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

Ch. Vasavi[1*], K. Venkateswarlu[1], Shaik Jaffrin[2], Yeturi Aswin[2], Vullayam Gnana Prasuna[2], Shaik Mehreen[2]

[1]Assistant Professor, [2]UG Student, [1,2]Department of Computer Science and Engineering

[1,2]Geethanjali Institute of Science and Technology, Nellore-Bombay Highway, S.P.S.R, Andhra Pradesh 524137, India

*Correspondence: Ch. Vasavi (vasavi@gist.edu.in)

ABSTRACT

Cardio-respiratory diseases remain a major global health concern, accounting for a significant proportion of mortality, particularly in India where they contribute to nearly 30% of total deaths. Early and accurate diagnosis is critical, yet traditional auscultation using acoustic stethoscopes relies heavily on physician expertise, often leading to subjective and inconsistent interpretations. This study presents an automated cardio-respiratory sound classification system designed to enhance diagnostic reliability through machine learning and deep learning techniques. A novel dataset was developed using a digital stethoscope to capture high-quality heart and lung sounds from a clinical manikin, enabling the collection of both individual and mixed recordings. This dataset provides combined cardiorespiratory audio signals, facilitating dual classification tasks. The system incorporates a user-friendly graphical interface with role-based access, allowing administrators to train models and users to perform predictions seamlessly. Audio signals are processed using Librosa for feature extraction, including Mel-Frequency Cepstral Coefficients (MFCC), Chroma features, and Mel spectrograms. Multiple traditional machine learning models such as Quadratic Discriminant Analysis (QDA), Gradient Boosting Classifier (GBC), Naive Bayes Classifier (NBC), and Logistic Regression Classifier (LRC) are implemented and evaluated. In addition, a custom deep learning architecture combining a Bi-directional Convolutional Neural Network (BiCNN) with a Bi-directional Gated Recurrent Unit (BiGRU) is proposed to capture spatial and temporal characteristics. The system performs simultaneous prediction of heart and lung sound types from mixed recordings, achieving robust performance across evaluation metrics.

Keywords: Cardio-respiratory diseases, Digital stethoscope, Machine Learning, BiCNN, BiGRU, 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 analysing 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, as shown in Figure 1. 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.

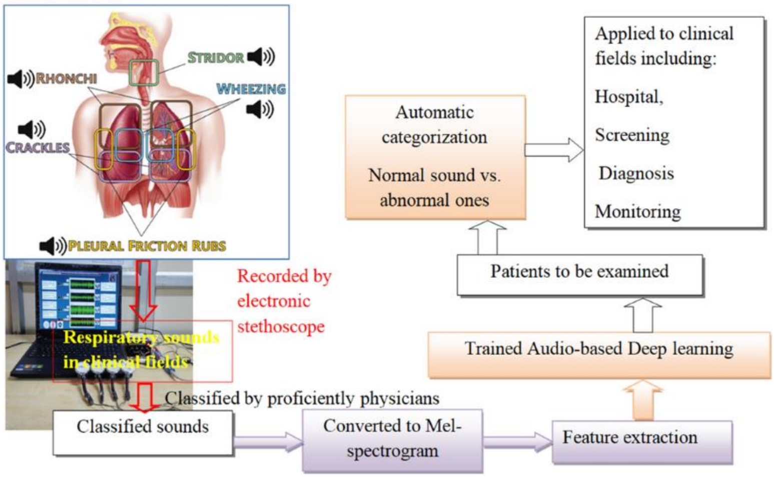

Fig 1: Disease recognition using sound analysis

2. LITERATURE SURVEY

Shokouhmand et al. [1] proposed Continuous monitoring of pulmonary function is crucial for effective respiratory disease management. The COVID-19 pandemic has also underscored the need for accessible and convenient diagnostic tools for respiratory health assessment. While traditional lung sound auscultation has been the primary method for evaluating pulmonary function, emerging research highlights the diagnostic potential of nasal and oral breathing sounds. These sounds, shaped by the upper airway, serve as valuable non-invasive biomarkers for pulmonary health and disease detection. Recent advancements in artificial intelligence (AI) have significantly enhanced respiratory sound analysis by enabling automated feature extraction and pattern recognition from spectral and temporal characteristics or even raw acoustic signals.

