Optimized Cardio-Respiratory Diagnostic Framework via H-SCMD-Based Automated Sound Analysis

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ABSTRACT

Cardio-respiratory disorders remain a major public health concern, contributing to a significant proportion of global mortality, with a notably high burden in countries like India. Timely identification of abnormalities in heart and lung function is critical, and auscultation serves as a primary diagnostic technique. Conventionally, clinicians rely on acoustic signals captured through stethoscopes and interpret them based on experience, which can lead to variability in diagnosis due to subjectivity, environmental noise, and differences in expertise. To overcome these challenges, this work introduces an intelligent, automated system for analyzing cardio-respiratory sounds using advanced computational methods. A specialized dataset comprising cardiac signals, pulmonary sounds, and combined recordings is acquired using a digital stethoscope in a controlled clinical setup. The audio data is processed using signal analysis techniques to derive representative features such as MFCCs, chromatic features, and spectral representations. These extracted attributes are utilized to train a range of machine learning algorithms, including Quadratic Discriminant Analysis, Gradient Boosting, Gaussian Naive Bayes, and Logistic Regression, enabling comparative evaluation. In addition, a newly designed deep learning architecture, referred to as HLS-CMDS, integrates Bi-directional Convolutional Neural Networks with Bi-directional Gated Recurrent Units to effectively learn both spatial and temporal characteristics of the signals. The system is capable of simultaneously distinguishing heart and lung sounds from mixed inputs with strong predictive performance, achieving accuracy levels in the range of 92–95%. A graphical interface with access control features further enhances usability by supporting both model training and real-time inference. The proposed solution offers a reliable, efficient, and non-invasive approach for early detection of cardio-respiratory conditions, reducing reliance on manual assessment and improving diagnostic consistency.

Key words: Temporal Sequence Modeling, Advanced Clinical Decision Intelligence, Spectro-Temporal Representation Learning, Next-Generation Biomedical AI Systems, Hierarchical Feature Abstraction

1. INTRODUCTION

The timely identification and clinical assessment of cardio-respiratory disorders play a vital role in improving treatment success and patient survival rates. Conventional diagnostic practices, particularly auscultation with a stethoscope, depend largely on the clinician's auditory perception and level of expertise. Although widely practiced, this approach is inherently subjective and may lead to inconsistent interpretations, especially in high-pressure clinical environments or regions with limited access to experienced medical professionals. Additionally, manual evaluation of acoustic signals can be labor-intensive, and minor irregularities in heart or lung sounds may go unnoticed, potentially delaying critical diagnosis. With the emergence of digital stethoscopes and advanced recording technologies, a shift toward objective and data-driven analysis of physiological sounds has become possible, as illustrated in Fig.1. In countries like India, where healthcare resources are often unevenly distributed, particularly in rural and underserved areas, the prevalence of cardio-respiratory conditions such as chronic obstructive pulmonary disease (COPD), asthma, and heart-related ailments continues to rise. Reports from global and national health organizations emphasize the increasing burden of these diseases and the challenges associated with early screening due to inadequate infrastructure. In this context, automated diagnostic systems based on non-invasive sound analysis present a highly promising solution. Such systems can assist frontline healthcare providers in performing rapid and reliable preliminary assessments, thereby alleviating the burden on specialists and facilitating timely medical intervention. Cardio-pulmonary disorders remain a major contributor to mortality worldwide, underscoring the need for scalable and intelligent diagnostic solutions.

