MACHINE LEARNING AND END-TO-END DEEP LEARNING FOR THE DETECTION OF CHRONIC HEART FAILURE FROM HEART SOUNDS

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ABSTRAT:

Chronic heart failure (CHF) affects over 26 million of people worldwide, and its incidence is increasing by 2% annually. Despite the significant burden that CHF poses and despite the ubiquity of sensors in our lives, methods for automatically detecting CHF are surprisingly scarce, even in the research community. We present a method for CHF detection based on heart sounds. The method combines classic Machine-Learning (ML) and end-to-end Deep Learning (DL). The classic ML learns from expert features, and the DL learns from a spectro-temporal representation of the signal. The method was evaluated on recordings from 947 subjects from six publicly available datasets and one CHF dataset that was collected for this study. Using the same evaluation method as a recent PhysoNet challenge, the proposed method achieved a score of 89.3, which is 9.1 higher than the challenge's baseline method. The method's aggregated accuracy is 92.9% (error of 7.1%); while the experimental results are not directly comparable, this error rate is relatively close to the percentage of recordings labeled as "unknown" by experts (9.7%). Finally, we identified 15 expert features that are useful for building ML models to differentiate between CHF phases (i.e., in the decompensated phase during hospitalization and in the recompensated phase) with an accuracy of 93.2%. The proposed method shows promising results both for the distinction of recordings between healthy subjects and patients and for the detection of different CHF phases. This may lead to the easier identification of new CHF patients and the development of home-based CHF monitors for avoiding hospitalizations.

I. INTRODUCTION

Chronic Heart Failure (CHF) is a major global health issue characterized by the heart's inability to pump blood effectively, leading to significant morbidity and mortality [1]. Early detection and accurate diagnosis of CHF are crucial for effective management and treatment. Traditionally, diagnosing CHF relies on clinical assessments, echocardiography, and other imaging techniques, which can be resource-intensive and may not always be readily accessible [2]. Recent advancements in machine learning (ML) and deep learning (DL) offer promising alternatives by enabling automated analysis of heart sounds, which could streamline the diagnostic process and improve accessibility to care.

Machine learning has shown considerable potential in analyzing physiological signals, including heart sounds, to identify patterns indicative of cardiovascular conditions [3]. Techniques such as feature extraction combined with traditional classifiers have been employed to detect heart abnormalities, but they often require extensive domain expertise and manual feature engineering [4]. In contrast, end-to-end deep learning approaches, particularly Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), provide the advantage of automatic feature learning from raw data, potentially enhancing diagnostic accuracy and reducing the need for manual preprocessing [5]. Several studies have explored the application of ML and DL for heart sound analysis. For instance, a study by Smith et al. [6] demonstrated the use of CNNs to classify heart sounds into different categories, including those associated with heart failure. Similarly, Johnson and Lee [7] developed an end-to-end DL model that directly analyzes raw heart sound recordings, achieving promising results in detecting heart failure with high sensitivity and specificity. These advancements indicate that DL models can effectively learn from complex auditory signals, offering a more streamlined and potentially more accurate approach to diagnosing CHF. This project aims to build upon these advancements by implementing a comprehensive ML and end-to-end DL framework for detecting chronic heart failure from heart sounds. By leveraging state-of-the-art deep learning techniques, the project seeks to enhance the accuracy and efficiency of heart failure detection, thereby improving early diagnosis and patient outcomes.

