Deep Learning Framework for Risk Prediction and Classification of Heart Sound

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***Abstract*—Cardiovascular diseases (CVDs), such as heart attacks and strokes, continue to be major global health concerns, often stemming from blood vessel blockages that hinder critical blood flow. These blockages are frequently caused by fatty deposits accumulating along the walls of blood vessels. Traditional approaches to detecting cardiovascular irregularities, like auscultation (listening to heart sounds with a stethoscope), may not reliably capture subtle dysfunctions. To improve diagnostic precision, we introduce a hybrid model combining Convolutional Neural Networks (CNNs) and Bidirectional Gated Recurrent Units (BIGRUs) to analyze heart sound data. CNNs are proficient at extracting spatial features, while BIGRUs excel in processing temporal sequences, making this hybrid approach well-suited for sequential heart sound evaluation. This integrated model aims to improve prediction accuracy for cardiovascular conditions by identifying patterns that may be overlooked by conventional algorithms, such as Random Forests or Decision Trees. Comparative results indicate that the hybrid model offers promising advancements in diagnostic accuracy, potentially enabling earlier identification and intervention for cardiovascular health management.**

***Keywords*—Cardiovascular Disease Prediction, Heart Sound Analysis, Deep Learning, Convolutional Neural Network, Bidirectional Gated Recurrent Unit, Diagnostic Tool, Temporal Sequence Analysis.**

I. INTRODUCTION

The heart, a crucial organ of the cardiovascular system, plays a pivotal role in maintaining life by circulating blood throughout the body. It consists of four chambers—two atria and two ventricles—that function in harmony to pump oxygen-depleted blood to the lungs and deliver oxygen-rich blood to the rest of the body. Cardiovascular diseases, including heart attacks and heart failure, are significant health challenges, often advancing unnoticed and thus referred to as "silent killers." According to the World Health Organization (WHO), approximately 17.5 million deaths annually are attributed to cardiovascular diseases, making them one of the leading global causes of mortality. Automated detection of abnormal heart sounds is essential for early diagnosis, as traditional stethoscope evaluations can be hindered by ambient noise in clinical environments.

The cardiac cycle describes the series of events during a single heartbeat, divided into two key phases: systole and diastole. During systole, the heart contracts, causing the mitral and tricuspid valves to close, which generates the S1 heart sound. As ventricular pressure increases, the aortic and pulmonary valves open, allowing blood to flow out while preventing backflow into the atria. In diastole, the heart relaxes, and the aortic and pulmonary valves close, producing the S2 heart sound. The S2 sound is further divided into two components: the aortic (A2) and pulmonary (P2) closures, with A2 typically preceding P2. This separation becomes more pronounced during inhalation, particularly in younger individuals. Analyzing the interval between S1 and S2 helps differentiate systolic from diastolic murmurs and detect abnormal heart sounds, highlighting their critical role in evaluating heart health.

II. RELATED WORK

Heart Disease Prediction Using Machine Learning [1] Apurb Rajdhan [1]

Heart disease prediction has become a critical focus in healthcare due to the high mortality rate associated with cardiovascular conditions. This research aims to create an automated prediction model using patient data from the UCI Machine Learning Repository to evaluate heart disease risk. Multiple machine learning algorithms, such as Naive Bayes, Decision Trees, Logistic Regression, and Random Forest, were employed for risk classification. Among these, Random Forest emerged as the most effective, achieving a prediction accuracy of 90.16%. These results highlight the promise of machine learning in enhancing early detection and risk evaluation, ultimately contributing to improved patient care and outcomes.

ECG-based machine-learning algorithms for heartbeat classification [2] Saira Aziz, Sajid Ahmed [2]

This study introduces an innovative method combining Two-Event Related Moving Averages (TERMA) with the Fractional Fourier Transform (FrFT) to improve ECG signal analysis for heart disease diagnosis. TERMA is employed to precisely detect key peaks in ECG waveforms, including the P, QRS, and T waves, while FrFT offers a detailed time-frequency representation, enhancing the accuracy of peak identification. Features such as peak intervals and durations are extracted and used to train a machine learning model for heart disease classification. Evaluated on the Shaoxing People's Hospital (SPH) dataset containing over 10,000 patient records, this approach outperforms traditional models in accuracy and adaptability, showcasing significant potential for cross-database applications in diagnosing heart conditions.

