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"Lub and Dub": An Optimized Approach for Heart Disease Classification Based on Heart Sound Using Bi-LSTM

[1]Ms.Kummari Jayasri, [2]Prof. N. Satheesh Kumar

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Abstract: CVD detection strategies encompass statistical, image-based, and audio-based approaches, emphasizing analyzing systolic and diastolic sounds. While statistical methods rely on traditional risk factors, image-based techniques utilize deep learning, particularly CNNs, for early detection by analyzing Electrocardiogram data. Audio-based methods, including time-frequency analysis of phonocardiogram signals, show promise in detecting cardiovascular abnormalities, yet specific sound disorders remain insufficiently addressed. Real-time monitoring of systolic and diastolic sound irregularities holds potential for mitigating heart attack risks. Recent observations underscore the critical need for dynamic, real-time monitoring, shifting from conventional systematic assessments to ongoing observations. This paper introduces a Bi-LSTM model to detect abnormal heart sound patterns, achieving an accuracy of 0.74 and demonstrating a favorable ROC curve across all classes.

***Keywords**. Bi-LSTM, Hear sound, classification, deep learning, spectrogram features.*

1. Introduction

CVDs remain one of the leading causes of morbidity and mortality worldwide, underscoring the critical need for effective methods of early detection and intervention. Among the various modalities for cardiovascular health monitoring, the analysis of heart sounds presents a promising avenue for detecting abnormalities indicative of underlying cardiac conditions. Recent advancements in deep learning techniques have enabled researchers to leverage vast amounts of heart sound data to develop accurate and efficient automated analysis and prediction models.

Sound analysis plays a crucial role in the early detection of heart diseases, especially during critical events like heart attacks. Traditional diagnostic methods, relying on statistical data such as blood pressure, age, and cholesterol levels, have limitations in capturing heart conditions' dynamic and intricate nature. By scrutinizing the rhythmic "Lub" and "Dub" sounds, medical professionals can discern subtle changes in the heart's function and structure, facilitating early diagnosis and intervention.

Researchers, such as Pant, A [3], [4], and [27], have leveraged ECG images to train machine learning or deep learning models for disease segmentation in various heart-related conditions. Using CNN models, they successfully classified diseases based on ECG patterns. However, a significant challenge remains, particularly in addressing the sudden onset of heart attacks, which may occur without typical symptoms.

In a comparative study, researchers like Bao X et al. [9] explored time-frequency-based analysis methods for diagnosing heart-related diseases. While image-based approaches have been effective, challenges persist in addressing the sudden onset of heart-related conditions. Additionally, Alkayyali Z et al. [11] investigated statistical-based approaches, highlighting the robustness of machine learning models in heart disease diagnosis when considering various statistical features.

Ren, Z. et al. [12] took a distinctive approach by exploring sound-based analysis of heart diseases, focusing on different heart sounds like systolic and diastolic sounds. Subsequent studies [13], [14], [15], and [16] extended this work by extracting various features from sound signals, including frequency, Mel spectrogram, and time-frequency characteristics. These features were then used to train deep learning models, showcasing the potential of sound-based methods in advancing healthcare diagnostics.

The primary objective is to develop an automated system that detects heart diseases by analyzing distinctive patterns present in heart sounds. Consistency is crucial, aiming for reliable performance across diverse cases and real-world healthcare situations. This advanced methodology holds substantial potential to transform early diagnosis, enhance accuracy in identifying heart-related

[1]*Research Scholar, Department of Computer Science and Engineering, Chaitanya Deemed To Be University, Kishanpura, Hanamkonda, Warangal – 506001, Telangana*
[2]*Professor, Department of Computer Science and Engineering, Chaitanya Deemed To Be University, Kishanpura, Hanamkonda, Warangal – 506001, Telangana*
Email: kummari.jayashree@gmail.com
Email: meet.nskumar@gmail.com

conditions, and ultimately improve overall cardiovascular health outcomes.