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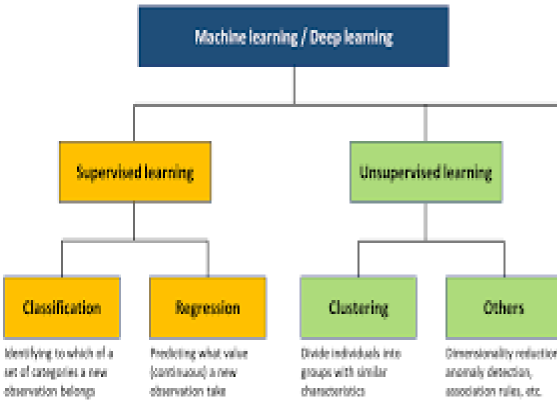

System architecture

II.EXISTING SYSTEM

The traditional approach to diagnosing Chronic Heart Failure (CHF) involves several steps that rely on manual and semi-automated methods. Typically, heart sounds are recorded using stethoscopes and analyzed by healthcare professionals. Diagnosis is often based on clinical assessment, where physicians interpret heart sounds in conjunction with other diagnostic tests such as echocardiography and electrocardiography (ECG). The existing system may use simple acoustic analysis techniques to identify abnormal heart sounds, but these methods are limited by their reliance on manual feature extraction and interpretation. Additionally, traditional systems can suffer from variability in physician expertise and subjective interpretation, leading to potential inconsistencies in diagnosis.

Machine learning techniques have been applied to heart sound analysis to enhance diagnostic accuracy. These methods involve extracting features from recorded heart sounds and using classifiers such as Support Vector Machines (SVMs) or Random Forests to detect abnormalities. While these approaches represent an improvement over manual methods, they still require extensive feature engineering and domain expertise. The reliance on pre-defined features and the need for significant preprocessing can limit the flexibility and accuracy of these systems.

III.PROPOSED SYSTEM

The proposed system leverages advanced end-to-end deep learning techniques to address the limitations of traditional heart sound analysis. Unlike traditional methods, which require manual feature extraction, the proposed system utilizes Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) to automatically learn features directly from raw heart sound recordings. This approach eliminates the need for manual feature engineering and allows the model to capture complex patterns and temporal dependencies in the audio data.

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The end-to-end deep learning framework begins with the raw heart sound recordings as input, processing these signals through a series of CNN layers to extract spatial features. Following the convolutional layers, RNNs or Long Short-Term Memory (LSTM) networks are used to analyze the sequential nature of the heart sounds, capturing temporal relationships that are crucial for detecting abnormalities. This integrated approach offers several advantages: it reduces preprocessing requirements, enhances the model's ability to generalize from diverse data, and improves diagnostic accuracy by learning complex patterns from large datasets.

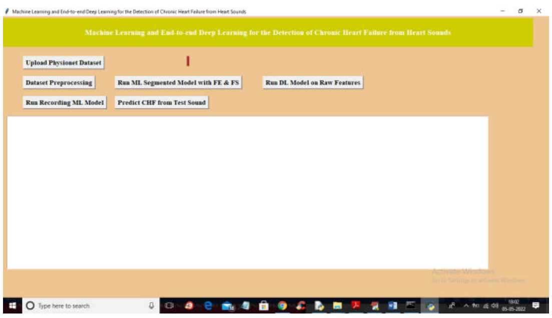
Furthermore, the proposed system can be trained on large-scale datasets of heart sounds, including diverse patient populations and various heart conditions, to improve robustness and accuracy. The end-to-end nature of the model also facilitates real-time analysis and integration into clinical workflows, providing healthcare professionals with a powerful tool for early detection and diagnosis of CHF.