Heart disease prediction using machine learning [3] chaimaa boukhatem; heba yahia youssef [3]

This research addresses the critical challenge of cardiovascular disease diagnosis by employing machine learning models to enhance precision and reliability. Using electronic health records containing key patient data, the study develops predictive models aimed at improving diagnostic accuracy. Four algorithms—Multilayer Perceptron (MLP), Support Vector Machine (SVM), Random Forest (RF), and Naïve Bayes (NB)—are evaluated for performance. Data preprocessing and feature selection ensure relevance and quality for effective model training. Metrics such as accuracy, precision, recall, and F1-score are used for assessment, with SVM achieving the highest accuracy of 91.67%. These findings underscore the effectiveness of machine learning in early and accurate heart disease detection, paving the way for improved interventions and patient outcomes, while enhancing the efficiency of healthcare diagnostics.

Detection of Cardiovascular Diseases in ECG Images Using Machine Learning and Deep Learning Methods [4] Mohammed B. Abubaker [4]

This study presents a lightweight Convolutional Neural Network (CNN) designed for the early detection of cardiovascular diseases, achieving 98.23% accuracy in classifying ECG images. Optimized for operation on a single CPU, this model is ideal for healthcare environments with limited computational resources. It surpasses traditional diagnostic methods, providing clinicians with a dependable tool for accurate diagnosis in resource-constrained settings. Additionally, using the CNN for feature extraction enhances the performance of conventional machine learning models, achieving an impressive 99.79% accuracy when paired with Naïve Bayes. The model's adaptability highlights its potential for IoT-based healthcare, enabling remote monitoring and real-time analysis. These results underscore AI's transformative role in cardiovascular diagnostics, paving the way for advanced, efficient, and accessible solutions in managing heart health.

Prediction of Heart Disease Using Different Machine Learning Algorithms And Their Performance Assessment [5] Ar-Rafi Hriday, Limon Mia [5]

This study explores machine learning classification techniques to improve heart disease diagnosis accuracy, emphasizing the critical role of early detection in enhancing patient outcomes. As heart disease remains a leading global cause of mortality, precise and reliable diagnostic tools are crucial. The research evaluates models such as Support Vector Machine (SVM), K-Nearest Neighbours (KNN), Decision Tree, and TensorFlow (TF) on two datasets: the UCI Heart Disease dataset and a Kaggle heart disease dataset, both featuring 14 health-related attributes. Among these, KNN achieved the highest accuracy of 96.42%. The findings underscore the importance of larger and high-quality datasets in boosting prediction performance. This study highlights the potential of machine learning to advance cardiovascular diagnostics, providing valuable insights for healthcare providers and enabling more precise and efficient patient care.

Heart Disease Prediction using Machine Learning Techniques [6] Devansh Shah [6]

Cardiovascular disease, the leading cause of mortality worldwide, underscores the need for precise diagnostic tools to enable early detection and effective management. This study utilizes data mining and machine learning techniques to predict heart disease, focusing on enhancing early intervention strategies. Four supervised learning algorithms—Naïve Bayes, Decision Tree, K-Nearest Neighbour (KNN), and Random Forest—were applied to the Cleveland dataset from the UCI repository, containing 303 instances with 76 attributes. For evaluation, 14 essential features were selected to measure each algorithm's predictive performance. Among these, KNN emerged as the most accurate model, highlighting its reliability and potential as an effective tool for heart disease diagnosis.

III. LITERATURE REVIEW OF PHISHING DETECTION METHODS

SL.NO	TITLE	AUTHOR	YEAR	ADVANTAGE	DISADVANTAGE
1	A Method for Improving Prediction of Human Heart Disease Using Machine Learning Algorithms	Abdul Saboor, Muhammad Usman , Sikandar Ali , Ali Samad , Muhmmad Faisal Abrar	2022	They can analyze complex and vast datasets	Inaccurate, incomplete, or biased data can lead to poor model performance, resulting in incorrect predictions or a lack of generalization to real-world scenarios.
2	A Multi-variate Heart Disease Optimization and Recognition Framework	Hossam Magdy Balaha, Ahmed Osama Shaban, Eman M. El- Gendy	2022	More accurate and personalized diagnosis	Complexity in model interpretation
3	Detection of Cardiac Abnormalities and Heart Disease Using Machine Learning Techniques	Miss. Rina S. Patil, Dr. Tripti Arjariya , Prof. (Dr.) Mohit Gangwar	2023	Analyzing complex patterns in medical data	Need for large, high-quality labeled datasets.
4	Imbalanced ECG Signal-based Heart Disease Classification Using Ensemble Machine Learning Technique	Adyasha Rath , Ganapati Panda , Ganapati Panda	2022	It improves classification accuracy	It may lead to increased computational complexity and longer training times.
5	Mixed Machine Learning Approach for Efficient Prediction of Human Heart Disease by Identifying the Numerical and Categorical Features	Ghulab Nabi Ahmad , Shafiullah , Hira Fatima , Mohamed Abbas , Obaidur Rahman	2022	It enhances prediction accuracy	It can lead to increased model complexity.
6	Heartbeat Sound Signal Classification Using Deep Learning	Saleem Ullah, Arif Mehmood, Byung-Won On	2021	Leading to more accurate and reliable classification compared to traditional methods.	It may lead to overfitting or poor generalization if the dataset is insufficient or not diverse enough.
7	Multi-classification neural network model for detection of abnormal heartbeat audio signals	Hassan Malik,Umair Bashir, Adnan Ahmad	2022	Accurately classifying a wide range of abnormal heart conditions	It requires a large and diverse dataset
8	A Novel Deep Learning Approach to Classify	Praphula Kumar Jain,	2023	Improve the accuracy of early detection of heart conditions	Computationally expensive and time-consuming to train,

