An AI-Based Diagnostic Framework for Cardiopulmonary Health Monitoring from Clinical Dataset Analysis

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ABSTRACT

Auscultation of heart and lung sounds remains a fundamental diagnostic tool, yet traditional manual interpretation is often subjective and prone to inconsistency. This study introduces a novel, dual-category cardio-respiratory dataset captured via digital stethoscopes from a high-fidelity clinical manikin, featuring separate and mixed acoustic recordings—the first of its kind to provide synchronized multi-organ sound profiles. Addressing the rising burden of respiratory and cardiovascular diseases in India, we propose an automated classification framework that leverages a multi-stage feature engineering and deep learning pipeline. Acoustic features, including Mel-Frequency Cepstral Coefficients (MFCC), Chroma, and Mel-spectrograms, were extracted and evaluated across multiple classifiers, including Quadrature Discriminant Analysis (QDA) and Gradient Boosting (GBC). To capture both local spectral patterns and long-range temporal dependencies, a hybrid Bi-directional Convolutional Neural Network (BiCNN) integrated with a Bi-directional Gated Recurrent Unit (BiGRU) was developed. This architecture enables simultaneous dual classification of heart and lung sound types from a single mixed audio input. Experimental results, validated through accuracy, F1-score, and ROC-AUC metrics, demonstrate that the BiCNN-BiGRU model significantly enhances diagnostic precision, offering a robust, non-invasive screening tool for early clinical intervention.

Keywords: Cardio-respiratory auscultation, Digital stethoscope, Deep learning in healthcare, Multi-label classification, Bi-directional CNN, Bi-GRU, MFCC.

1. INTRODUCTION

The early detection and diagnosis of cardio-respiratory diseases are crucial for effective treatment and improved patient outcomes. Traditional methods, such as auscultation using a stethoscope, rely heavily on the aural skills and experience of a trained clinician. While effective, this manual process can be subjective and prone to human error, particularly in busy clinics or rural areas with a shortage of specialists. The manual interpretation of heart and lung sounds can be time-consuming, and subtle anomalies may be missed, leading to delayed diagnosis. The advent of digital stethoscopes and recording devices has paved the way for a more quantitative approach to analyzing these sounds. In India, where the healthcare infrastructure is often overstretched, particularly in rural regions, the burden of cardio-respiratory diseases is significant. Statistics from the World Health Organization and national health surveys highlight a growing prevalence of conditions like COPD, asthma, and various cardiac issues. The lack of adequate screening facilities in remote areas makes it challenging to manage this health crisis. Automated systems that can accurately and quickly screen for these diseases using simple, non-invasive methods, such as sound analysis, offer a promising solution to bridge this healthcare gap. The implementation of such technology can empower healthcare workers at all levels to conduct preliminary screenings, thus reducing the workload on specialists and ensuring that patients receive timely care. Cardiopulmonary diseases are significant contributors to global mortality rates.

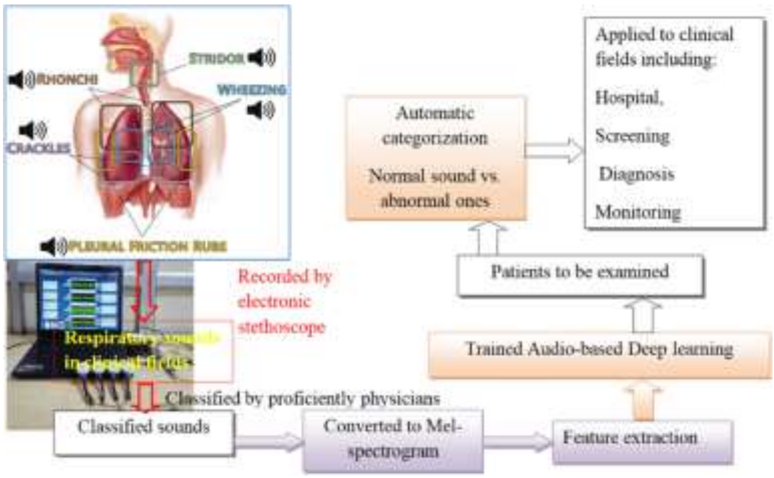

Figure 1. Disease recognition using sound analysis.