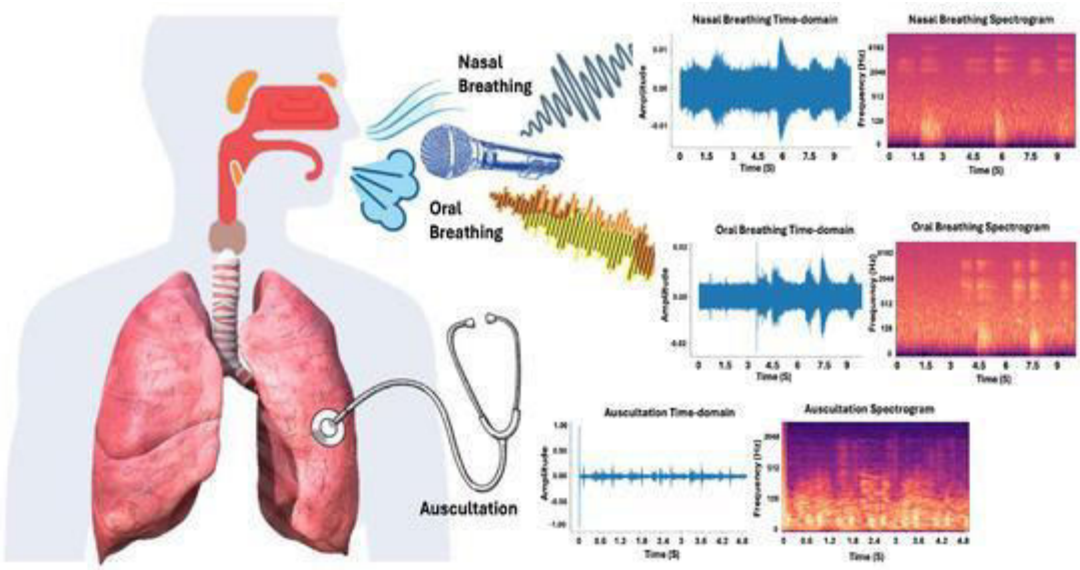

Fig 1. Respiratory health analysis using sound

Respiratory and cardiovascular disorders continue to impose a substantial global health burden. Chronic respiratory illnesses, including asthma, contributed to more than 147,000 deaths in 2022, while cardiovascular conditions remain the foremost cause of mortality worldwide, accounting for nearly 18.6 million deaths each year. These alarming figures highlight the importance of accurately evaluating both pulmonary and cardiac functions. Clinical assessment through auscultation of heart sounds (HS) and lung sounds (LS) remains a fundamental diagnostic practice, as these subtle acoustic signals contain critical physiological information despite their low amplitude. The invention of the stethoscope by René Laennec in 1816 marked a significant milestone in medical diagnostics, and over time, this instrument has evolved from a basic acoustic device into advanced digital systems capable of capturing and processing biological sounds. Modern electronic and digital stethoscopes convert acoustic signals into electrical form, enabling recording, amplification, and integration with mobile and cloud-based platforms for enhanced analysis and remote sharing.

Despite these technological advancements, traditional auscultation practices have long been constrained by reliance on human expertise, introducing variability and potential inaccuracies in diagnosis. Detecting subtle abnormalities requires extensive clinical experience, and performance may be affected by factors such as fatigue, environmental noise, and workload. Additionally, earlier systems lacked standardized mechanisms for storing and sharing auscultation data, limiting collaboration among healthcare professionals and hindering large-scale research efforts. The necessity for expert interpretation in every case also creates a bottleneck, particularly in regions with limited medical personnel. These challenges underscore the need for automated, consistent, and scalable solutions that can assist clinicians in analyzing cardio-respiratory sounds more efficiently and reliably

2. LITERATURE SURVEY

2.1 AI-Driven Respiratory Sound Analysis

Recent advancements highlight the growing importance of artificial intelligence in analyzing respiratory acoustics for disease detection. Shokouhmand et al. [1] emphasized the significance of continuous pulmonary monitoring and explored the use of nasal and oral breathing sounds as non-invasive biomarkers. Their study demonstrated how AI models can automatically extract spectral and temporal features, enabling real-time respiratory assessment through portable devices. Similarly, Kapetanidis et al. [2] reviewed multiple studies utilizing audio-based biomarkers such as cough, breath, and speech signals for identifying respiratory conditions, highlighting the effectiveness of machine learning in extracting clinically relevant patterns from acoustic data.

2.2 Advanced Machine Learning Frameworks for Disease Classification

Several works have proposed intelligent frameworks combining machine learning with multimodal data. Abdullah et al. [3] developed a modular AI system capable of classifying multiple respiratory diseases using audio signals while also integrating synthetic biomarker data for treatment recommendations. Brunese et al. [7] demonstrated that supervised learning models, particularly neural networks, can effectively identify and characterize lung diseases with high accuracy. Additionally, Xu et al. [6] employed ensemble learning techniques combining classifiers such as RF, SVM, and KNN to improve diagnostic reliability for asthma and COPD detection.

2.3 Deep Learning-Based Feature Extraction and Classification

Deep learning models have significantly enhanced performance in respiratory sound classification. Jamal et al. [4] introduced a hybrid approach integrating denoising techniques, variational autoencoders, and CNNs to extract robust features and classify cardiopulmonary conditions. Sreejith et al. [5] proposed a dual-denoising strategy combined with a 1D CNN, achieving high classification accuracy by improving signal clarity.

