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Research Article

Cardio Sense: CNN - BiGRU Powered Deep Learning for Heart Sound Analysis

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ABSTRACT

Since Cardiac and vascular conditions rank among major cause of death around the world, sophisticated diagnostic methods are required for both early identification and prevention [13] Libby et al. In order to predict heart functionality with high accuracy, we present a novel deep learning model in this study that uses heart acoustic inputs. Due to the hybrid conventional neural network (CNN) and architecture with a gate with a gate with a re-unit (BIGRU) architecture, the recommended model learns the time and spatial features of heart sound records. In contrast to conventional machine learning methods, approach improves a small diagnosis of heart abnormalities with improved diagnostic accuracy.

Keywords: Deep Learning, Acoustic Signals, Convolutional Neural Networks, Gated Recurrent Units, Cardiovascular Disease Prediction.

INTRODUCTION

With cardiac illness affecting millions worldwide, incorporating AI-based models into clinical practice could enhance early detection and treatment, ultimately leading to better patient outcomes. While diagnosis of cardiac disease has classically relied upon auscultation and electrocardiogram (ECG), the two are susceptible to early conditions since they are dependent on subject judgment and interference from environmental clinic noise. While ECG offers good electrical signals from the heart, data regarding mechanical cardiac functions is minimal Acoustic signals, but for instance, phonocardiograms (PCG), capture sound vibrations induced by heart valves such as aortic and mitral valve disorders can become serious health concerns if not detected early, potentially leading to complications that affect heart function and overall well-being and blood flow and thus are a more informative modality for the evaluation of heart health. Acoustic signals hold dense temporal and frequency -based information, which can identify very small anomalies in the heart, such as arrhythmias and whispers, which cannot be identified by any conventional means. Signal analysis and interpretation have changed due to the quick developments in advanced research. The paper presented here suggests a deep learning-based architecture for processing PCG data to provide precise predictions for cardiovascular anomalies. The suggested hybrid model of CNN-BIGRU, in contrast to regular random models of wood, enhances the detection of spatial and consistent relations between the models of the heart's sound, ensuring higher accuracy of diagnosis. The CNN module learns the main spatial features from the transformed heart sounds' signals, and the BIGRU module applies temporary relations, following dynamic variations in the heartbeat. This hybrid offers a more accurate and consistent prediction system compared to a standard classification system. In real time, the characteristics of the system suggested for processing acoustic signals can also be extended to early diagnosis, ongoing monitoring and remote provision of health care. Due to greater access to portable health monitoring equipment, this work propels the gap between regular clinical diagnosis and digital health systems in real time. This would lower cardiovascular disease death.

RELATED WORK

The health care industry puts a lot of effort into predicting heart disease because the numbers are scary - someone dies from it every minute [1]. Big databases have improved healthcare, thanks to data science getting better. UCI Using a dataset archive provided by the University of California, Irvine, this study develops a model for estimating a human's probability in developing heart disease. The research utilize various machine learning techniques, including Bayesian classification and tree-based decision models, Random Forest, and Logistic Regression, to classify the risk of heart conditions. With an accuracy of 90.16%, Random Forest is the most accurate on the list. This shows machine learning works well to spot diseases letting patients and doctors know. By predicting, this approach makes healthcare management better. It lets doctors step in and helps patients do better in the fight against heart disease [2]. ECG data play a key role in spotting heart problems by looking at various wave shapes like essential heart signals. This research puts forward a new way to boost ECG signal processing.