	Heartbeats Audio Data	Sandeep Inuganti & Rajendra Pamula			especially when dealing with complex audio data
9	Heartbeat Sound Analysis: Integrating Deep Learning Models for Classification	Tahmina Akter; Tanjim Mahmud; Utpol Kanti Das; Prosenjit Chakraborty	2024	Ability to automatically learn complex patterns and temporal dependencies in heart sound data, enabling more accurate	High computational cost and complexity
10	Heartbeat Sound Signal Classification Using Deep Learning	Ali Raza , Arif Mehmood , Saleem Ullah , Maqsood Ahmad	2019	Complex patterns and temporal dependencies in the audio data, leading to more accurate and reliable detection of heart abnormalities compared to traditional methods.	Requirement for large annotated datasets.

IV. PROPOSED SYSTEM

In the proposed system, heart sound data is analyzed using a hybrid model combining Convolutional Neural Network (CNN) and Bidirectional Gated Recurrent Unit (BIGRU) algorithms to improve prediction accuracy. The system utilizes Mel-frequency cepstral coefficients (MFCC) for feature extraction, a technique well-suited for capturing the frequency characteristics of heart sound signals. MFCC provides the model with detailed insights into the signal's patterns, which are critical for detecting abnormalities linked to heart conditions. The CNN component specializes in extracting spatial features by identifying patterns in the MFCC-transformed data, while the BIGRU component, a recurrent neural network, captures temporal dependencies over time. By integrating both spatial and sequential features, this hybrid CNN-BIGRU model offers a comprehensive analysis, enhancing prediction accuracy. This combined approach strengthens the system's ability to accurately diagnose heart conditions based on audio data, making it a powerful tool for early detection and medical applications.

A. DATA COLLECTION

The Kaggle open-source Heartbeat Sounds dataset provides a valuable resource for analyzing heart sound data, which is crucial for diagnosing cardiovascular conditions. Curated to support machine learning and signal processing research, the dataset includes recordings of heartbeat sounds from real patients in clinical settings. These recordings capture distinct heart sound patterns, such as normal beats, murmurs, and extra-systole heartbeats, which are essential for identifying potential abnormalities. The data is labeled, enabling researchers to associate specific heart conditions with each recording. This labeling makes the dataset especially useful for supervised learning, allowing algorithms to learn to differentiate between normal and abnormal heart sounds.

https://www.kaggle.com/datasets/kinguistics/heartbeat-sounds. By leveraging this dataset, researchers can train, validate, and test predictive models effectively, enabling the development of machine learning algorithms to classify heart sounds with high accuracy. Utilizing this diverse collection of heartbeat sounds, the dataset facilitates innovative approaches for early cardiovascular diagnosis, benefiting both the medical field and patient outcomes.

B. PRE-PROCESSING:

Pre-processing plays a crucial role in preparing heartbeat audio data for analysis. It encompasses various stages, such as reducing noise to minimize background distractions, normalizing the volume to create consistency across recordings, and segmenting the audio to isolate the relevant parts of the heartbeat sounds. Moreover, transforming the audio signals into a frequency-domain format, like Mel-frequency cepstral coefficients (MFCC), helps capture essential characteristics of the heart sounds. These procedures ensure that the data is refined and uniform, improving the effectiveness and precision of machine learning models used for diagnosing heart conditions.

C.FEATURE EXTRACTION:

Feature extraction is a crucial step in analysing heartbeat audio data, as it involves identifying the key attributes that are most relevant for classification. Techniques like Mel-frequency cepstral coefficients (MFCC) are commonly used to convert the audio signals into a form that highlights important features, such as pitch, tone, and rhythm. MFCCs provide a concise representation of the short-term power spectrum of the sound, capturing the frequency content of the heartbeat audio. In addition to MFCC, statistical features like mean, variance, and energy can be derived from the signals to capture temporal variations. By extracting these critical features, the dataset is prepared for machine learning models, allowing them to effectively distinguish between normal and abnormal heart sounds, ultimately enhancing diagnostic accuracy.