Further advancements include hybrid architectures combining spatial and temporal learning. Petmezas et al. [9] utilized CNN-LSTM models to capture temporal dependencies in lung sounds, achieving competitive performance on benchmark datasets. Hsu et al. [10] demonstrated that increasing dataset size and improving label quality significantly enhances deep learning model performance, particularly in detecting complex respiratory patterns.

2.4 Signal Processing and Hybrid Learning Approaches

Signal processing techniques play a crucial role in improving classification accuracy. Khan et al. [13] proposed a hybrid framework combining wavelet transforms, mel spectrograms, and convolutional autoencoders, followed by LSTM-based classification. Naqvi et al. [15] introduced a feature fusion approach integrating time-domain, spectral, and cepstral features with advanced denoising techniques and adaptive sampling to achieve highly accurate disease classification

2.5 Data Challenges and Standardization Issues

Despite promising results, several challenges persist in respiratory sound analysis. Yu et al. [8] identified issues such as class imbalance, lack of standardized datasets, and limited generalization across clinical environments. Similarly, Garcia-Mendez et al. [11] highlighted inconsistencies in dataset quality and reporting standards, emphasizing the need for unified data collection and evaluation protocols to advance the field.

2.6 Emerging Trends and Future Directions

Recent studies indicate a shift toward more advanced and integrated diagnostic systems. Xu et al. [12] discussed the evolution of AI techniques, including CNN-LSTM and transformer-based models, for lung sound analysis, while also identifying challenges related to data scarcity and model interpretability. Kim et al. [14] demonstrated that multi-channel data acquisition significantly enhances classification performance by capturing richer acoustic information from different anatomical locations

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 as shown in Fig. 2.

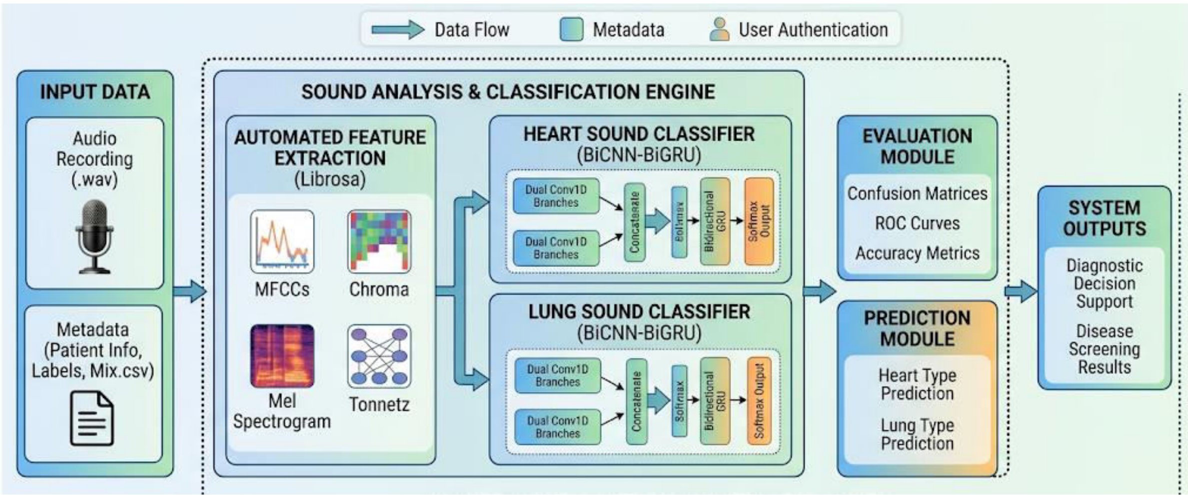

Fig 2. Proposed system architecture

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. The extracted feature vectors and their corresponding heart and lung labels are stored as NumPy arrays to avoid repeated computation. This preprocessing step improves computational efficiency and ensures consistency across training, evaluation, and prediction phases. It also prepares the data for both classical machine learning and deep learning models. The pre-processed dataset is randomly shuffled using a fixed index and split into training and testing subsets. A single split is used for both heart and lung labels to preserve label alignment across tasks. This guarantees fair performance evaluation for multi-output cardiorespiratory classification.