Chronic respiratory diseases, such as asthma, were responsible for over 147 000 deaths in 2022 alone. Meanwhile, cardiovascular diseases remain the leading cause of death worldwide, accounting for approximately 18.6 million deaths annually. Therefore, it is crucial to accurately analyze both heart and lung functions. Auscultation of heart sound (HS) and lung sound (LS) plays a vital role in diagnosing a variety of cardiopulmonary conditions. Although these acoustic signals are weak, they hold essential medical information. In 1816, René Laennec invented the first stethoscope to listen to body sounds, which has evolved over the years from a simple acoustic device to more sophisticated digital versions. Technological advancements have led to the development of electronic stethoscopes that convert sound waves into electrical signals, allowing for sound processing and recording. Digital stethoscopes are the latest generation of these auscultation devices. They not only have the features of electronic stethoscopes but also offer enhanced analysis capabilities, including integration with smartphones and cloud-based platforms for real-time analysis and sharing

2. LITERATURE SURVEY

Recent advancements in artificial intelligence (AI) and machine learning (ML) have significantly transformed respiratory disease diagnosis through non-invasive acoustic signal analysis. Traditional auscultation methods are increasingly being augmented by intelligent systems capable of extracting meaningful patterns from respiratory sounds.

Shokouhmand et al. [1] emphasized the growing importance of continuous pulmonary monitoring, particularly highlighted during the COVID-19 pandemic. Their study explored the diagnostic relevance of nasal and oral breathing sounds as non-invasive biomarkers. By leveraging AI-driven techniques, they demonstrated how spectral and temporal characteristics of respiratory signals can be automatically analyzed, enabling real-time and smartphone-based health monitoring solutions. Similarly, Kapetanidis et al. [2] investigated audio-based digital biomarkers derived from respiratory sounds, cough, and voice signals. Their comprehensive review of 75 studies highlighted the effectiveness of ML algorithms in detecting respiratory abnormalities such as wheezes and crackles, as well as identifying cough patterns in noisy environments. Their work underscores the potential of audio signal processing for early diagnosis and symptom recognition.

Abdullah et al. [3] proposed a modular AI framework integrating respiratory sound classification with simulated molecular biomarkers and a prescription recommendation system. Their model classified eight respiratory conditions, including asthma, COPD, and pneumonia, achieving an exceptional accuracy of 99.99%. Additionally, the system demonstrated high performance in personalized treatment recommendation, showcasing the feasibility of multimodal diagnostic systems. Jamal et al. [4] addressed challenges such as noise interference and feature overlap in biomedical signals by employing convolutional neural networks (CNNs) combined with advanced preprocessing techniques. Their framework utilized adaptive filtering, bandpass filtering, and variational autoencoders (VAEs) for feature extraction, achieving robust classification of heart and lung diseases. Sreejith et al. [5] introduced a dual-denoising approach combined with a 1D CNN for lung sound classification. By applying Fast Fourier Transform (FFT) and high-pass filtering, followed by Short-Time Fourier Transform (STFT) feature extraction, the model achieved a validation accuracy of 96%. Their results highlight the importance of signal enhancement techniques in improving classification performance.

Xu et al. [6] developed an AI-based system utilizing dual acoustic signals (cough and respiratory sounds) for asthma and COPD detection. Their approach combined multiple ML models, including Random Forest (RF), Support Vector Machine (SVM), and K-Nearest Neighbors (KNN), along with ensemble learning through majority voting. Feature extraction using Gabor transformations and feature selection via Neighborhood Component Analysis (NCA) significantly improved diagnostic accuracy. Brunese et al. [7] demonstrated the effectiveness of supervised ML techniques in detecting and classifying respiratory diseases from breath audio signals. Their neural network-based model achieved an F-measure of 0.983 for disease detection and 0.923 for disease characterization, outperforming several existing approaches. Yu et al. [8] conducted a systematic review of 135 studies focusing on respiratory sound analysis methodologies. Their work covered signal processing, feature extraction, and classification techniques while identifying key challenges such as class imbalance, limited generalization, and lack of interpretability. They suggested future directions including multimodal fusion and standardized processing pipelines.