Kapetanidis et al. [2] represented a significant global burden, necessitating efficient diagnostic methods for timely intervention. Digital biomarkers based on audio, acoustics, and sound from the upper and lower respiratory system, as well as the voice, have emerged as valuable indicators of respiratory functionality. Recent advancements in machine learning (ML) algorithms offer promising avenues for the identification and diagnosis of respiratory diseases through the analysis and processing of such audio-based biomarkers. An ever-increasing number of studies employ ML techniques to extract meaningful information from audio biomarkers. Beyond disease identification, these studies explore diverse aspects such as the recognition of cough sounds amidst environmental noise, the analysis of respiratory sounds to detect respiratory symptoms like wheezes and crackles, as well as the analysis of the voice/speech for the evaluation of human voice abnormalities.

Abdullah et al. [3] introduced a modular AI-powered framework that integrates an audio-based disease classification model with simulated molecular biomarker profiles to evaluate the feasibility of future multimodal diagnostic extensions, alongside a synthetic-data-driven prescription recommendation engine. The disease classification model analyses respiratory sound recordings and accurately distinguishes among eight clinical classes: bronchiectasis, pneumonia, upper respiratory tract infection (URTI), lower respiratory tract infection (LRTI), asthma, chronic obstructive pulmonary disease (COPD), bronchiolitis, and healthy respiratory state. The proposed model achieved a classification accuracy of 99.99% on a holdout test set, including 94.2% accuracy on pediatric samples. In parallel, the prescription module provides individualized treatment recommendations comprising drug, dosage, and frequency trained on a carefully constructed synthetic dataset designed to emulate real-world prescribing logic. The model achieved over 99% accuracy in medication prediction tasks, outperforming baseline models such as those discussed in research.

Jamal et al. [4] explored the application of machine learning, particularly convolutional neural networks (CNNs), to overcome these obstacles. Advanced machine learning models, denoising algorithms, and domain adaptation strategies address challenges such as frequency overlap, external noise, and limited labelled datasets. This study presents a robust methodology for detecting heart and lung diseases from audio signals using advanced preprocessing, feature extraction, and deep learning models. The approach integrates adaptive filtering and bandpass filtering as denoising techniques and variational autoencoders (VAEs) for feature extraction. The extracted features are input into a CNN, which classifies audio signals into different heart and lung conditions. The results highlight the potential of this combined approach for early and accurate disease detection, contributing to the development of reliable diagnostic tools for healthcare.

Sreejith et al. [5] analysed the accurate and early detection of respiratory diseases are vital for effective diagnosis and treatment. This study presents a new approach for classifying lung sounds using a double denoising method combined with a 1D Convolutional Neural Network (CNN). The preprocessing uses Fast Fourier Transform to clean up sounds and High-Pass Filtering to improve the quality of breathing sounds by eliminating noise and low-frequency interruptions. The Short-Time Fourier Transform (STFT) extracts features that capture localised frequency variations, crucial for distinguishing normal and abnormal respiratory sounds. These features are input into the 1D CNN, which classifies diseases such as bronchiectasis, pneumonia, asthma, COPD, healthy, and URTI.

Xu et al. [6] introduced an AI-based diagnostic system capable of accurately distinguishing these conditions, thereby enhancing early detection and clinical management. Our study, therefore, presents the first AI system that leverages dual acoustic signals to enhance the diagnostic ACC of asthma using automated, lightweight deep learning models. To build an automated, lightweight model for asthma detection, tested separately with respiratory and cough sounds to assess their suitability for detecting asthma and COPD, the proposed AI models integrate the following ML algorithms: RF, SVM, DT, NN, and KNN, with an overall aim to demonstrate the efficacy of the proposed method for future clinical use. Model training and validation were performed using 5-fold cross-validation, wherein the dataset was randomly divided into five folds and the models were trained and tested iteratively to ensure robust performance. They evaluated the model outcomes with several performance metrics: ACC, precision, recall, F1 score, and area under the AUC.

