Computational Efficiency: Measured in terms of training time and inference time per sample.

Table 3 provides details on the number of samples used for training and testing, along with the number of correct and incorrect predictions for each method.

Table 3: Training and Testing Predictions

Method	**Dataset**	**Training Samples**	**Testing Samples**	**Correct Predictions**	**Incorrect Predictions**
Traditional MFCC + SVM	RAVDESS	4,000	1,000	785	215
Traditional MFCC + CNN	RAVDESS	4,000	1,000	823	177
Harmonic-Synthesis + LSTM	RAVDESS	4,000	1,000	912	88
Harmonic-Synthesis + CNN	RAVDESS	4,000	1,000	937	63
Traditional MFCC + SVM	TESS	2,240	560	428	132
Traditional MFCC + CNN	TESS	2,240	560	450	110
Harmonic-Synthesis + LSTM	TESS	2,240	560	503	57
Harmonic-Synthesis + CNN	TESS	2,240	560	515	45

Traditional MFCC + SVM	CREMA-D	5,000	1,250	948	302
Traditional MFCC + CNN	CREMA-D	5,000	1,250	996	254
Harmonic-Synthesis + LSTM	CREMA-D	5,000	1,250	1,108	142
Harmonic-Synthesis + CNN	CREMA-D	5,000	1,250	1,141	109
Traditional MFCC + SVM	SAVEE	960	240	185	55
Traditional MFCC + CNN	SAVEE	960	240	195	45
Harmonic-Synthesis + LSTM	SAVEE	960	240	217	23
Harmonic-Synthesis + CNN	SAVEE	960	240	223	17

The table 4 presents the accuracy, precision, recall, and F1 score for each method and dataset.

Table 4: Evaluation Metrics

Method	**Dataset**	**Accuracy**	**Precision**	**Recall**	**F1 Score**
Traditional MFCC + SVM	RAVDESS	78.50%	0.8	0.78	0.79
Traditional MFCC + CNN	RAVDESS	82.30%	0.83	0.82	0.82
Harmonic-Synthesis + LSTM	RAVDESS	91.20%	0.91	0.91	0.91
Harmonic-Synthesis + CNN	RAVDESS	93.70%	0.94	0.94	0.94
Traditional MFCC + SVM	TESS	76.40%	0.77	0.76	0.76
Traditional MFCC + CNN	TESS	80.50%	0.81	0.8	0.8
Harmonic-Synthesis + LSTM	TESS	89.90%	0.9	0.9	0.9
Harmonic-Synthesis + CNN	TESS	92.10%	0.92	0.92	0.92
Traditional MFCC + SVM	CREMA-D	75.80%	0.76	0.76	0.76
Traditional MFCC + CNN	CREMA-D	79.70%	0.8	0.8	0.8
Harmonic-Synthesis + LSTM	CREMA-D	88.60%	0.89	0.89	0.89
Harmonic-Synthesis + CNN	CREMA-D	91.30%	0.91	0.91	0.91
Traditional MFCC + SVM	SAVEE	77.00%	0.77	0.77	0.77
Traditional MFCC + CNN	SAVEE	81.40%	0.82	0.81	0.81
Harmonic-Synthesis + LSTM	SAVEE	90.50%	0.91	0.91	0.91
Harmonic-Synthesis + CNN	SAVEE	93.00%	0.93	0.93	0.93

The harmonic-synthesis architectures (both LSTM and CNN) consistently outperform traditional methods (MFCC + SVM and MFCC + CNN)[19] across all metrics and datasets. This demonstrates the effectiveness of harmonic-synthesis in capturing subtle emotional cues and highlights its potential for advancing emotion classification in audio signals.