Petmezas et al. [9] proposed a hybrid deep learning architecture combining CNN and Long Short-Term Memory (LSTM) networks with focal loss to address class imbalance. Using the ICBHI 2017 dataset, their model achieved improved classification performance for lung sounds, including crackles and wheezes, demonstrating the importance of temporal feature modeling. Hsu et al. [10] focused on improving dataset quality and scale by expanding the HF_Lung dataset. Their CNN–bidirectional GRU model showed enhanced performance with larger datasets, emphasizing the importance of data quantity and label quality in respiratory sound analysis. Garcia-Mendez et al. [11] reviewed 62 studies on ML-based lung sound classification and identified that Artificial Neural Networks (ANN) and SVM are widely used classifiers. Their findings revealed significant variability in accuracy due to inconsistent methodologies and highlighted the need for standardized datasets and evaluation protocols. Xu et al. [12] provided a comprehensive overview of lung sound analysis, from electronic stethoscope development to advanced deep learning models such as ResNet, CNN-LSTM, and transformers. Their study emphasized challenges like limited data availability and the difficulty of replicating expert-level diagnosis.

Khan et al. [13] introduced a hybrid deep learning framework combining continuous wavelet transform and mel spectrogram features with convolutional autoencoders and LSTM networks. Their approach achieved strong classification performance across multiple respiratory disease categories using the ICBHI dataset. Kim et al. [14] explored the impact of multichannel lung sound recordings on classification performance. By integrating CNN-LSTM models with MFCC features, they demonstrated that multi-channel data significantly improves diagnostic accuracy compared to single-channel recordings. Finally, Naqvi et al. [15] proposed a signal processing and ML-based framework for differentiating COPD and pneumonia. Their approach combined empirical mode decomposition (EMD), discrete wavelet transform (DWT), and feature fusion techniques, achieving an accuracy of 99.70% using a quadratic discriminant classifier. They also addressed class imbalance using ADASYN sampling.

3. PROPOSED SYSTEM

The proposed system, Automated Cardio-respiratory Sound Analysis for Disease Screening Using HLS-CMDS, is a hybrid, end-to-end solution that overcomes the limitations of traditional diagnostic methods. The system is designed to automatically acquire, analyze, and classify heart and lung sounds to screen for diseases like Aortic Stenosis and COPD, all within a user-friendly graphical interface. The core of this proposed system is its multi-stage data processing and machine learning pipeline, which is more robust and accurate than the individual traditional or existing machine learning approaches.