Contributions

- The implemented Bi-LSTM deep learning model achieves an impressive accuracy of 0.69, showcasing consistent proficiency in identifying heart-related disorders through various methods.
- Through comparative evaluations, our model outperforms specified benchmarks, showcasing a swift and robust ability to detect sound disorders associated with heart conditions.
- The unique features embedded in our model contribute significantly to its efficacy in accurately identifying and categorizing heart-related disorders.

2. Related Work

Exploration of predictive and detection strategies for CVD encompasses three pivotal features: statistical, image-based, and audio-based, explicitly focusing on systolic and diastolic sounds. While statistical methods hold promise in early detection, their reliance on limited features such as age, blood pressure, and cholesterol levels necessitate refinement to achieve a more comprehensive and nuanced approach.

Researchers have extensively explored image-based approaches, particularly utilizing Electrocardiogram data, as demonstrated by Martin-Isla et al. [6]. Their implementation of deep learning models like CNNs represents a significant advancement in this field. However, it is essential to recognize that ECG-based predictions, while valuable, primarily focus on early-stage detection and diagnosis.

Pasha et al. [1] employ deep learning techniques to predict cardiovascular disease, offering insights into analyzing cardiovascular risk factors and predicting the likelihood of heart disease development.

Majumder et al. [2] propose a method for heart disease prediction utilizing concatenated hybrid ensemble classifiers. This study explores the effectiveness of combining multiple classification algorithms to enhance the accuracy and robustness of predictive models.

Pant et al. [3] investigate heart disease prediction using image segmentation through one dimensional CNN models. And they used vertical techniques to avoid overfitting. This model when compared all machine learning models performed better with training and testing accuracy of 0.97 and 0.96. In a comprehensive review, Joshi et al. [4] discuss the evolution and applications of CNNs, providing insights into their strength and weakness in terms of bandwidth compared all versions and types of CNN models that will help for image analysis.

Chang et al. [5] presents AI based approach for heart disease detection using machine learning algorithms. In this they used continuous and categorical variables to train random forest models and got an accuracy of 0.83. But they used statistical features like temperature, blood pressure etc. Martin-Isla et al. [6] review image-based cardiac diagnosis with machine learning techniques, in this cardiac images, geographic images, ECG, anagenetic features are used to train their models. With all these features their model can able to detect whether it is diseased or not.

Muhammad et al. [7] propose an intelligent computational model for early and accurate detection and diagnosis of heart disease, they compared all metrics like precision and recall with their support score and discussed the imbalanced data problems and importance.

Nova et al. [8] propose automated image segmentation for cardiac septal defects based on contour regions with CNNs, presenting a preliminary investigation into using deep learning for automated detection and segmentation of cardiac abnormalities.

Bao et al. [9] conducted a comparative study using CNNs to analyze time-frequency distributions of heart sound signals, and explored all the combinations of CNN models and also exploring different approaches for feature extraction and classification of heart sound data and observe the differences. And also studied S1, S2, S3 and S4 signal over disease prediction.

Panah et al. [10] investigate the impact of noise and degradation on heart sound classification models, exploring the robustness of heart sound analysis algorithms in real-world noisy environments. And their results show that various noise levels in audio, and different approaches to disease identification.

Studies such as those referenced in [17] have delved into time-frequency analysis of phonocardiogram signals in the audio-based category. This involves integrating wavelet transforms and neural network training, yielding promising results in detecting cardiovascular abnormalities. Similarly, other works such as [18], [19], and [20] have utilized phonocardiogram signals and time-frequency analyses with wavelet signals to train deep learning models, optimizing outcomes. Additionally, research addressing heart valve diseases [21] [22] has focused on detecting valve positions critical for preventing blood clotting, thus ensuring proper heart pumping. Significantly, all these models leverage deep learning methodologies.

In [23], [24], and [25], researchers have explored heart sounds, extracting features like time-frequency and spectral frequencies to train deep learning models. However, there remains a notable gap in addressing disorders specific to systolic and diastolic sounds, which can pose significant threats to human health. Real-time monitoring of these disorders, observed second to second, could mitigate the risk of heart attacks, warranting further investigation for comprehensive heart health monitoring and early intervention.