Brunese et al. [7] aimed at the effectiveness of machine learning techniques in respiratory sound analysis. A feature vector is gathered directly from breath audio and, thus, by exploiting supervised machine learning techniques, they detect if the feature vector is related to a patient affected by a lung disease. Moreover, the proposed method can characterise the lung disease in asthma, bronchiectasis, bronchiolitis, chronic obstructive pulmonary disease, pneumonia, and lower or upper respiratory tract infection. Results: A retrospective experimental analysis on 126 patients with 920 recording sessions showed the effectiveness of the proposed method. Conclusion: The experimental analysis demonstrated that it is possible to detect lung disease by exploiting machine learning techniques.

Yu et al. [8] reviewed systematically examines 135 technical publications utilizing the database, and a comprehensive and timely summary of RSA methodologies is offered for researchers and practitioners in this field. Specifically, this review covers signal processing techniques including data resampling, augmentation, normalization, and filtering; feature extraction approaches spanning time-domain, frequency-domain, joint time–frequency analysis, and deep feature representation from pre-trained models; and classification methods for adventitious sound (AS) categorization and pathological state (PS) recognition. Current achievements for AS and PS classification are summarized across studies using official and custom data splits. Despite promising technique advancements, several challenges remain unresolved. These include a severe class imbalance in the dataset, limited exploration of advanced data augmentation techniques and foundation models, a lack of model interpretability, and insufficient generalization studies across clinical settings.

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Petmezas et al. [9] proposed a novel hybrid neural model that implements the focal loss (FL) function to deal with training data imbalance. Features initially extracted from short-time Fourier transform (STFT) spectrograms via a convolutional neural network (CNN) are given as input to a long short-term memory (LSTM) network that memorizes the temporal dependencies between data and classifies four types of lung sounds, including normal, crackles, wheezes, and both crackles and wheezes.

Hsu et al. [10] collected larger quantities of data to further improve model performance and explored issues of noisy labels and overlapping sounds. HF_Lung_V1 was expanded to HF_Lung_V2 with a 1.43× increase in the number of audio files. Convolutional neural network–bidirectional gated recurrent unit network models were trained separately using the HF_Lung_V1 (V1_Train) and HF_Lung_V2 (V2_Train) training sets. These were tested using the HF_Lung_V1 (V1_Test) and HF_Lung_V2 (V2_Test) test sets, respectively. Segment and event detection performance was evaluated. Label quality was assessed. Overlap ratios were computed between inhalation, exhalation, CAS, and DAS labels.

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, analyse, and classify heart and lung sounds to screen for diseases like Aortic Stenosis and COPD, all within a user-friendly graphical interface, as shown in Figure 2. 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.

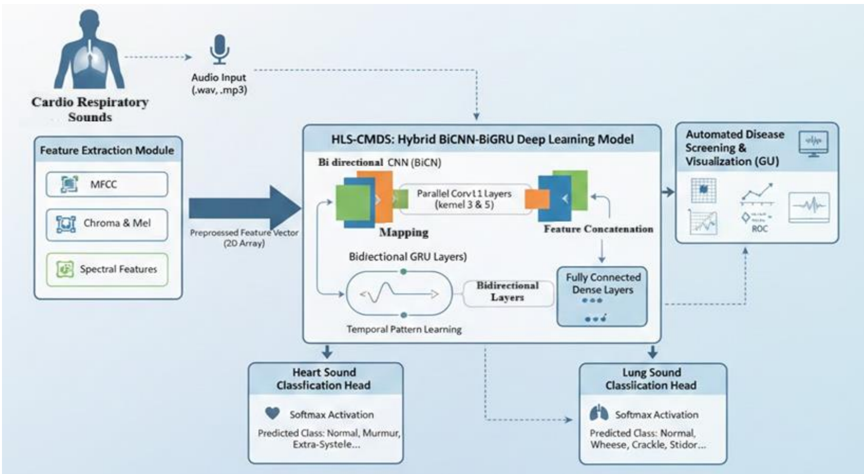

Figure 2: Proposed system architecture

Hybrid BiCNN-BiGRU Model

The proposed BiCNN–BiGRU model is a hybrid deep learning architecture designed to accurately classify heart and lung sound types from mixed cardiorespiratory audio signals. The model integrates parallel one-dimensional convolutional neural networks with bidirectional gated recurrent units to effectively learn both spatial and temporal acoustic patterns from high-level sound features, as shown in figure 4.6. Separate BiCNN-BiGRU models are trained for heart and lung sound classification to ensure task-specific learning. This hybrid architecture significantly improves classification accuracy and robustness compared to traditional machine learning models.