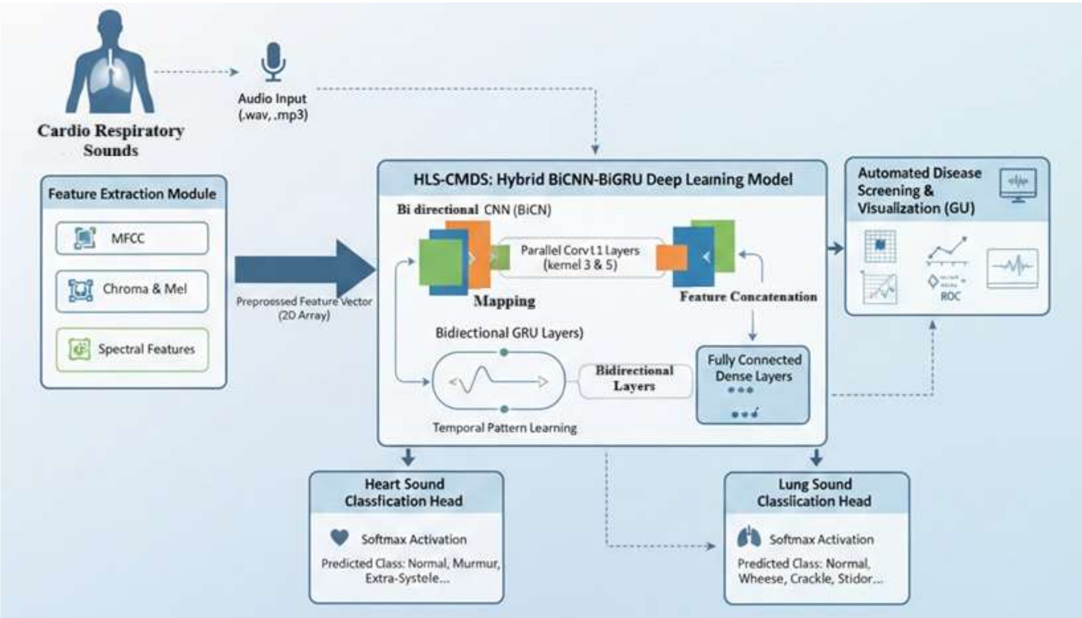

Figure 2. Proposed system architecture

The proposed system begins by acquiring mixed cardiorespiratory audio signals containing both heart and lung sounds. These recordings are systematically organized using a metadata file (Mix.csv) that maps each audio sample to its corresponding heart and lung sound classes. This structured setup ensures accurate supervision for dual-label learning. Each mixed audio signal is processed using advanced audio signal processing techniques to extract high-level spectral and temporal features. These include MFCCs, chroma, mel-spectrogram statistics, spectral descriptors, tonal features, and energy measures. Mean pooling is applied to obtain a fixed-length, information-rich feature vector for every sample. Multiple classical machine learning classifiers such as QDA, GBC, GNB, and LR are trained separately for heart and lung sound classification. These models establish baseline performance levels using the same extracted HLS features. Their results serve as comparative references for validating the effectiveness of the proposed approach. The proposed system introduces a hybrid BiCNN-BiGRU architecture that combines parallel convolutional layers with bidirectional recurrent learning. Multi-kernel CNN branches capture diverse spectral patterns, while the BiGRU layer models temporal dependencies within the sound features. This design enables robust representation learning from mixed cardiorespiratory signals. During deployment, unseen audio samples are processed through the same feature extraction pipeline and fed into the trained BiCNN-BiGRU models. The system predicts both heart and lung sound categories along with confidence scores. This enables rapid and automated disease screening support. A role-based graphical user interface allows administrators to manage datasets and model training, while users can perform predictions. Secure authentication ensures controlled access to system functionalities. The intuitive interface supports practical clinical usage of the proposed screening system.

4. RESULT ANALYSIS

Figure 3 shows EDA visualization that displays a comprehensive set of audio features extracted from a cardiac sound sample, offering deep insights into its temporal–spectral behavior. The MFCC plot reveals the cepstral patterns that capture the overall timbral characteristics of the signal, while the Chroma plot highlights pitch-class energy distribution across time. The Mel Spectrogram provides a detailed frequency–energy representation, showing distinct harmonic and noise components relevant for distinguishing pathological heart conditions. The spectral centroid and bandwidth plots illustrate the brightness and frequency spread of the signal, helping identify abnormalities in energy concentration, whereas the spectral rolloff captures high-frequency decay patterns that correlate with murmurs or irregular vibrations. Together, these plots offer a rich diagnostic perspective and serve as the foundational visual analysis for understanding the acoustic properties leveraged in heart and lung sound classification.