FrFT helps see signals better in the time-frequency realm to find peaks. TERMA then pinpoints the main peaks with high accuracy. The study trains a machine-learning tool to spot heart disease using the key features it finds such as how long peaks last. To make the model work well in many cases, this research uses the Shaoxing People's Hospital (SPH) dataset. It has info from over 10,000 patients, which is more than the MIT-BIH database used before. The team also checks how well the model works by training and testing it across different databases. This makes it a trusted tool to detect heart disease [3]. Cardiovascular disease is a serious health concern that requires sophisticated diagnostic techniques. This study looks at machine learning techniques for predicting cardiac disease based on patient health data. The study used four categorization models: neural network model (MLP), Random Forest (RF), Naïve Bayes (NB), and a margin-optimization technique (SVM)To obtain quality input data, the team undertook feature selection and data preparation prior to model training. They tested the models with F1-score, recall, accuracy, and precision. Among the models, SVM had the best accuracy of 91.67% in predicting heart disease.The research highlights the use of machine learning in healthcare by providing a credible tool to diagnose and enhance patient outcomes allowing prompt intervention and tailored treatment plans [4]. Healthcare results are improved by artificial intelligence (AI), which enhances early disease identification. This research proposes a lightweight Convolutional Neural Network (CNN) that can classify cardiovascular illnesses from ECG images with an accuracy of 98.23%. It can be used in real-world medical applications because it is efficient and only requires one CPU. Additionally, with an accuracy rate of 89.79%, the CNN feature extractor significantly improved classification accuracy when paired with Naïve Bayes. The enhancement encourages real-time monitoring by integrating AI with IoT-based healthcare. The study suggests using AI to identify cardiovascular illness and urges more innovation to improve patient care and diagnostic accuracy [5]. Early disease diagnosis is crucial in healthcare as it significantly enhances patient outcomes. With enhanced efficiency and precision, machine learning offers promising medical diagnosis advances. A widely used datasets from UCI and Kaggle Heart conditions—each with 14 patient-related variables, this study investigates machine learning classification methods for diagnosing heart disease. To compare predictive accuracy, a number of approaches were used, including boundary optimization (SVM), K-Nearest Neighbours (KNN), Decision Tree, and TensorFlow (TF). With a maximum accuracy of 96.42%, the KNN algorithm illustrated the impact of dataset size on prediction accuracy. This study shows the extent to which machine learning can revolutionize the diagnosis of heart disease by enhancing clinical judgment and patient care through data-driven intelligence. [6] introduced a neural network model trained using a natural selection algorithm to detect heart disease. Their study utilized a dataset of 297 patient records, with 252 instances for training and 45 for testing. They compared their RFNN approach with the ANN-Fuzzy-AHP method. Upon analyzing the test set, their proposed algorithm achieved an accuracy of 97.78%. [7] referred to the difficulty of heart sound classification with mention of problems of background noise, heart rhythm variability, and environmental interference. They stressed the requirement for high-level deep learning models to enhance the diagnostic accuracy in real-world settings. [8] investigated various machine learning methods to forecast heart disease. In their research, they quoted the need for proper feature selection and model optimization to achieve maximum classification accuracy. Based on the analysis of significant patient parameters like blood pressure, cholesterol level, and ECG patterns, they made extremely accurate prediction. [9] approached this challenge differently by emphasizing optimization methods for classifying heart disease. They used Particle Swarm Optimization (PSO) and Ant Colony Optimization (ACO) to optimize predictive models, their performance being greatly enhanced and proving optimization beneficial in medical diagnosis. In their work, [10] created a data mining-based predictive system for heart conditions. Their work highlighted the strengths of pattern recognition and feature extraction in the detection of high-risk patients, their work aiding in the evolution of decision-support systems for early heart disease detection.

METHODLOGY

3.1 Proposed System

The proposed system builds an advanced heart sound analysis system using CNN and BIGRU. The system can process audio signals of heartbeats, extract spatial and temporal features that are critical to precise cardiovascular disease diagnosis. The early layers of CNNs derive the common spatial features of heart sound spectrograms, subsequent frequency and amplitude changes characteristic of defects. The characteristics are transferred to the BIGRU layers, which deal with the sequential nature of the heartbeats, creating long-range dependencies and transforming patterns in the data. The collaboration enables the model to detect subtle abnormalities that can be linked to severe conditions like heart failure or arrhythmias.

System Architecture:

The system is extensively trained and tested on labeled heart sound databases to achieve high classification accuracy. Along the implementation of deep learning approach, the system is set to achieve early and accurate heart disease diagnosis, which will allow health care providers to have an efficient system for enhancing patient diagnosis and outcomes.