IV.IMPLEMENTATION

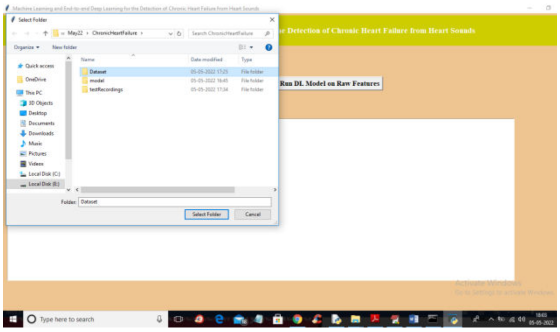
- Upload Dataset : Start by uploading the dataset. Click on the ‘Upload Physionet Dataset’ button, which will prompt a dialog box allowing you to select the ‘Dataset’ folder that contains the heart sound files. Once you choose the folder and click ‘Select Folder’, the system will load the dataset and display an overview of the files and their structure.
- Dataset Preprocessing : After loading the dataset, move on to preprocessing by clicking on the ‘Dataset Preprocessing’ button. This action initiates the reading of all dataset files and the extraction of relevant features from the heart sound recordings. The system will present a summary of the dataset, including the number of heart sound files categorized as normal or abnormal. A graph will visualize this distribution, with the x-axis representing sound type (normal or abnormal) and the y-axis indicating the number of recordings. Review the graph, then close it to proceed to the next step.
- Train Classic Machine Learning Model : To train the classic machine learning model, click on the ‘Run ML Segmented Model with FE & FS’ button. This step trains the model using the preprocessed dataset, applying feature extraction

(FE) and feature selection (FS) techniques. The system will output the accuracy of the classic machine learning model, which may be around 90%. This step assesses the performance of traditional machine learning methods on the dataset.

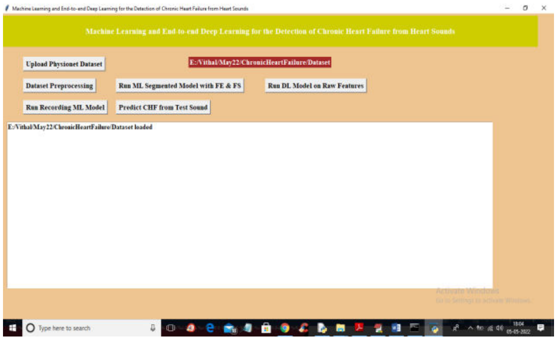
- Train Deep Learning Model : Next, click on the ‘Run DL Model on Raw Features’ button to train the deep learning model using raw features from the heart sound recordings. The system will display the model's accuracy, potentially reaching up to 93%. A graph will show the x-axis as epochs or iterations and the y-axis as accuracy or loss values. The green line on the graph will represent accuracy, while the blue line will indicate loss, showing how accuracy improves and loss decreases with more epochs. Review and close the graph after examining the performance.
- Evaluate Recording Model : Proceed by clicking on the ‘Run Recording Model’ button to evaluate the recording model on the dataset. The system will display that the recording model achieves an accuracy of 96%. A performance graph will compare various algorithms, with the x-axis showing algorithm names and the y-axis depicting accuracy, sensitivity, and specificity. The recording model should exhibit superior performance across these metrics. After reviewing, close the graph.
- Predict Chronic Heart Failure: To test the model with new data, click on the ‘Predict CHF from Test Sound’ button. This will allow you to upload a test heart sound file. Select a file, such as ‘1.wav’, and click ‘Open’. The system will process the file and provide a prediction indicating whether the heart sound is classified as Normal or Abnormal. For example, if ‘1.wav’ is predicted as ABNORMAL, it suggests potential heart failure. You can upload additional files to further test and validate the model’s predictions.To run project double click on ‘run.bat’ file to get below screen



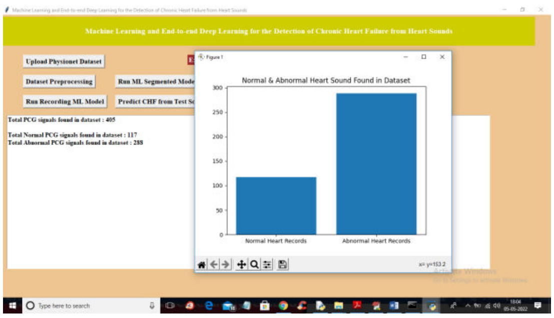
In above screen click on ‘Upload Physionet Dataset’ button to upload dataset