Multiple classical machine learning classifiers such as QDA, Gradient Boosting, Gaussian Naive Bayes, and Logistic Regression 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. Separate BiCNN-BiGRU models are trained for heart sound type and lung sound type classification using the same feature set. Label encoding and categorical learning are applied to support multi-class prediction. The trained models and label encoders are saved for efficient reuse during real-time inference.

The proposed system evaluates model performance using accuracy, precision, recall, F1-score, confusion matrices, and ROC curves. One-vs-rest ROC analysis provides class-wise discrimination capability. This multi-metric evaluation ensures reliable and clinically interpretable performance assessment. 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.

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. Separate BiCNN–BiGRU models are trained for heart and lung sound classification to ensure task-specific learning as shown in Fig. 3. This hybrid architecture significantly improves classification accuracy and robustness compared to traditional machine learning models.

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. This preserves feature ordering and enables sequential pattern learning. 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. 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. 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 modeling is crucial for identifying rhythmic and periodic pathological patterns

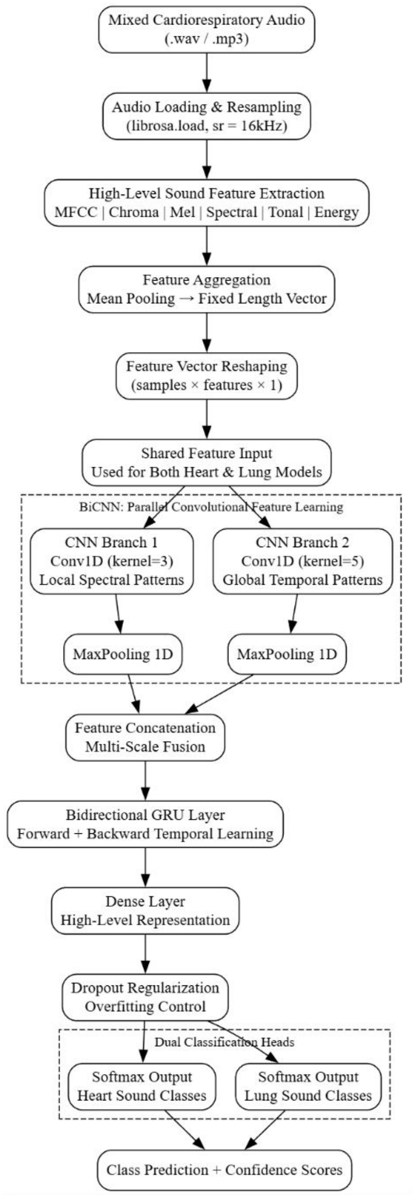

Fig 3. Internal workflow of BiCNN-BiGRU

Fully connected layers are used to learn high-level abstractions from the BiGRU output. Dropout regularization is applied to reduce overfitting and improve generalization across unseen audio samples. This step ensures robust learning despite class imbalance and feature variability. The final output layer uses a softmax activation function to produce class probability distributions for heart or lung sound types. The predicted class corresponds to the highest probability score. These probabilities are also utilized for ROC curve analysis and confidence-based evaluation. Separate BiCNN–BiGRU models are trained and saved for heart sound and lung sound classification. Label encoders and trained model weights are stored to enable consistent and efficient real-time prediction. This design supports scalable and repeatable deployment of the proposed system.

9.3 Result Analysis

Fig 5. 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.