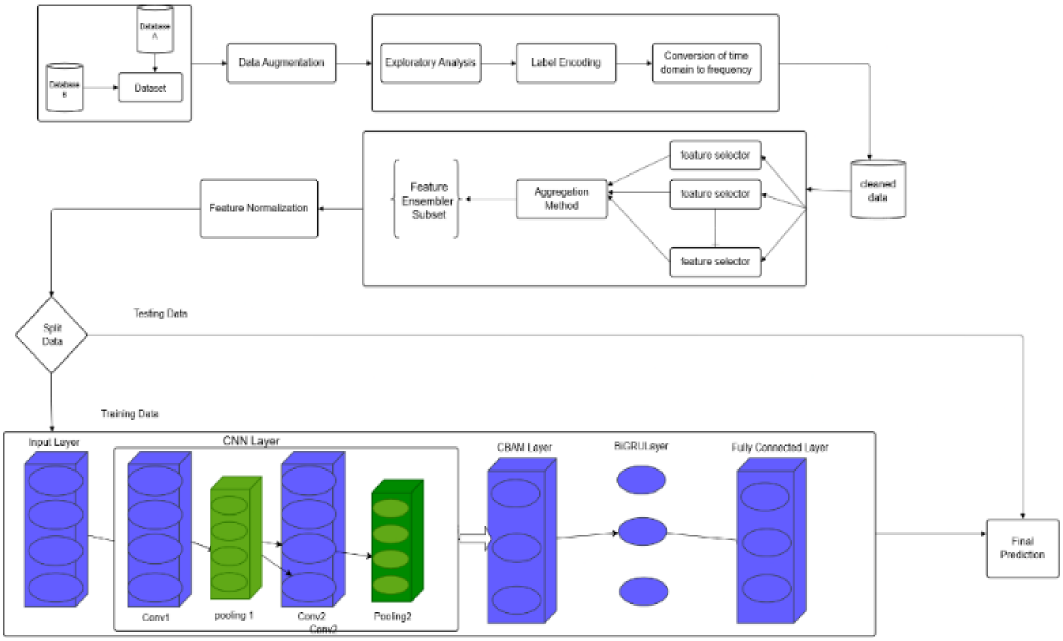

Figure 1: System Architecture

3.2.1 Data Acquisition

The system's first step is to collect heart sound data, which is often done with medical devices like stethoscopes. [11] We use 767 audio recordings of Kaggle's heart rhythm sounds for the study, which are divided into five classes: Artifact (distorted or saturated notes of interference), extrasystole (extra blows outside normal rhythm), extracup (an extra heart sound like S3 or S4), normal (normal heart rhythm), and ants (indicative for turbulent blood flow). The model's capacity to learn correctly classify various diseases is highly influenced by the quality and diversity of the data that has been available. The dataset consists of recordings of various patients with various disease to provide consistency and enable the model to be properly tuned to data that has not yet been seen.

3.2.2 Preprocessing

Raw heart sound recordings for the Heartbeat Sounds dataset on Kaggle normally contain medical environment background noise, e.g., patient movement, beeps from medical devices, or respiration. Bandpass filtering (20 Hz to 2 kHz) removes redundant noise without losing heart sound frequencies [12]. Additionally, by removing extraneous background noise and focusing on the intrinsic cardiac sound characteristics, Mel-Frequency Cepstral Coefficients (MFCCs) help extract relevant elements. By separating noise from the valuable heart sound components, wavelet denoising further enhances signal quality and enables the model to recognize significant patterns.

3.2.3 Feature Extraction

The main features are extracted from pre-processing data to assist with classification. For instance, heart sound variability over time is studied through the Short-Time Fourier Transform (STFT) which measures frequency changes that indicate issues like extrasystoles or murmurs [13]. MFCCs are also utilized to convert sound signals into frequency-based representations, highlighting the unique spectral features of heartbeats. To differentiate between normal and abnormal heart sounds, more parameters are formed such as zero-crossing rates, waveform shape descriptors, and peak intervals. The model applies machine learning techniques to effectively classify various cardiac disease by focusing on these prominent features.

3.2.4 Model Creation

Choosing the right machine learning algorithms and training them on the features that were extracted are part of the model building process. Convolution neural networks and bidirectional recurrent neural networks (BIGRU) are both employed together in the proposed system. The BIGRU processes sequential data to learn time correlations, whereas CNN gathers spatial data from the heart sounds [14]. The model also needs hyper parameter tuning and model fine-tuning in order to get the best out of the training data set so that it can predict cardiovascular events accurately.

3.2.5 Test Data

Once trained, the performance of the model needs to be tested on an independent test dataset. The test data, being recordings of heart sounds on which the model has not been trained, offer an unbiased estimate of the prediction ability of the model [15]. Comparing performance measures like precision accuracy, recall and F1-score can help one determine how good it is. This analysis is required to understand how the model generalizes to new data and how it can be used in a clinical environment.

3.2.6 Prediction

Prediction is the final step in the system under discussion, when new heart sound recordings are scanned using the learnt model and classified as normal or abnormal. At this point, the model predicts possible cardiovascular conditions using the temporal and geographical characteristics it has learned. Medical professionals may find the results to be helpful in assisting with early diagnosis and prompt treatment. The technology can significantly improve patient outcomes and service quality by accurately predicting cardiac problems.