Recent observations suggest that heart diseases manifest as disorders in heart sounds [26], such as two or more consecutive systolic sounds or two or more diastolic sounds back-to-back, highlighting the critical need for real-time monitoring. Traditionally, assessments of cardiovascular health primarily centered on systematic examinations. However, contemporary approaches underscore the significance of ongoing, real-time observations to identify abnormalities promptly. This shift towards emphasizing the dynamic aspects of heart sounds signifies an evolving comprehension of the complexity of cardiovascular health. It also underscores the importance of harnessing advanced technologies, such as deep learning approaches, for timely identification and intervention in response to subtle sound disorders. By addressing these particular facets, the potential exists to revolutionize the early detection and management of heart diseases, offering a more comprehensive and real-time method for monitoring cardiovascular health, ultimately enhancing patient outcomes.

3. Methodology

Our novel approach leverages the Bi-LSTM architecture, a robust RNN variant capable of capturing long-term dependencies in sequential data. By incorporating features extracted from MFCC, as well as the mean and median of the spectrogram, our model gains a comprehensive understanding of the underlying patterns in heart sound data.

In our architecture figure 1, these features are concatenated into a single list, facilitating their incorporation into the Bi-LSTM network. Using Bi-LSTM allows us to capture information from past and future time steps, enabling the model to retain contextual information critical for accurate analysis effectively.

The input size of the Bi-LSTM is 585**40**1, aligning with the dimensions of the data fed into the model. The selection of appropriate units for each layer (64 and 32) ensures that the network has sufficient capacity to learn complex representations while avoiding excessive computational overhead. Additionally, incorporating dropout layers with a dropout rate of 0.05% at each layer aids in regularization, mitigating the risk of overfitting and enhancing the model's generalization capability.

We employ the SoftMax activation function and the Adam optimizer for weight updates to facilitate efficient learning. The SoftMax function allows the model to output probabilities across multiple classes, while the Adam optimizer adapts the learning rate during training, speeding up convergence and improving overall performance.

In addition to the Bi-LSTM layers, our architecture includes a dense layer with dimensions of 32*3. This final layer is the output layer, mapping the learned representations to three classes: Murmur, Extra stole, and Normal. By leveraging this dense layer, our model can comprehensively classify heart sound abnormalities with enhanced accuracy and reliability.