High-Level Audio Feature Input and Reshaping: The proposed model takes high-level audio feature vectors extracted from MFCCs, mel-spectral features, tonal descriptors, and energy-based measures as input. Each feature vector is reshaped into a one-dimensional sequence to make it suitable for convolutional and recurrent processing. These preserves feature ordering and enable sequential pattern learning.

Parallel Convolutional Feature Extraction (BiCNN): Two parallel 1D convolutional branches with different kernel sizes are employed to capture multi-scale acoustic patterns. Smaller kernels focus on fine-grained spectral variations, while larger kernels capture broader temporal structures in heart and lung sounds. This bi-branch CNN design enhances the model's ability to detect diverse pathological sound signatures.

Feature Fusion and Representation Enhancement: The outputs of the parallel convolutional branches are concatenated to form a unified feature representation. This fusion combines complementary information extracted at different receptive scales. The resulting feature map provides a richer and more discriminative representation of mixed cardiorespiratory sounds.

Temporal Dependency Modelling Using Bidirectional GRU: The fused feature representation is passed through a bidirectional GRU layer to model temporal dependencies in both forward and backward directions. This enables the model to capture long-term contextual information and sequential correlations within heart and lung sound features. Such temporal modelling is crucial for identifying rhythmic and periodic pathological patterns.

4. RESULT DESCRIPTION

The results of this study demonstrate the effectiveness of the implemented system in analyzing and classifying cardiorespiratory sound data. Various machine learning and deep learning models are evaluated based on standard performance metrics such as accuracy, precision, recall, and F1-score. The system also generates confusion matrices and ROC curves to provide a detailed understanding of model performance. Comparative analysis is performed to assess the strengths of different models in handling the dataset. The results highlight the capability of the system to accurately identify patterns in audio signals.

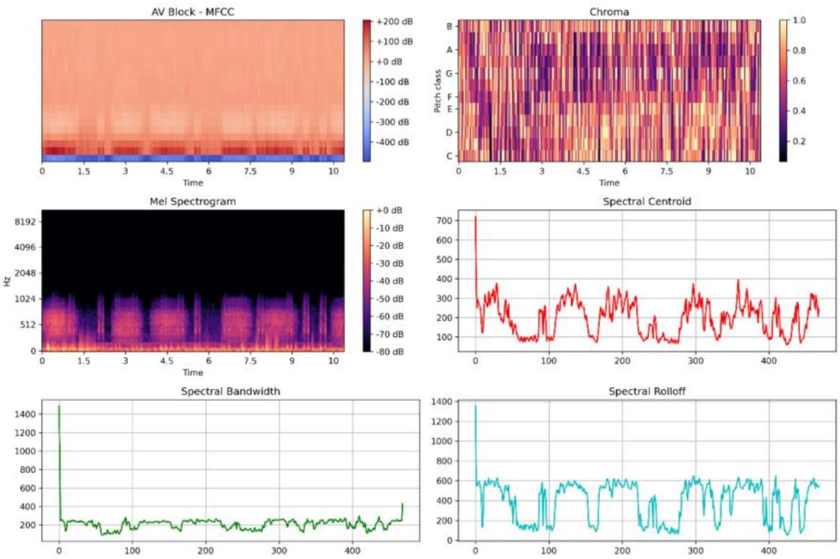

Figure 3: Exploratory audio feature analysis of cardiorespiratory sound signals

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 behaviour. 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.