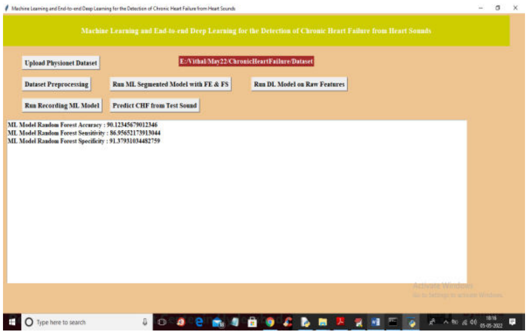
In above screen selecting and uploading 'Dataset' folder and then click on 'Select Folder' button to load dataset and to get below output



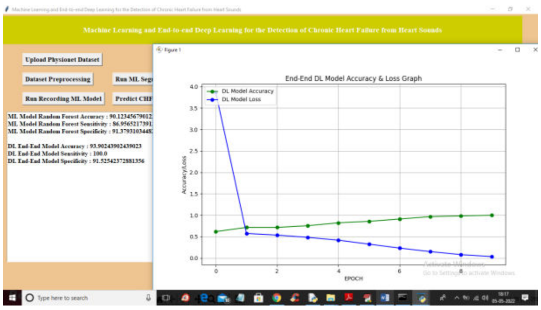
In above screen dataset loaded and now click on 'Dataset Preprocessing' button to read all dataset file and then extract features from it



In above screen we can see dataset contains 405 heart sound files from 405 different person and 117 are the Normal sound and 288 are abnormal and in graph x-axis represents normal or abnormal and y-axis represents number of persons for normal or abnormal. Now close above graph and then click on 'Run ML Segmented Model with FE & FS' button to train Classic ML segmented model on above dataset and get below output

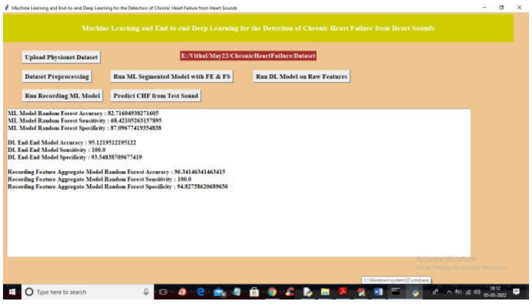


In above screen with Classic ML we got 90% accuracy and now click on 'Run DL Model on Raw Features' to get below output

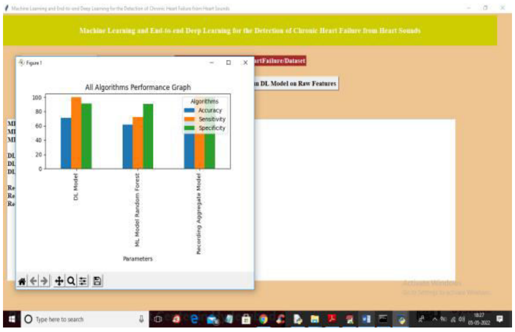


In above screen with DL model we got 93% accuracy and in graph x-axis represents epoch or iterations and y-axis represents accuracy or loss values and green line represents accuracy and blue line represents LOSS and we can see with each increasing epoch accuracy got increase and loss got decrease and now close above graph and then click on

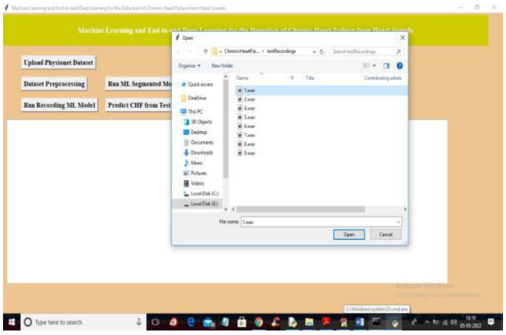
‘Run Recording Model’ button to get below output