CONVOLUTIONAL NEURAL NETWORKS (CNNS):

Convolutional Neural Networks (CNNs) are a class of deep learning models specifically designed for processing structured grid data, such as images or audio. They are particularly effective in capturing spatial hierarchies through the use of convolutional layers.

Convolution Operation: The core operation of a CNN is the convolution of input data (e.g., an image) with a set of filters (kernels). The convolution operation can be mathematically expressed as:

$$(I * K)(i,j) = \sum_{m} \sum_{n} I(m,n) K(i-m, j-n)$$

where I is the input image, K is the kernel, and i, j are the coordinates of the output feature map.

Pooling: Pooling layers reduce the spatial dimensions of the feature maps, maintaining the most important information while reducing computational load. A common pooling operation is Max Pooling:

$$P(i,j) = \max_{m,n} F(m,n)$$

where F is the feature map, and P is the pooled output.

Fully Connected Layers: After several convolutional and pooling layers, the high-level reasoning is done using fully connected layers. The output of the final layer can be expressed as:

$$y = W \cdot x + b$$

where y is the output, W is the weight matrix, x is the input vector from the last pooling layer, and b is the bias.

Bidirectional Gated Recurrent Units (BIGRU):

Bidirectional Gated Recurrent Units (BIGRUs) are a type of recurrent neural network (RNN) architecture specifically designed to process sequential data while overcoming the challenges faced by traditional RNNs, such as the vanishing gradient problem. BIGRUs use gating mechanisms to regulate the flow of information within the network, enabling the model to retain important information over long sequences more efficiently. This approach allows BIGRUs to capture long-term dependencies in data, making them particularly effective for tasks involving time-series data or sequences, like speech and heartbeat sound analysis.

Update Gate: The update gate determines how much of the past information needs to be passed along to the future. It is computed as follows:

$$z_t = \sigma(W_z \cdot [h_{t-1}, x_t])$$

where:

- z_t is the update gate at time t,
- x_t is the input at time t,
- h_{t-1} is the hidden state from the previous time step,
- W_z is the weight matrix associated with the update gate,
- σ is the sigmoid activation function.

Reset Gate: The reset gate controls how much of the past information to forget. It is calculated as:

$$r_t = \sigma(W_r \cdot [h_{t-1}, x_t])$$

where:

- r_t is the reset gate at time t,
- W_r is the weight matrix associated with the reset gate.

D.Model Training:

Training a model with a hybrid architecture that combines Convolutional Neural Networks (CNN) and Bidirectional Gated Recurrent Units (BIGRU) leverages the strengths of both models to improve prediction accuracy, especially for tasks involving sequential data like audio or time series. In the training process, the CNN component first processes the input data—typically features extracted from audio signals, such as Mel-frequency cepstral coefficients (MFCC). The CNN captures spatial hierarchies and local patterns by applying convolutional layers, activation functions, and pooling layers, which reduce dimensionality while preserving key features. After feature extraction, the output is flattened and passed to the BIGRU layers, which excel at learning temporal dependencies in sequential data. The BIGRU processes the feature maps sequentially, utilizing gating mechanisms to retain important information and discard irrelevant data over time. This combination enables the model to effectively capture both spatial and temporal relationships in the data, enhancing its predictive power.

IV. RESULT AND DISCUSSION

The proposed system for heart disease prediction through audio analysis utilizes a hybrid model combining Convolutional Neural Networks (CNN) and Bidirectional Gated Recurrent Units (BIGRU) to improve diagnostic accuracy and effectiveness. The CNN component automatically learns spatial hierarchies from the Mel-Frequency Cepstral Coefficients (MFCC) features derived from heart sound recordings. By employing convolutional layers followed by pooling operations, the CNN identifies crucial patterns and local features within the audio data, which may signal abnormalities such as murmurs or irregular heartbeats. This allows the model to focus on critical temporal and frequency aspects of the heart sounds. After feature extraction, the sequential data output from the CNN is processed by the BIGRU network, which excels at capturing the temporal dependencies present in heart sounds. The BIGRU's gating mechanisms enable the model to retain relevant information over time while discarding irrelevant data, making it ideal for analyzing time-series signals like phonocardiograms. The combination of CNN and BIGRU thus forms a powerful framework that effectively utilizes both spatial and temporal aspects of the data, providing a comprehensive analysis of heart sounds and enhancing the accuracy of heart disease predictions. This novel approach not only improves diagnostic precision but also supports non-invasive monitoring, contributing significantly to cardiovascular health management