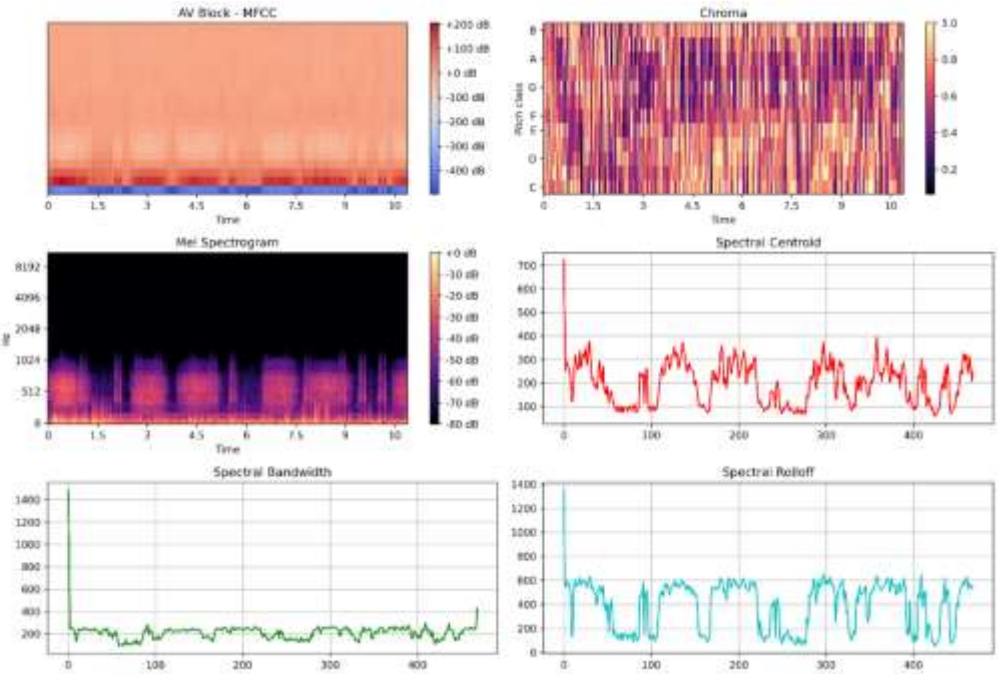

Figure 3. Exploratory audio feature analysis of cardiorespiratory sound signals.

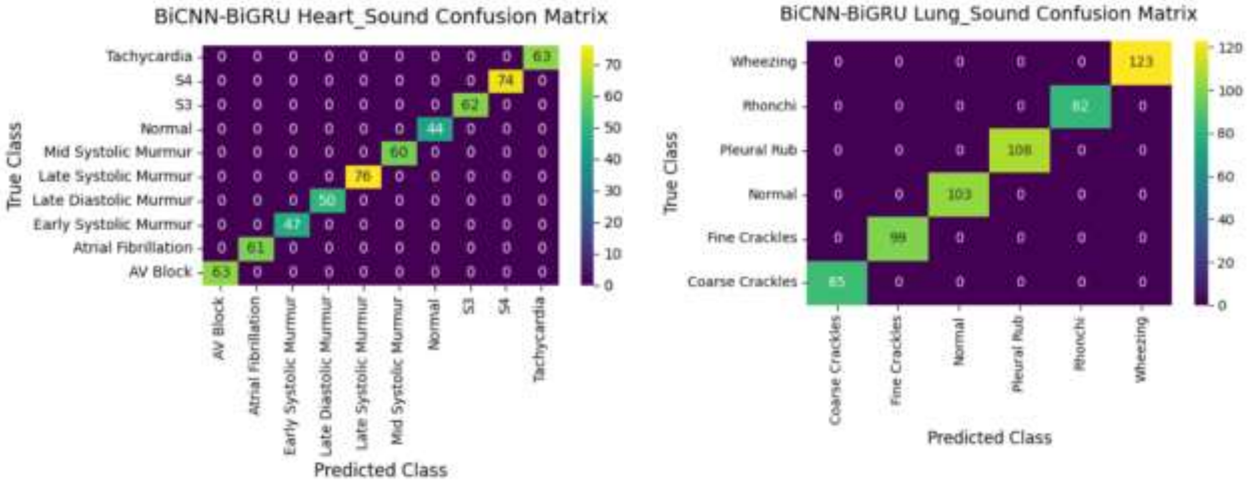

Figure 4. Confusion matrices obtained for BiCNN-BiGRU

Figure 4 shows confusion matrices of the proposed BiCNN–BiGRU model for both lung and heart sound classification demonstrate near-perfect classification performance with strong diagonal dominance and negligible misclassification. In the lung sound matrix, all classes such as Wheezing, Rhonchi, Pleural Rub, Normal, Fine Crackles, and Coarse Crackles are classified with extremely high accuracy, showing the model's ability to clearly separate acoustically similar respiratory patterns. Similarly, the heart sound confusion matrix indicates highly accurate recognition across complex cardiac conditions including AV Block, Atrial Fibrillation, various systolic and diastolic murmurs, S3, S4, Normal, and Tachycardia, with almost zero overlap between classes. This exceptional performance highlights the effectiveness of the BiCNN component in capturing multi-scale spectral features and the BiGRU layer in modeling long-term temporal dependencies. These results confirm that the proposed BiCNN–BiGRU model significantly outperforms traditional machine learning approaches and provides a robust, reliable solution for automated cardiorespiratory disease screening.