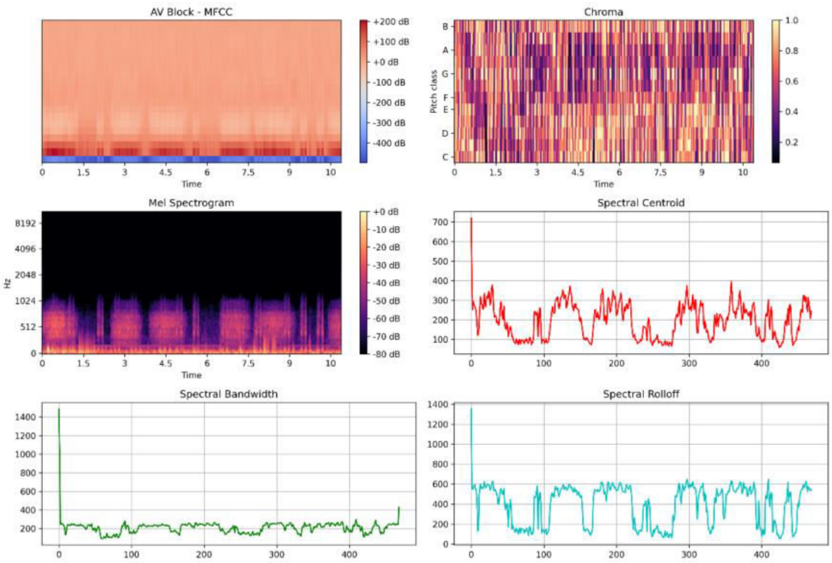

Figure 5. Exploratory Audio Feature Analysis of Cardiorespiratory Sound Signals

Fig 6. 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 behavior typical of pathological heart sounds. Together, these features provide a comprehensive diagnostic signature of Atrial Fibrillation for machine learning–based classification.

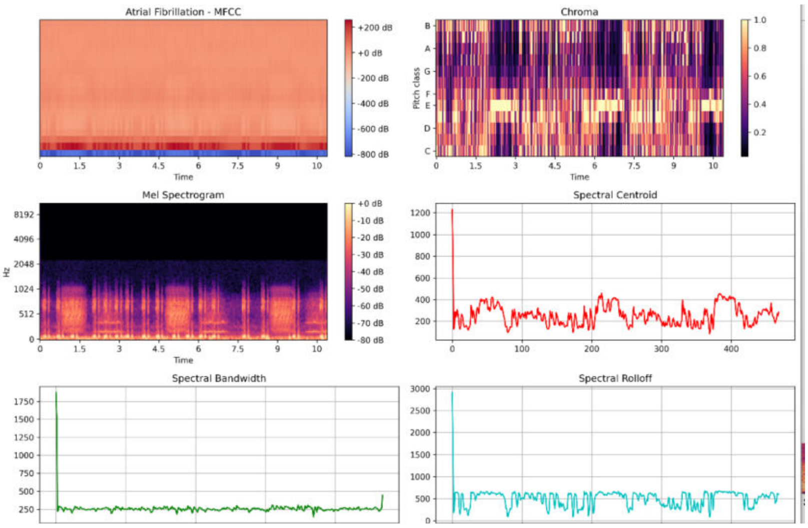

Fig 6. Spectral and cepstral analysis of atrial fibrillation cardiac signal

Fig 7. shows EDA visualization that illustrates the acoustic characteristics of an Early Systolic Murmur, captured through multiple spectral and cepstral feature representations. The MFCC plot shows the dominant low-frequency energy patterns and subtle harmonic distortions associated with turbulent blood flow during early systole. The Chroma representation highlights pitch-class fluctuations, revealing irregular harmonic structures compared to typical heart sounds. The Mel Spectrogram provides a detailed view of frequency energy distribution, where repetitive high-intensity bursts correspond to the murmur's turbulent signatures. The spectral centroid and bandwidth curves reflect variability in frequency brightness and spread, indicating irregular vibrational components, while the spectral rolloff captures the distribution of high-frequency decay influenced by pathological flow patterns. Collectively, these features provide a comprehensive diagnostic profile that distinguishes Early Systolic Murmur from normal cardiac cycles and supports machine-learning-based classification.