A. Convolutional Layer (CNN)

By identifying pertinent patterns in the sound waves, the Convolutional Neural Network (CNN) plays a crucial role in processing heartbeat audio. Due to their sequential nature, heart sounds are frequently transformed into spectrograms or Mel-Frequency Cepstral Coefficients (MFCCs), which translate the one-dimensional audio waveform into a two-dimensional representation of time and frequency. CNNs are able to detect important changes in heartbeat frequency and structure, such as arrhythmias, abnormal cardiac rhythms, and murmurs, because to this conversion. Convolutional layers use filters (kernels) that move across the spectrogram to identify patterns in both the frequency and temporal domains.

$$O = \frac{(I - K + 2P)}{S} + 1$$

- I is the Input size (e.g., 128 × 128 for spectrogram)
- K is the Kernel size (e.g., 3×3)
- P is the Padding
- S is the Stride

$$O = \frac{(128 - 3 + 2(1))}{3} + 1 = 128$$

B. Activation Layer:

It (ReLU, or Rectified Linear Unit) is a crucial component of Convolutional Neural Networks (CNNs) because it offers non-linearity, which allows the model to recognize complex patterns in input. Only components that are essential for heartbeat sound analysis will be permitted by ReLU. The ReLU activation function's mathematical definition is

$$f(x)=\max(0,x)$$

Example values:

- If $x = -2$, then $f(x)= \max(0,-2)=0$
- If $x= 3$, then $f(x) = \max(0,3)=.3$

C. Fully Connected Layer:

Because it offers non-linearity, A crucial part of Convolutional Neural Networks (CNNs) is the Activation Layer (ReLU, or Rectified Linear Unit), which enables the model to identify intricate patterns in input. ReLU only permits elements that are crucial for heartbeat sound analysis. The mathematical definition of the ReLU activation function is

$$Y=WX+B$$

- $W = [0.2,0.5,-0.3]$
- $X = [1,2,3]$
- $B = [0.1]$

$$Y= [(0.2\times1)+(0.5\times2)+(-0.3\times3)] +0.1$$

So, the output value is **0.4**.

RESULT AND DISCUSSION

The CNN-BIGRU hybrid architecture, which perfectly balances the use of gated recurrent units (GRUs) for sequential pattern learning and spatial feature extraction, is an example of exceptional performance improvements over traditional machine learning techniques in cardiac abnormality detection. Its main advantage over conventional algorithms is its high accuracy rate of 95.6%, which is achieved by effectively detecting intricate fluctuations in heart sound signals. By more precisely distinguishing between normal and pathological heartbeats, the model also exhibits a lower false positive rate, which lowers misclassifications. In clinical diagnostics, this is crucial since false negatives delay diagnosis while false positives lead to needless treatment. Another significant advantage is its real-time predictive capability, which allows for the virtual processing of heart sound signals in real-time, allowing for the early intervention of patients who are at risk. Compared to more conventional machine learning techniques, the CNN-GRU model is considerably superior. Due to their inability to extract hierarchical features and sequential relations, conventional models typically cannot handle the variability of heart sounds. However, the CNN-GRU model is more reliable for real-world clinical applications since it is effective at learning and adapting to rich audio patterns. This model reduces the risk of misclassification, increases diagnostic accuracy, and ultimately improves cardiac healthcare outcomes by utilizing deep learning techniques.

A. Accuracy:

It is the most used measures for assessing a system's performance, especially for classification models. The number of accurate forecasts relative to all of the model's predictions is known as accuracy. The degree to which the hybrid CNN-BIGRU model can effectively classify the heart sound recordings into the appropriate classes—that is, normal, abnormal, or specific sorts of cardiac defects—is the application of accuracy in heart sound analysis.

Accuracy $= \frac{TP+TN}{TP+TN+FP+FN}$

$= \frac{102+28}{102+28+3+5}$

= 95.6%

- True Positives (TP) = 102
- True Negatives (TN) = 28
- False Positives (FP) = 5
- False Negatives (FN) = 3