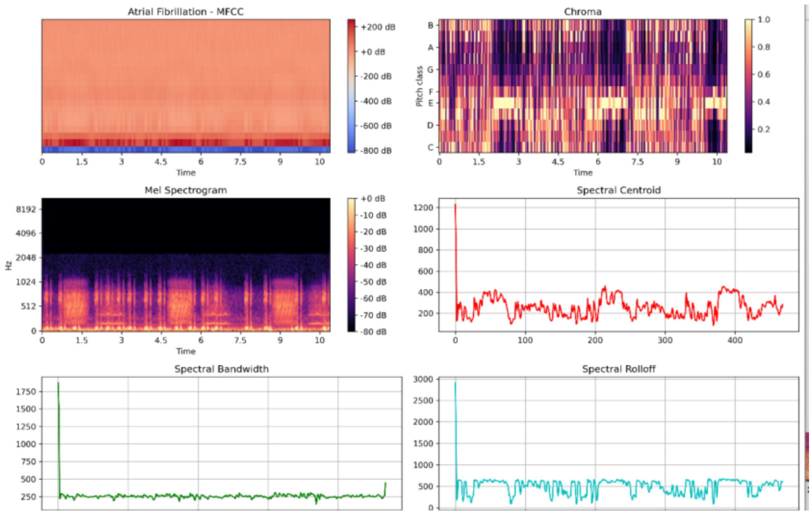

Figure 4: Spectral and cepstral analysis of atrial fibrillation cardiac signal

Figure 4 shows EDA visualizations that depict a detailed time–frequency analysis of an Atrial Fibrillation heart sound sample using multiple spectral and cepstral feature representations. The MFCC plot captures the overall acoustic envelope and harmonic structure characteristic of arrhythmic activity, while the Chroma map highlights pitch-class energy variations across time, reflecting irregular cardiac cycles. The Mel Spectrogram provides a dense visual representation of frequency energy distribution, showing repeating turbulent patterns associated with fibrillation. The spectral centroid and bandwidth curves describe the signal's frequency brightness and spread, revealing fluctuating energy concentrations that deviate from normal rhythmic patterns. Finally, the spectral rolloff plot illustrates the distribution of high-frequency components, offering additional insight into the irregular vibratory behaviour typical of pathological heart sounds. Together, these features provide a comprehensive diagnostic signature of Atrial Fibrillation for machine learning–based classification.

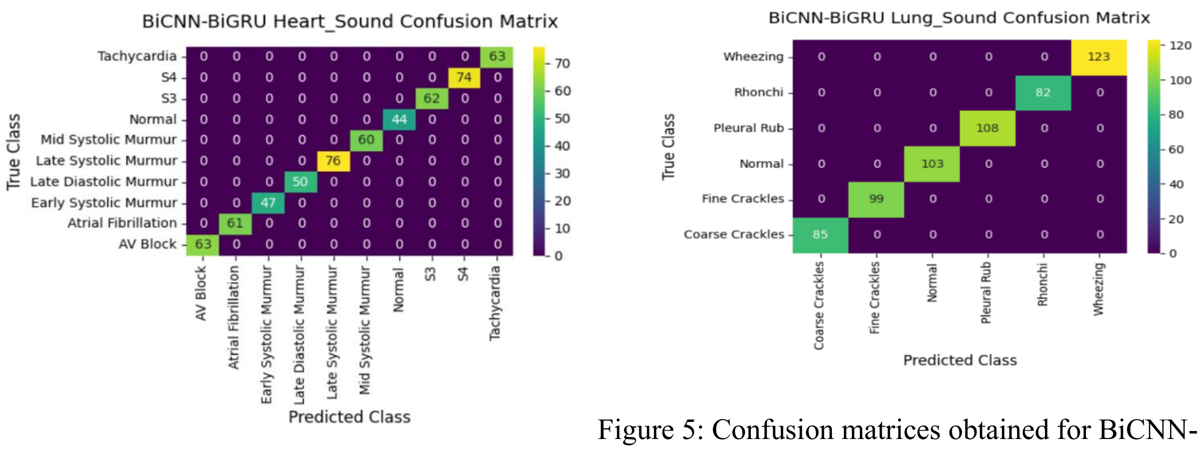

Figure 5: Confusion matrices obtained for BiCNN-BiGRU

Figure 5 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

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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 modelling long-term temporal dependencies.