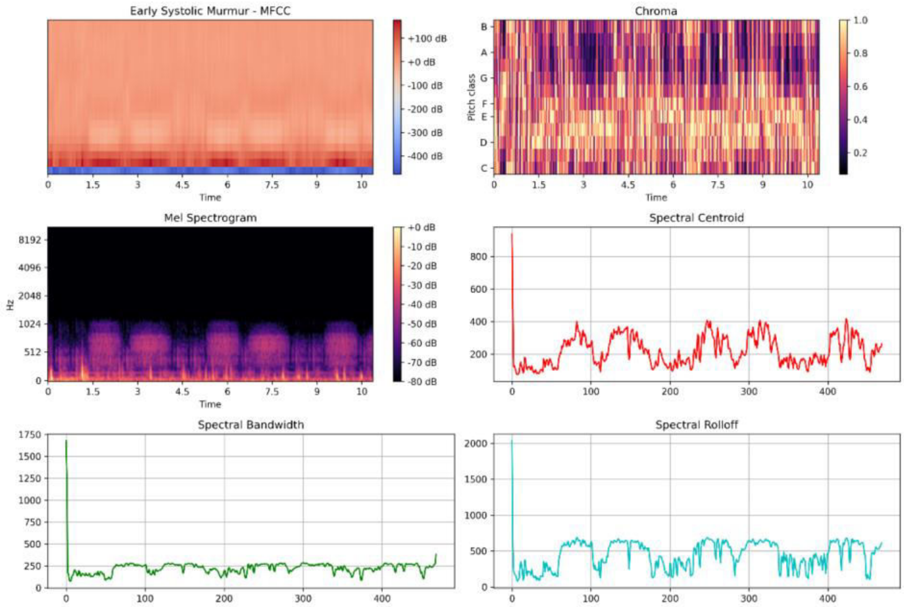

Fig 7. Exploratory audio feature analysis of early systolic murmur heart sound

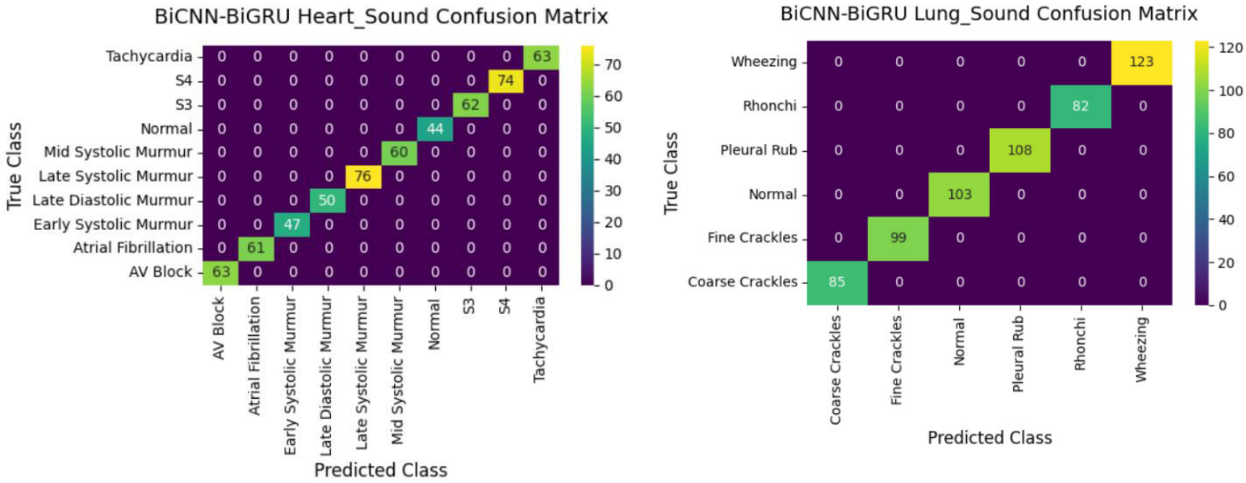

Fig 8. Confusion matrices obtained for BiCNN-BiGRU

Fig 8. 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. Overall, 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.