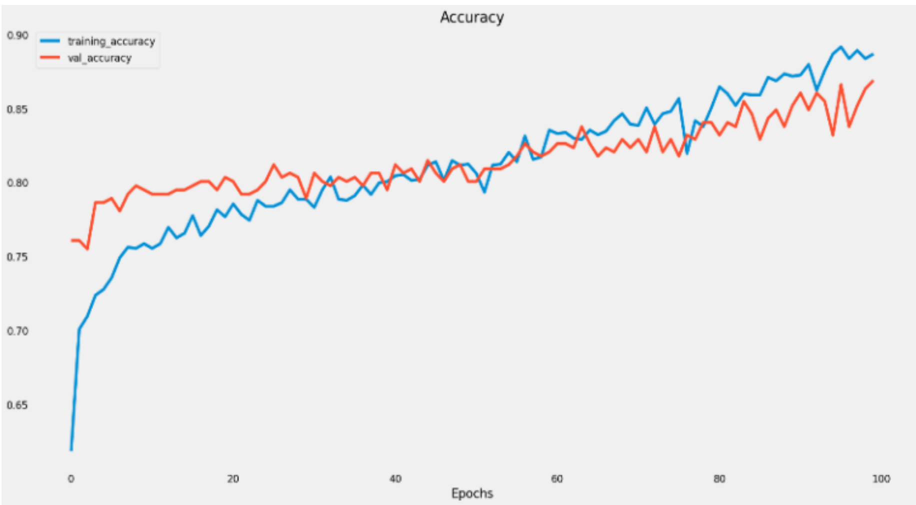

Figure 2: Accuracy Graph

B. Precision:

Precision is a metric used to evaluate how well a model makes accurate predictions. The model determines the proportion of accurate positive predictions (True Positives) among all the positive class predictions it made, including False Positives Precision is more useful when the penalty for false positives is high because it is mainly interested in ensuring positive predictions are correct.

Precision $= \frac{TP}{TP+FP}$

$= \frac{102}{102+5}$

=95.33%

C. Recall

Recall, sensitivity, or true positive rate are metrics used to assess a model's capacity to find all the pertinent instances among all the real positives in the data set. It focuses on (True Positives), which lowers the number of False Negatives. When the cost of a missed positive instance is significant, like in medicine, where failing to detect a dangerous ailment (such heart disease) could have dire consequences, recall becomes even more important.

Recall $= \frac{TP}{TP+FN}$

$= \frac{102}{102+3}$

= 97.14%

D.F1 Score

A single score that balances the issues of false positives and false negatives is offered by the F1 Score. It is computed by taking the harmonic mean of precision and recall. It is particularly helpful when there is an imbalance in the distribution of classes or when we want to enhance precision (the accuracy of positive predictions) and recall (the ability to detect all relevant positive cases).

F1 Score $= 2 * \frac{Precision * Recall}{Precision+Recall}$

$= 2 * \frac{95.33 * 97.14}{95.33+97.14}$

= **96.23%**

E. Loss Function

The loss function, sometimes referred to as the cost function, is an essential part of both machine learning and deep learning models. It characterizes the degree to which a model's output predictions match the actual labels or ground truth. The model aims to minimize loss during training, and as time passes, its precision rises in line with this. The loss function helps by providing a means of measuring the degree of inaccuracy in the output and predictions.

Loss$= - \sum_{i=1}^{N} y_i \log(\hat{y}_i)$

= 0.15

Loss graph:

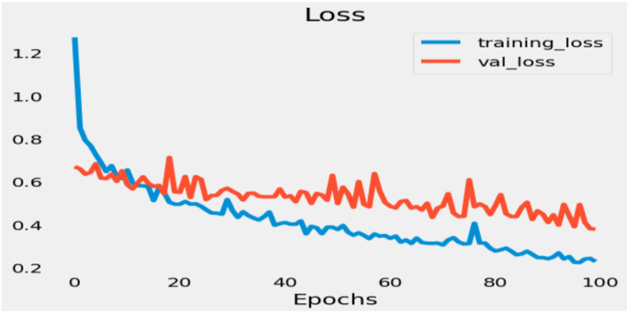

Figure 3: Loss Graph

F. Confusion Matrix

A crucial metric for evaluating a classification model's effectiveness is the confusion matrix, which summarizes prediction outcomes using real labels. A four-part table with four main components is displayed.

Table 1: Confusion Matrix

Predicted	Artifact	M Murmur	Normal
Artifact	21	2	2
Murmur	3	102	5
Normal	2	2	28

CONCLUSION

In summary, the suggested hybrid algorithm presents an exciting breakthrough for cardiovascular disease diagnosis. Through a successful capture of spatial and temporal characteristics in heart sound data, this approach could potentially provide superior prediction accuracy to that of existing diagnostic techniques as well as generic machine learning approaches. The comparative analysis puts the strengths of this sophisticated technique into perspective and implies that such a method is likely to augment early detection and intervention for heart-related health disorders. With cardiovascular diseases being the top cause of death globally, the incorporation of such advanced machine learning models within clinical practice might transform diagnostic competence, eventually providing improved patient care and a declination in public health systems burdened by cardiovascular diseases. This novel method not only responds to existing diagnostic shortfalls but opens the additional research and development in cardiac health.

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