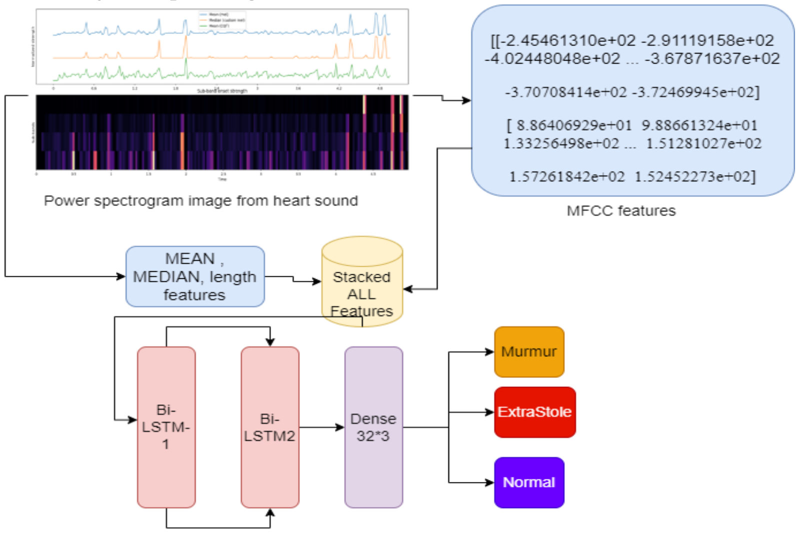


Figure 1 Architecture of proposed model

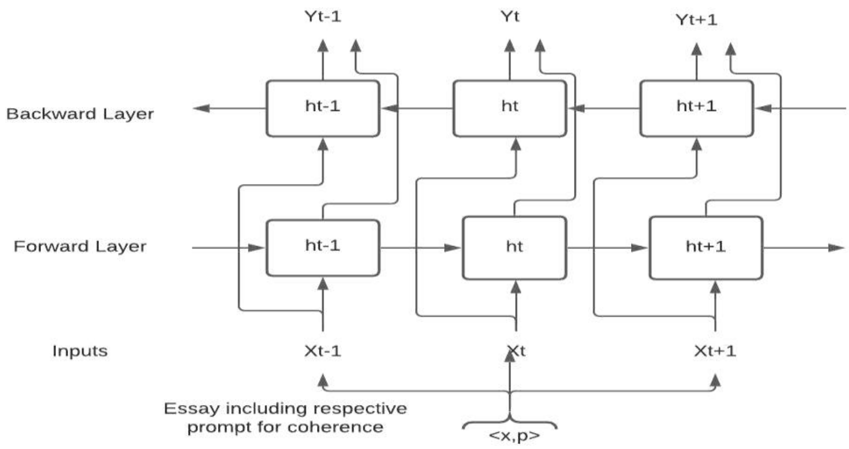


Figure 2 Working of Bi-LSTM model

3.1 Data Preprocessing and Feature Extraction.

Utilizing the Kaggle heart disease challenge dataset showcases a meticulous approach to feature extraction and processing. We selectively analyze normal, extra stole, and murmur audio files for a more precise analysis of heart sounds, considering both ordered and disordered WAV files. Extraction of diverse features, such as time-frequency, harmonic features, harmonic percussive source, spectral features, rhythm features, and MFCC, reflects a comprehensive understanding of the acoustic attributes of heart sounds.

We apply a signal length of 16000 and a clip duration of 12, focusing on extracting spectrogram features, as illustrated in Figures 3 and 4. This attention to detail ensures robust feature extraction. Normalizing the data and employing max pooling techniques improve data consistency and enhance the model's robustness.

Stacking the extracted features into a single list, formatted into three dimensions (585 * 40 * 1), with an average duration of 4.9 and a sample rate of 22050, demonstrates a thoughtful preparation of input data for subsequent model training. This structured approach, encompassing various features and preprocessing steps, is essential for developing a well-performing model for heart disease classification using deep learning techniques. Consolidating all features into a single list, as depicted in Table 1, facilitates efficient data management and model training processes.