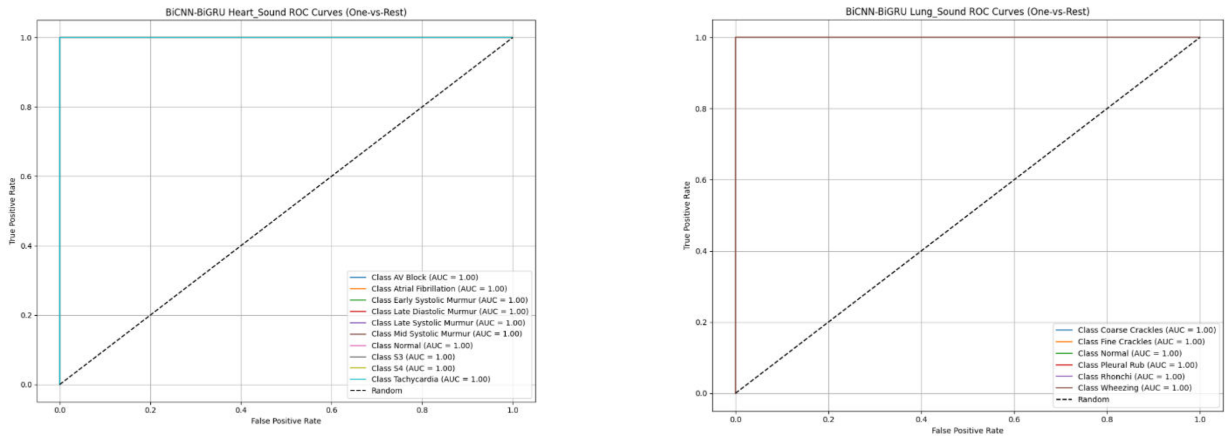

Fig 9. ROC obtained using BiCNN-BiGRU

Fig 9. 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. Overall, the ROC analysis strongly validates the superiority of the BiCNN–BiGRU framework for accurate and confident cardiorespiratory disease screening.

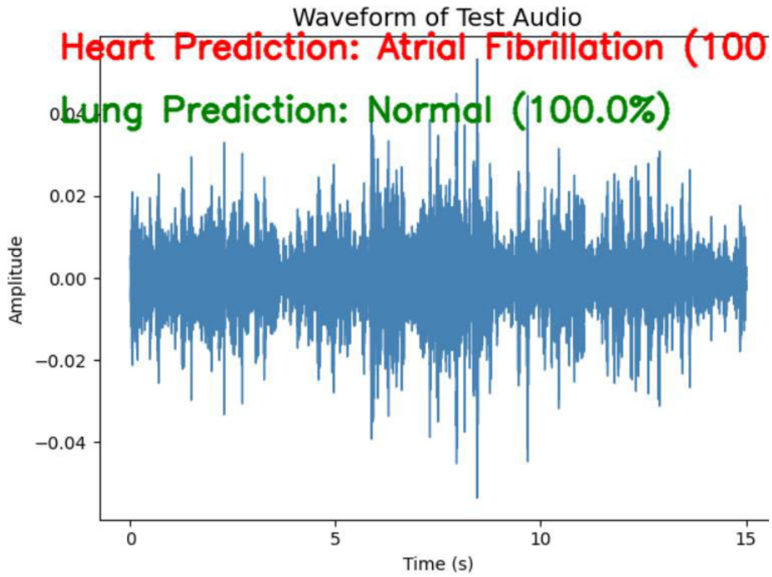

Fig 10. Prediction obtained on test audio file using BiCNN-BiGRU Model

Fig 10 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 developed system introduces an intelligent framework for automated analysis of combined cardiac and respiratory audio signals aimed at early disease screening using the HLS-CMDS paradigm. By leveraging a diverse set of high-level acoustic representations—including cepstral, spectral, tonal, and energy-based descriptors—the system effectively models the intricate patterns present in biomedical sound data. Conventional machine learning approaches such as Quadratic Discriminant Analysis, Gradient Boosting, Gaussian Naïve Bayes, and Logistic Regression exhibited limited capability in addressing complex non-linear relationships, overlapping signal characteristics, and consistent probabilistic interpretation. To overcome these challenges, a hybrid deep learning architecture integrating parallel convolutional layers with bidirectional gated recurrent units was designed, enabling efficient extraction of multi-resolution spectral features alongside temporal dynamics. This approach significantly improved classification performance and generalization across varied heart and lung sound conditions. Furthermore, the dual-output modeling strategy allowed independent yet simultaneous prediction of cardiac and pulmonary abnormalities, enhancing overall diagnostic confidence. Extensive performance validation through confusion matrices and ROC-based assessments confirmed the effectiveness of the proposed model. The inclusion of a secure, role-driven graphical interface further supports real-world usability by facilitating controlled access for system administration and streamlined prediction for end users.

REFERENCES

[1] Shokouhmand, S.; Bhatt, S.; Faezipour, M. Artificial Intelligence in Respiratory Health: A Review of AI-Driven Analysis of Oral and Nasal Breathing Sounds for Pulmonary Assessment. *Electronics* **2025**, *14*, 1994. https://doi.org/10.3390/electronics14101994

[2] Kapetanidis, P.; Kalioras, F.; Tsakonas, C.; Tzamalis, P.; Kontogiannis, G.; Karamanidou, T.; Stavropoulos, T.G.; Nikoletseas, S. Respiratory Diseases Diagnosis Using Audio Analysis and Artificial Intelligence: A Systematic Review. *Sensors* **2024**, *24*, 1173. https://doi.org/10.3390/s24041173