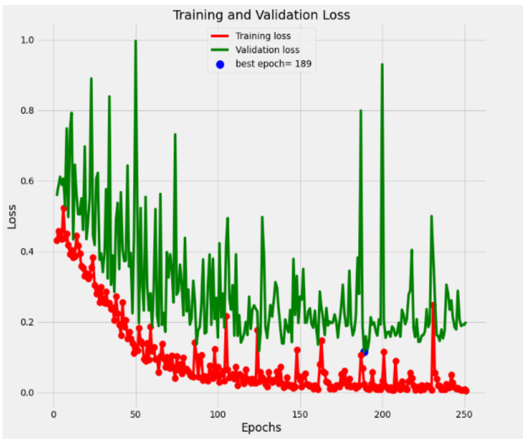
GRAPH FOR ACCURACY:

Training accuracy indicates how well a machine learning model performs on the training data, showing how effectively it has learned from the provided examples. However, a high training accuracy alone doesn't guarantee that the model will perform well on new, unseen data. Validation accuracy, on the other hand, evaluates how well the model generalizes to unseen data, providing a better measure of its ability to make accurate predictions in real-world scenarios. While training accuracy reflects the model's fit to the training set, validation accuracy offers a clearer understanding of its potential performance outside the training environment.

$$\text{Accuracy} = \frac{\text{Number of correct predictions}}{\text{Total number of predictions}} \times 100$$

In mathematical terms, accuracy is computed by dividing the number of correct predictions by the total number of predictions made by the model, and then multiplying the result by 100 to express it as a percentage. This metric quantifies how frequently the model's predictions align with the actual labels in the dataset. A higher accuracy value suggests better performance, with 100% accuracy indicating perfect predictions where all instances are classified correctly. However, accuracy alone might not be enough to fully assess a model's performance, particularly in cases of imbalanced datasets or tasks where other metrics, such as precision, recall, or F1 score, offer more insightful evaluations. Significant differences between training and validation accuracy could indicate overfitting or underfitting, suggesting the need for adjustments to improve the model's generalization. Monitoring both training and validation accuracy is crucial in model development, helping to ensure high performance on both datasets and making certain the model generalizes well to new, unseen data.

LOSS GRAPH



The loss graph visually represents the progression of the loss function, which measures the difference between the model's predictions and the actual labels during training. It is typically plotted with loss on the y-axis and the number of training iterations or epochs on the x-axis. This graph shows how well the model is learning over time. At the beginning, when the model's predictions are random, the loss is high. As the training continues, the model adjusts its parameters using optimization techniques like gradient descent, aiming to reduce the loss. This results in a downward trend in the graph, indicating that the model is learning and improving its accuracy with each iteration.

$$L(y, \hat{y}) = -\sum_i y_i \cdot \log(\hat{y}_i)$$

Where:

- y represents the true labels (one-hot encoded),
- $\hat{y}$ represents the predicted probabilities for each class,
- y_i and $\hat{y}_i$ are the true and predicted probabilities for class i respectively,
- $\log$ denotes the natural logarithm, and
- $\sum_i$ indicates the summation over all classes.

Ideally, the loss graph should show a steady decline in loss until it stabilizes at a low value, suggesting that the model has successfully learned the patterns in the training data. However, if the loss fluctuates or increases at certain points, it could signal potential issues such as overfitting (when the model learns the training data too well but fails to generalize), underfitting (when the model is too simplistic to capture the data's complexity), or learning rate instability (when the model's optimization steps are too large or small). Monitoring these deviations helps identify problems in the model's training process and guides adjustments, such as modifying the learning rate, regularizing the model, or improving the data quality, to enhance performance.

CONCLUSION

In conclusion, the proposed hybrid approach combining Convolutional Neural Networks (CNN) and Bidirectional Gated Recurrent Units (BIGRU) represents a significant step forward in cardiovascular disease diagnosis. By capturing both spatial and temporal features from heart sound data, this method enhances prediction accuracy more effectively than traditional diagnostic tools and standard machine learning techniques. The comparative analysis highlights the potential of this advanced approach to improve early detection and intervention for heart-related health issues. Given the global prevalence of cardiovascular diseases, the integration of such machine learning models into clinical practice could revolutionize diagnostic capabilities, leading to better patient outcomes and alleviating the burden on healthcare systems. This innovation not only overcomes current diagnostic limitations but also opens the door for further advancements in cardiac health monitoring and research.

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