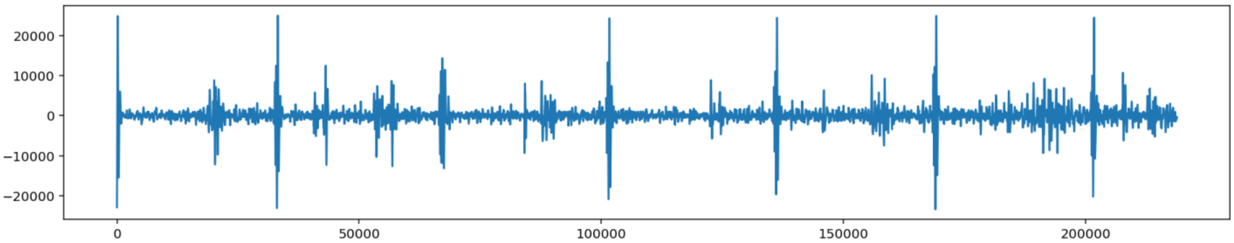


Figure 3 Wave frequency of heart sound

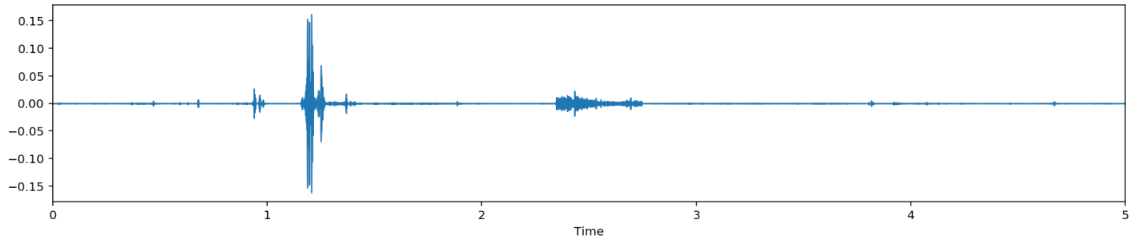
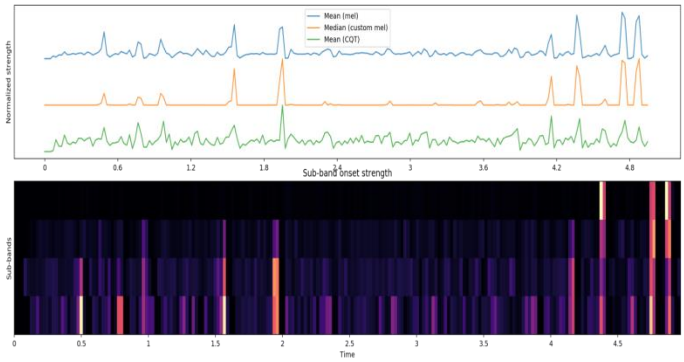


Figure 4 Wave plot of Heart sound

Table 1 MFCC features from heart sound

Spectrogram Image of Heart Sound	Extracted features
	[[-2.45461310e+02 -2.91119158e+02 -4.02448048e+02 ... -3.67871637e+02 -3.70708414e+02 -3.72469945e+02] [8.86406929e+01 9.88661324e+01 1.33256498e+02 ... 1.51281027e+02 1.57261842e+02 1.52452273e+02] [1.03978908e+02 8.56985019e+01 2.37443259e+01 ... 2.91626730e+01 2.93766991e+01 3.74463005e+01] ... [-1.33243318e+01 -8.19430184e+00 -1.18989196e+00 ... 9.66035179e-02 6.24897256e-01 1.19534810e+00] [3.16322374e-01 -4.99245923e-01 -1.58862224e-01 ... 2.22770953e+00 -2.15090204e-01 4.84898894e+00] [3.34313266e+00 -9.89011623e-01 -2.77108967e+00 ... 2.65077442e+00 -1.38751247e+00 1.85793453e+00]]

4. Training and Result Analysis

The Bi-LSTM model takes input vectors from both directions as shown in figure 2, and undergoes a process of hyperparameter tuning. Training iterations are conducted across various epochs, including 30, 35, and 40, with batch sizes ranging from 16 to 32. Additionally, the learning rate is randomly adjusted to optimize model performance.

Figure 4 illustrates the training and validation loss curves, providing insight into the model's generalization capabilities. Notably, the observed loss trends indicate that the model neither suffers from overfitting nor underfitting. This balanced performance suggests that the model effectively captures underlying patterns in the data without overly memorizing the training set or failing to capture its underlying structure.

Our approach ensures that the Bi-LSTM model achieves optimal performance across different training scenarios by systematically adjusting hyperparameters and monitoring performance metrics such as loss curves. This iterative process of experimentation and evaluation enhances the model's robustness and reliability in accurately classifying heart disease based on acoustic features extracted from heart sounds.

From Figure 5, a comparison between the LSTM and Bi-LSTM models reveals distinct performance trends across different classes. Specifically, for class 0 (Normal), the Bi-LSTM model demonstrates superior accuracy compared to the LSTM model, achieving an optimal score over the curve. However, both models exhibit lower performance for classes representing Murmur and extra stole. Notably, despite lower overall accuracy, the Bi-LSTM model outperforms the LSTM model regarding true positive and false negative rates, suggesting a more effective detection of these specific abnormalities.

Table 2 further quantifies the performance metrics, indicating that the Bi-LSTM model achieves an overall accuracy of 0.74. This comprehensive assessment underscores the Bi-LSTM model's strengths in accurately classifying heart disease cases, particularly in detecting normal heart sounds and effectively managing false negatives in identifying murmurs and extra stole instances.