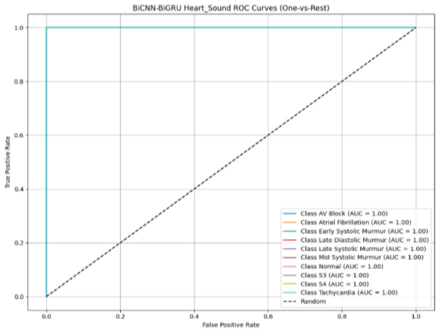


Figure 6: ROC obtained using BiCNN-BiGRU

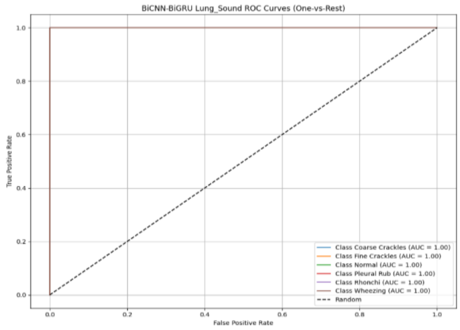
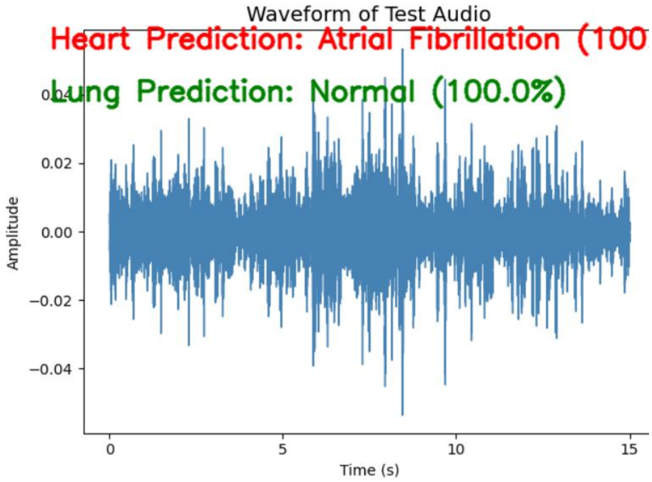
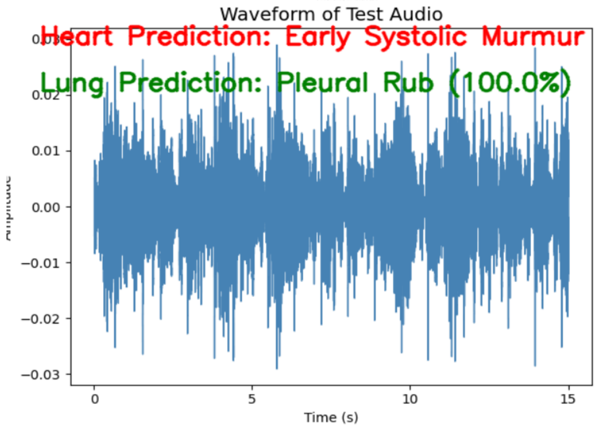


Figure 6 shows ROC curves of the proposed BiCNN–BiGRU model for both heart and lung sound classification exhibit ideal discriminative performance, with all class-wise curves tightly aligned along the top-left boundary and AUC values equal to 1.00. This indicates perfect separation between positive and 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.