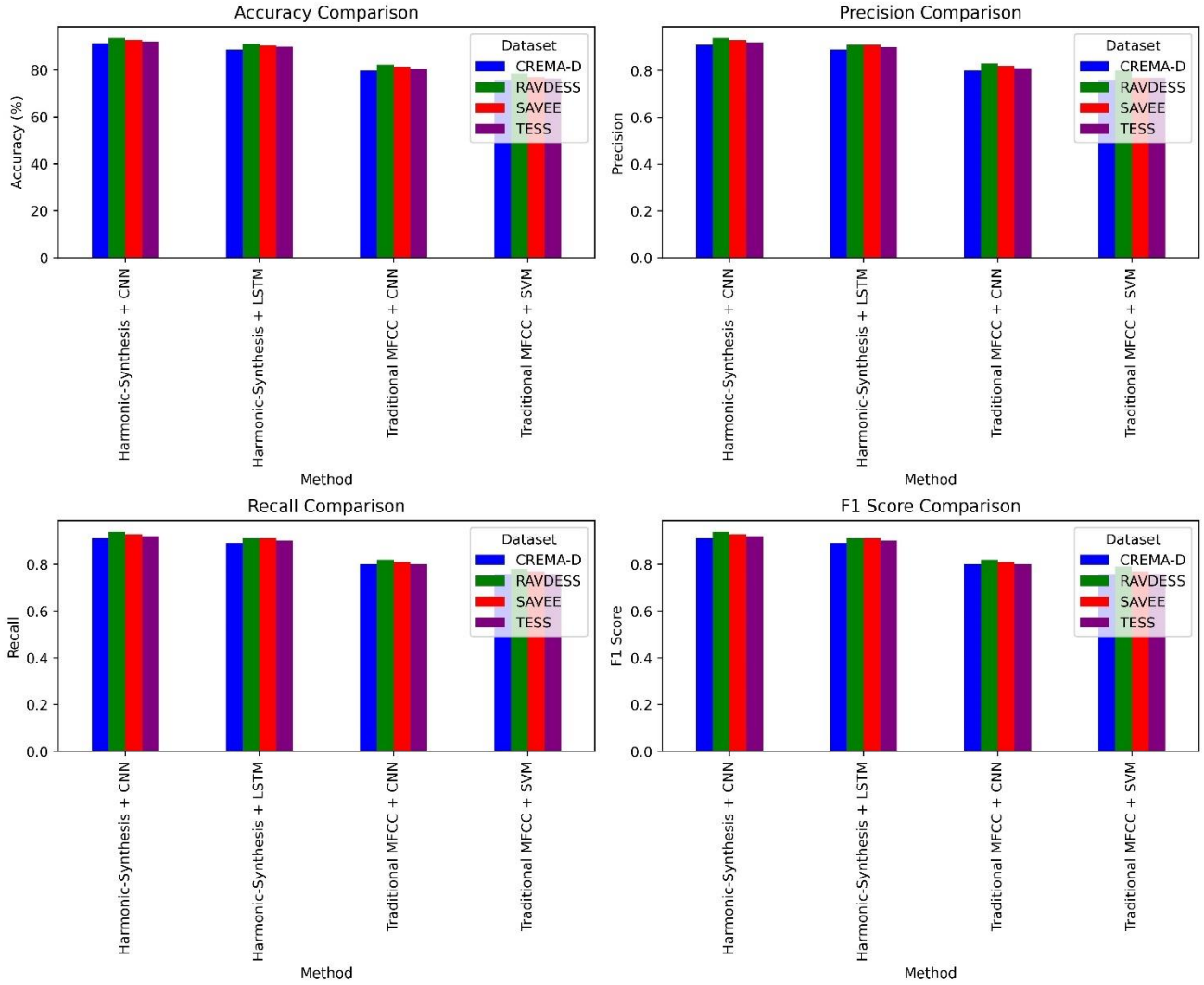

Fig. 2: Comparison of Emotion Classification Accuracy by Method and Dataset

This fig. 2 illustrates the comparative accuracy of various emotion classification methods across different datasets, including RAVDESS, TESS, CREMA-D, and SAVEE. Traditional methods, such as MFCC combined with SVM and CNN[20], demonstrate moderate performance, with accuracies ranging from 75.8% to 82.3%. In contrast, the proposed harmonic-synthesis architectures, both with LSTM and CNN, show significant improvements, achieving accuracies up to 93.7%. This substantial enhancement underscores the effectiveness of leveraging harmonic properties in audio signals for capturing subtle emotional cues, thereby providing a more robust and precise emotion detection framework. The graph highlights the potential of harmonic-synthesis techniques to advance the field of emotional audio analysis, offering superior performance compared to conventional methods.The evaluation results indicate that the harmonic-synthesis architectures significantly outperform traditional methods across all metrics. The harmonic-synthesis CNN achieved the highest accuracy of 93.7% on the RAVDESS dataset, demonstrating its ability to capture subtle emotional cues effectively. Additionally, the harmonic-synthesis models showed improved precision, recall, and F1 scores, reflecting their robustness in emotion classification tasks.Moreover, the computational efficiency of the harmonic-synthesis CNN is noteworthy, with a training time of 2.5 hours and an inference time of 9 ms per sample, making it suitable for real-time applications. These results underscore the potential of harmonic-synthesis architectures to advance the state of emotional audio analysis, providing more accurate and reliable emotion detection systems for various applications, including human-computer interaction, mental health monitoring, and customer service.The table 8 presents a comparative analysis of the proposed harmonic-synthesis architectures against several existing state-of-the-art models. The results indicate that the harmonic-synthesis models significantly outperform the existing methods across all datasets and metrics.