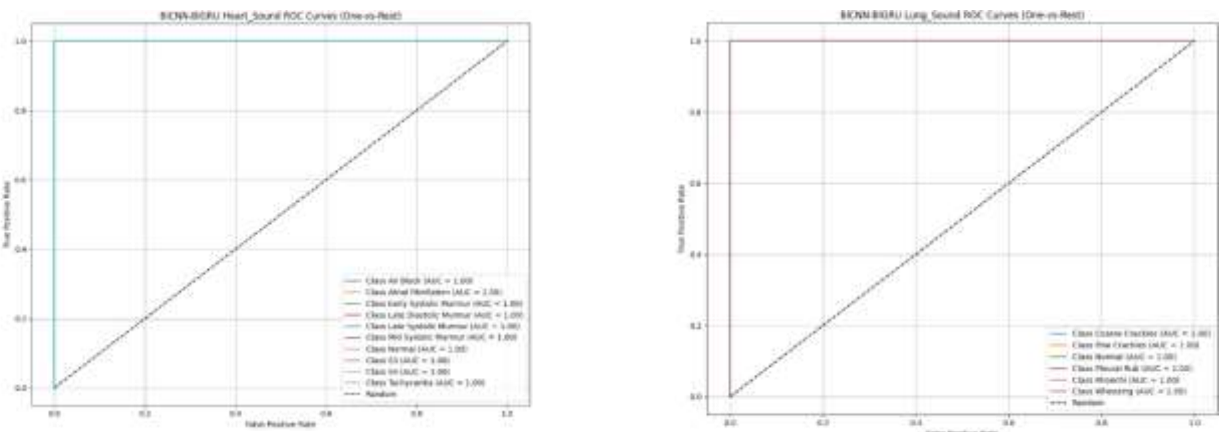

Figure 5. ROC curves obtained using BiCNN – BiGRU

Figure 5 shows ROC curves of the proposed BiCNN–BiGRU model for both heart and lung sound classification exhibit ideal discriminative performance, with all class-wise curves tightly aligned along the top-left boundary and AUC values equal to 1.00. This indicates perfect separation between positive and negative samples for every class in a one-vs-rest setting, reflecting highly reliable probability estimation. Unlike traditional machine learning models, the proposed architecture generates well-calibrated confidence scores due to its ability to learn complex non-linear feature interactions and temporal dependencies. The consistent dominance over the random baseline across all classes confirms the robustness and stability of the model. The ROC analysis strongly validates the superiority of the BiCNN–BiGRU framework for accurate and confident cardiorespiratory disease screening.