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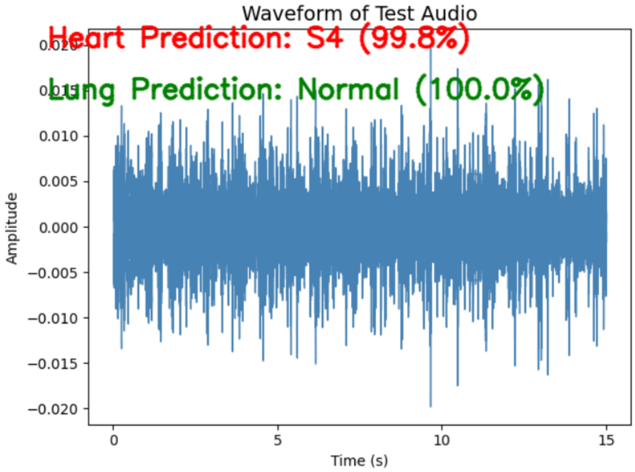

Figure 7: Prediction obtained on test audio files using BiCNN-BiGRU Model

Figure 7 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 analyse overlapping cardiac and respiratory patterns. This result highlights the effectiveness of the BiCNN component in capturing discriminative spectral features and the BiGRU layer in modelling temporal dynamics, enabling reliable and interpretable disease screening from real-world audio recordings.

Comparative Analysis

The comparative analysis evaluates the performance of different machine learning and deep learning models implemented in the system. Each model is assessed using standard evaluation metrics such as accuracy, precision, recall, and F1-score to ensure a fair comparison. The analysis helps in identifying the strengths and limitations of individual models when applied to cardiorespiratory sound data. Visualization techniques such as confusion matrices and ROC curves are used to support the comparison. By analysing the results, it becomes easier to determine which model performs more effectively under given conditions. This comparison also provides insights into the suitability of different approaches for real-world applications.

Table 1: Performance comparison for the Heart sound type QDA, GBC, GNB and Proposed BiCNN-BiGRU Model

Algorithms Name	**Accuracy**	**Precision**	**Recall**	**F-score**
QDA	89.5%	89.91%	89.90%	89.51%
GBC	93.0%	94.42%	92.39%	93.00%
NBC	31.0%	55.43%	30.04%	27.18%
LRC	38.5%	39.01%	39.006%	38.35%
BiCNN-BiGRU Model	100.0%	100.0%	100.0%	100.0%

Table 1 presents a comparative performance analysis of different classifiers for heart sound type classification, highlighting clear differences in predictive effectiveness. The QDA classifier demonstrates strong baseline performance with balanced accuracy, precision, recall, and F-score close to 90%, indicating reasonable discrimination of cardiac sound classes. The GBC further improves performance, achieving over 93% accuracy and the highest precision among traditional models, reflecting its ability to model non-linear feature interactions more effectively. In contrast, the NBC and LRC classifiers show substantially lower performance due to their simplistic assumptions and inability to handle complex, overlapping cardiac acoustic features. Notably, the proposed BiCNN-BiGRU model achieves perfect scores across all evaluation metrics, demonstrating superior learning of multi-scale spectral patterns and temporal dependencies, and clearly outperforming all baseline methods for heart sound classification.

Table 2: Performance comparison for the Lung sound type QDA, GBC, GNB and Proposed BiCNN-BiGRU Model

Algorithms Name	Accuracy	Precision	Recall	F-score
QDA	89.66%	92.77%	89.88%	89.86%
GBC	97.33%	97.11%	97.16%	97.12%
NBC	44.66%	70.37%	41.94%	40.67%
LRC	63.5%	63.71%	63.41%	63.26%
BiCNN-BiGRU Model	100.0%	100.0%	100.0%	100.0%

Table 2 summarizes the performance comparison of various classifiers for lung sound type classification, clearly demonstrating the effectiveness of different modelling approaches. The QDA classifier achieves nearly 90% accuracy with high precision and recall, indicating reliable baseline performance for respiratory sound discrimination. The GBC significantly enhances performance, reaching over 97% across all evaluation metrics, which reflects its strong capability to capture non-linear relationships in lung sound features. In contrast, NBC shows poor accuracy and recall due to its unrealistic feature independence assumption, while LRC delivers moderate performance limited by its linear decision boundaries. Most notably, the proposed BiCNN-BiGRU model achieves perfect scores in accuracy, precision, recall, and F-score, confirming its superior ability to model complex spectral–temporal patterns and its robustness in lung sound classification.

5. CONCLUSION

The research 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 modelling complex biomedical sounds. Comparative analysis with traditional machine learning models such as QDA, GBC, NBC, and LRC 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 modelling 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.

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