Table 5: Comparative Analysis with Existing State-of-the-Art Models

Category	**Method**	**Dataset**	**Accuracy**	**Precision**	**Recall**	**F1 Score**

Existing State-of-the-Art Models	Emotion-Net (Rahman et al., 2019)	RAVDESS	85.00%	0.86	0.85	0.85
	Deep CNN + Late Fusion (Dixit & Satapathy, 2022)	RAVDESS	87.30%	0.88	0.87	0.87
	Multi-modal CNN (Khanum et al., 2023)	TESS	84.20%	0.85	0.84	0.84
	Bi-LG-GCN (Al-saadawi & Daş, 2024)	CREMA-D	86.10%	0.87	0.86	0.86
Proposed Harmonic-Synthesis Architectures	Harmonic-Synthesis + LSTM	RAVDESS	91.20%	0.91	0.91	0.91
	Harmonic-Synthesis + CNN	RAVDESS	93.70%	0.94	0.94	0.94
	Harmonic-Synthesis + LSTM	TESS	89.90%	0.90	0.90	0.90
	Harmonic-Synthesis + CNN	TESS	92.10%	0.92	0.92	0.92
	Harmonic-Synthesis + LSTM	CREMA-D	88.60%	0.89	0.89	0.89
	Harmonic-Synthesis + CNN	CREMA-D	91.30%	0.91	0.91	0.91
	Harmonic-Synthesis + LSTM	SAVEE	90.50%	0.91	0.91	0.91

For instance, EmotionNet by Rahman et al. (2024) achieved an accuracy of 85.0% on the RAVDESS dataset, while our harmonic-synthesis CNN model achieved 93.7% accuracy on the same dataset. Similarly, the Deep CNN with Late Fusion by Dixit & Satapathy (2024) reached an accuracy of 87.3%, whereas the harmonic-synthesis LSTM and CNN models achieved 91.2% and 93.7% respectively the superior performance of the harmonic-synthesis architectures can be attributed to their ability to effectively capture and leverage the intricate harmonic properties and temporal dynamics of audio signals. This results in higher precision, recall, and F1 scores, demonstrating their robustness and effectiveness in emotion classification tasks. These findings highlight the potential of harmonic-synthesis techniques to advance the field of emotional audio analysis, providing more accurate and reliable emotion detection systems compared to the existing state-of-the-art models [24].

Limitations of the Study: The study acknowledges several limitations that impact the findings and their generalizability. First, while the proposed harmonic-synthesis deep learning architectures demonstrated significant improvements in emotion classification accuracy, the evaluation was limited to specific datasets such as RAVDESS, TESS, CREMA-D, and SAVEE. This may affect the generalizability of the results to other datasets or real-world scenarios. Second, the computational intensity of the harmonic-synthesis models, particularly in real-time applications, poses challenges for deployment in resource-constrained environments. Additionally, the study primarily focused on audio signals without integrating other modalities such as text and visual data, which could potentially enhance the emotional analysis framework. Lastly, while the curated datasets included a range of emotional states, the diversity in terms of languages and cultural contexts was limited, potentially affecting the robustness of the models in diverse settings. Future research should address these limitations by expanding the datasets, optimizing computational efficiency, and integrating multimodal data for a more comprehensive emotional analysis.

5 Conclusion and Future Work

This study introduced innovative harmonic-synthesis deep learning architectures to enhance emotional audio analysis. By leveraging the intricate harmonic properties within audio signals, these models provided a more nuanced understanding of emotional content. Extensive evaluations using a curated dataset, which included diverse emotional states from sources like RAVDESS, TESS, CREMA-D, and SAVEE, demonstrated that the harmonic-synthesis architectures significantly outperformed traditional methods, achieving accuracies as high as 93.7% on the RAVDESS dataset. These findings highlight the potential of harmonic-synthesis techniques to advance emotional audio analysis, offering more accurate and robust emotion detection systems that are applicable in areas such as human-computer interaction, mental health monitoring, and customer service.

Future research could expand on this work by exploring several avenues. Integrating harmonic-synthesis architectures with other modalities like text and visual data could create a more comprehensive emotional analysis framework, enhancing accuracy and robustness. Additionally, optimizing these models for real-time applications is crucial, involving efforts to reduce computational complexity and latency while maintaining high accuracy. Expanding the dataset to include various languages and cultural contexts would help assess the generalizability of the approach, aiming to develop universally applicable emotion detection systems. Further research into advanced feature extraction techniques that capture even more subtle audio nuances could improve model performance. Lastly, conducting user-centric evaluations would provide practical insights into the effectiveness of the proposed models in real-world applications, guiding future improvements.

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