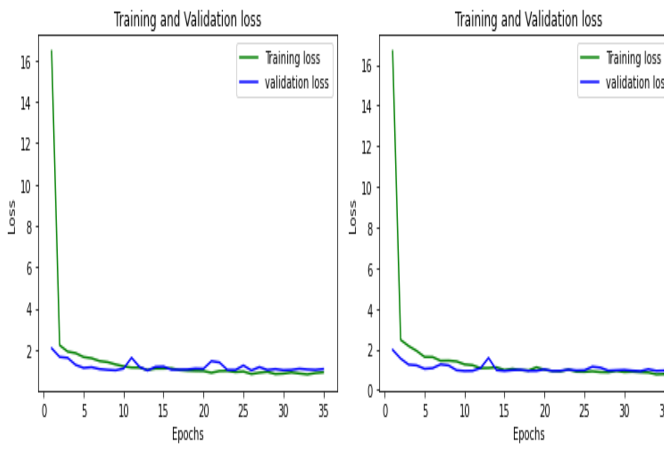


Figure 4 Training and validation loss- at batch size of 16,32

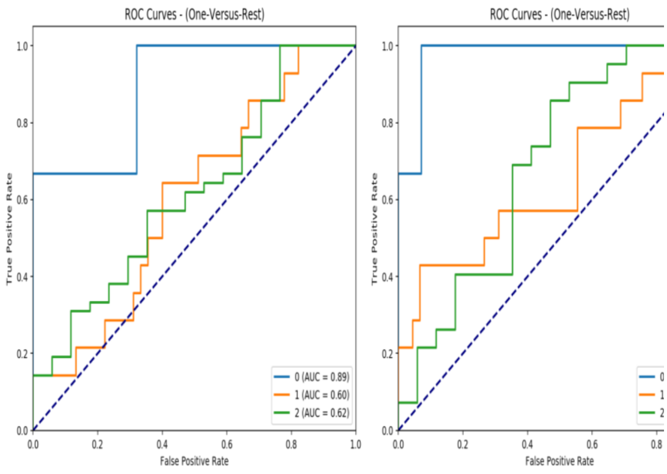


Figure 5 RoC curve of LSTM and Bi-LSTM models

Table 2 accuracy of two models

Model	Accuracy	Class	Accuracy
LSTM	0.69	Normal	0.89
		Extra Stole	0.60
		Murmur	0.62
Bi-LSTM	0.74	Normal	0.98
		Extra Stole	0.66
		Murmur	0.69

5. Conclusion

In conclusion, our study comprehensively examines heart disease classification using deep learning methodologies, explicitly focusing on comparing LSTM and Bi-LSTM models. Using the Kaggle heart disease challenge dataset, we meticulously extracted features from heart sound recordings, including spectrogram features and MFCCs, to facilitate robust model training. Our findings reveal that while both LSTM and Bi-LSTM models exhibit varied performance across different classes, the Bi-LSTM model stands out with superior accuracy, achieving an overall accuracy of 0.74.

Our study underscores the importance of leveraging bidirectional LSTM architecture, which effectively captures long-term dependencies in sequential data and contributes to enhanced performance in heart disease classification tasks. By integrating features from both forward and backward directions, the Bi-LSTM model demonstrates heightened sensitivity in detecting abnormal heart sounds, offering potential benefits for early disease detection and intervention.

Furthermore, our research emphasizes the critical role of meticulous hyperparameter tuning and model evaluation processes. Through systematic adjustments of parameters such as batch size, number of epochs, and learning rate, we optimize model performance and mitigate issues such as overfitting or underfitting, as evidenced by the observed loss curves.

Moving forward, we recognize the need to address class imbalance in our dataset. As observed, the dominance of the normal class may skew model performance. Therefore, future work will focus on balancing the dataset to ensure equitable representation across all classes, thereby enhancing the model's ability to classify heart disease cases across diverse populations accurately.

Abbreviations:

CVD	Cardiovascular disease
Bi_LSTM	Bi-directional Long short-term memory
CNN	Convolution Neural Network
RNN	Recurrent Neural Network
ECG	Electrocardiogram
MFCC	Mel-Frequency Cepstral Coefficients

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