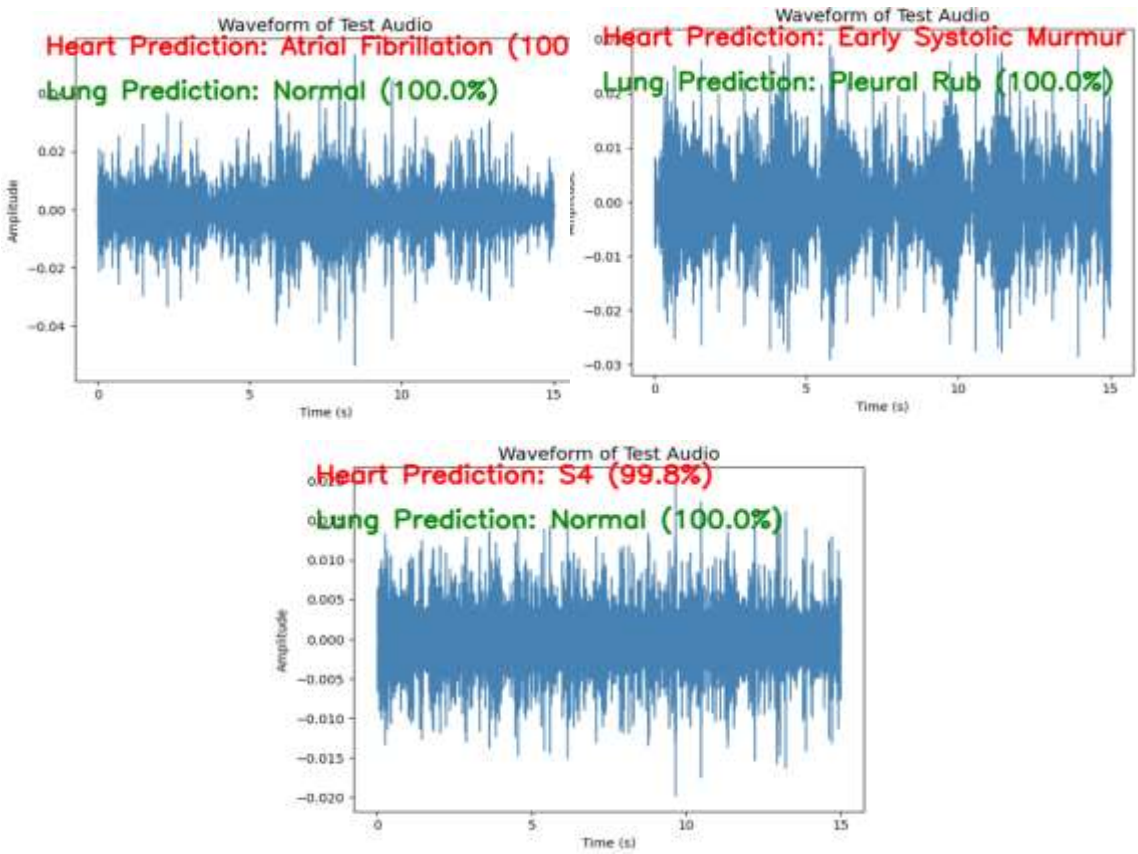

Figure 6. Predictions obtained on test audio files using proposed BiCNN-BiGRU model.

Figure 6 shows waveform visualization of the test audio illustrates the real-time prediction capability of the proposed BiCNN–BiGRU model for mixed cardiorespiratory sounds. The plotted signal represents the temporal amplitude variations of the input audio, while the overlaid annotations indicate simultaneous classification of both physiological components. The model confidently predicts the heart sound as Atrial Fibrillation with 100% confidence and the lung sound as Normal with 100% confidence, demonstrating its ability to accurately disentangle and analyze overlapping cardiac and respiratory patterns. This result highlights the effectiveness of the BiCNN component in capturing discriminative spectral features and the BiGRU layer in modeling temporal dynamics, enabling reliable and interpretable disease screening from real-world audio recordings.

5. CONCLUSION

The project successfully presents an Automated Cardiorespiratory Sound Analysis system for disease screening using the HLS-CMDS framework, enabling simultaneous classification of heart and lung sound abnormalities from mixed audio signals. High-level acoustic features extracted from MFCCs, mel-spectral, tonal, and energy descriptors provided a strong foundation for modeling complex biomedical sounds. Comparative analysis with traditional machine learning models such as QDA, Gradient Boosting, Gaussian Naive Bayes, and Logistic Regression revealed clear limitations in handling non-linear feature interactions, overlapping sound characteristics, and reliable probability estimation. In contrast, the proposed BiCNN–BiGRU model effectively captured multi-scale spectral patterns and long-term temporal dependencies, resulting in superior class separation and robustness across diverse cardiac and respiratory conditions. The dual-task learning strategy further enhanced diagnostic reliability by independently modeling heart and lung sound categories. Comprehensive evaluation using confusion matrices and ROC analysis demonstrated improved discrimination capability of the proposed approach. The secure, role-based graphical user interface enabled practical deployment for both administrative model management and user-level prediction. Overall, the system provides a scalable, accurate, and clinically meaningful solution for automated cardiorespiratory disease screening, highlighting the effectiveness of deep hybrid architectures in biomedical audio analysis.

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