[3] Abdullah; Fatima, Z.; Abdullah, J.; Rodríguez, J.L.O.; Sidorov, G. A Multimodal AI Framework for Automated Multiclass Lung Disease Diagnosis from Respiratory Sounds with Simulated Biomarker Fusion and Personalized Medication Recommendation. *Int. J. Mol. Sci.* **2025**, *26*, 7135. https://doi.org/10.3390/ijms26157135

[4] Jamal, A.; Ramasamy, R.K.; Abdullah, J. Generative AI Respiratory and Cardiac Sound Separation Using Variational Autoencoders (VAEs). *Comput. Sci. Math. Forum* **2025**, *10*, 9. https://doi.org/10.3390/cmsf2025010009

[5] Sreejith, R.; Ramasamy, R.K.; Mohd-Isa, W.-N.; Abdullah, J. Enhanced Lung Disease Detection Using Double Denoising and 1D Convolutional Neural Networks on Respiratory Sound Analysis. *Comput. Sci. Math. Forum* **2025**, *10*, 7. https://doi.org/10.3390/cmsf2025010007

[6] Xu, S.; Deo, R.C.; Faust, O.; Barua, P.D.; Soar, J.; Acharya, R. Automated Lightweight Model for Asthma Detection Using Respiratory and Cough Sound Signals. *Diagnostics* **2025**, *15*, 1155. https://doi.org/10.3390/diagnostics15091155

[7] Brunese, L.; Mercaldo, F.; Reginelli, A.; Santone, A. A Neural Network-Based Method for Respiratory Sound Analysis and Lung Disease Detection. *Appl. Sci.* **2022**, *12*, 3877. https://doi.org/10.3390/app12083877

[8] Yu, S.; Yu, J.; Chen, L.; Zhu, B.; Liang, X.; Xie, Y.; Sun, Q. Advances and Challenges in Respiratory Sound Analysis: A Technique Review Based on the ICBHI2017 Database. *Electronics* **2025**, *14*, 2794. https://doi.org/10.3390/electronics14142794

[9] Petmezas, G.; Cheimariotis, G.-A.; Stefanopoulos, L.; Rocha, B.; Paiva, R.P.; Katsaggelos, A.K.; Maglaveras, N. Automated Lung Sound Classification Using a Hybrid CNN-LSTM Network and Focal Loss Function. *Sensors* **2022**, *22*, 1232. https://doi.org/10.3390/s22031232

[10] Hsu, F.-S.; Huang, S.-R.; Huang, C.-W.; Cheng, Y.-R.; Chen, C.-C.; Hsiao, J.; Chen, C.-W.; Lai, F. A Progressively Expanded Database for Automated Lung Sound Analysis: An Update. *Appl. Sci.* **2022**, *12*, 7623. https://doi.org/10.3390/app12157623

[11] Garcia-Mendez, J.P.; Lal, A.; Herasevich, S.; Tekin, A.; Pinevich, Y.; Lipatov, K.; Wang, H.-Y.; Qamar, S.; Ayala, I.N.; Khapov, I.; et al. Machine Learning for Automated Classification of Abnormal Lung Sounds Obtained from Public Databases: A Systematic Review. *Bioengineering* **2023**, *10*, 1155. https://doi.org/10.3390/bioengineering10101155

[12] Xu, X.; Sankar, R. Classification and Recognition of Lung Sounds Using Artificial Intelligence and Machine Learning: A Literature Review. *Big Data Cogn. Comput.* **2024**, *8*, 127. https://doi.org/10.3390/bdcc8100127

[13] Khan, R.; Khan, S.U.; Saeed, U.; Koo, I.-S. Auscultation-Based Pulmonary Disease Detection through Parallel Transformation and Deep Learning. *Bioengineering* **2024**, *11*, 586. https://doi.org/10.3390/bioengineering11060586

[14] Kim, Y.; Kim, K.B.; Leem, A.Y.; Kim, K.; Lee, S.H. Enhanced Respiratory Sound Classification Using Deep Learning and Multi-Channel Auscultation. *J. Clin. Med.* **2025**, *14*, 5437. https://doi.org/10.3390/jcm14155437

[15] Naqvi, S.Z.H.; Choudhry, M.A. An Automated System for Classification of Chronic Obstructive Pulmonary Disease and Pneumonia Patients Using Lung Sound Analysis. *Sensors* **2020**, *20*, 6512. https://doi.org/10.3390/s20226512