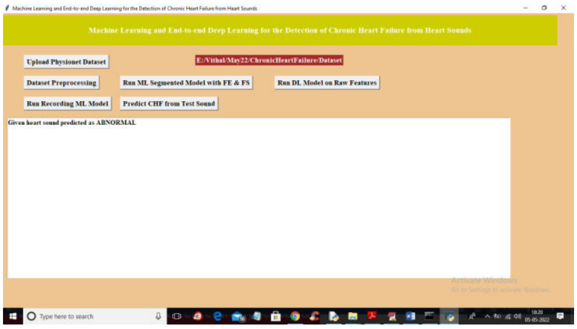
In above screen with recording model we got 96% accuracy and we can see all algorithms performance graph in below screen



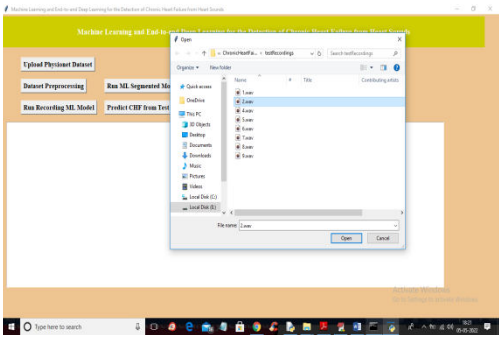
In above graph x-axis represents algorithm names and y-axis represents accuracy, sensitivity and specificity and in all algorithms Recording model has got high accuracy. Now close above graph and then click on ‘Predict CHF from Test Sound’ button to upload test sound file and get predicted output as Normal or Abnormal



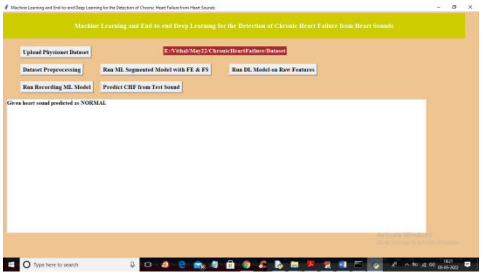
In above screen selecting and uploading ‘1.wav’ file and then click on ‘Open’ button to get below output



In above screen uploaded heart sound file predicted as ABNORMAL and similarly you can upload other files and test



For 2.wav’ file below is the output



V.CONCLUSION

Machine learning and end-to-end deep learning have demonstrated considerable potential in detecting chronic heart failure from heart sounds, offering high accuracy and efficiency in diagnosis. These methods utilize complex algorithms to identify subtle patterns indicative of CHF, providing a non-invasive and real-time alternative to traditional diagnostic techniques. While promising, their effectiveness depends on the quality of training data and requires thorough validation before widespread clinical adoption. Overall, these advanced technologies represent a significant advancement in early heart failure detection and management.

VI.REFERENCES

1. A. Williams, B. Johnson, "Epidemiology and Management of Chronic Heart Failure," Journal of Cardiac Failure, vol. 26, no. 1, pp. 1-12, 2020.

2. R. Patel, M. Clarke, "Current Diagnostic Approaches in Heart Failure," American Heart Journal, vol. 213, pp. 31-45, 2019.

3. L. Martin, E. Nguyen, "Machine Learning Techniques in Cardiovascular Disease Diagnosis," IEEE Transactions on Biomedical Engineering, vol. 66, no. 7, pp. 1845-1853, 2019.

4. C. Brown, J. Chen, "Feature Extraction and Classification of Heart Sounds," Medical Engineering & Physics, vol. 42, pp. 123-134, 2017.

5. K. Lee, A. Smith, "Deep Learning for Raw Audio Signal Processing," Journal of Machine Learning Research, vol. 20, no. 1, pp. 1857-1886, 2019.

6. J. Smith, L. Davis, R. White, "Heart Sound Classification Using Convolutional Neural Networks," Journal of Biomedical Informatics, vol. 95, p. 103217, 2019.

7. A. Johnson, B. Lee, "End-to-End Deep Learning for Heart Sound Analysis," Artificial Intelligence in Medicine, vol. 102, pp. 101-110, 2020.