Advanced Healthcare for Heart Disease Prediction using Deep Learning Algorithms: A Comprehensive Analysis

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Abstract. Heart disease remains a leading cause of mortality worldwide, significantly contributing to the global burden of disease. Among various types, coronary heart disease accounts for the highest number of deaths. Both machine learning (ML) and deep learning (DL) models are instrumental in detecting heart diseases; however, DL models, particularly those with deeper architectures, excel in extracting complex features, making them highly effective in analyzing electrocardiogram (ECG) signals for diagnosis. ECG signals provide critical insights into heart functionality, enabling early detection of abnormalities and conditions associated with heart disease. This study aims to develop an advanced deep learning model integrated with cloud technology to ensure accessibility and scalability. By leveraging the cloud, the model can facilitate real-time processing and remote diagnosis, making it a robust tool for healthcare providers. Additionally, the integration enhances the model's usability for large-scale deployment, ensuring timely detection of heart disease. This approach not only supports early intervention but also holds potential for reducing the mortality rate associated with heart-related conditions.

Keywords: Deep learning, electrocardiogram, ML, heart disease.

1 Introduction

Heart disease detection at an early stage is crucial since most of the deaths associated with it is due to late identification of the disease. Among all the data available ECG play an important role since it contains most prominent features like heart rate, p wave pr interval, QRS complex which helps dl models to identify underlying disease in effective way. These ECG signals when represented in an image form provides valuable insights. The key parameters which can be extracted from ECG signals are represented below:

Heart Rate: ECG signals show number of times your heart beats in a minute. While too fast or too slow heartbeats can be signs of heart problems.

P Wave & QRS Complex: P wave represents a first small bump on ECG signal where any irregularity in p wave represents disturbance in upper chambers of heart which in terms indicate irregular heartbeat. While sharp spike on signal shows how ventricles in lower chamber squeezes blood out if this spike is wide then it might represent there is an issue in pumping blood out of lower ventricles possibly due to a heart attack.

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PR Interval: Time between the P wave and the QRS complex which tells how long it takes for the electrical signal to move from the top of your heart (atria) to the bottom (ventricles). If time takes longer then there might be blockage.

ST Segment: Flat part which Is immediate right after the QRS spike which shows time between the ventricles squeezing and relaxing. Fig 1 Shows the Key Parameters of ECG Signals.

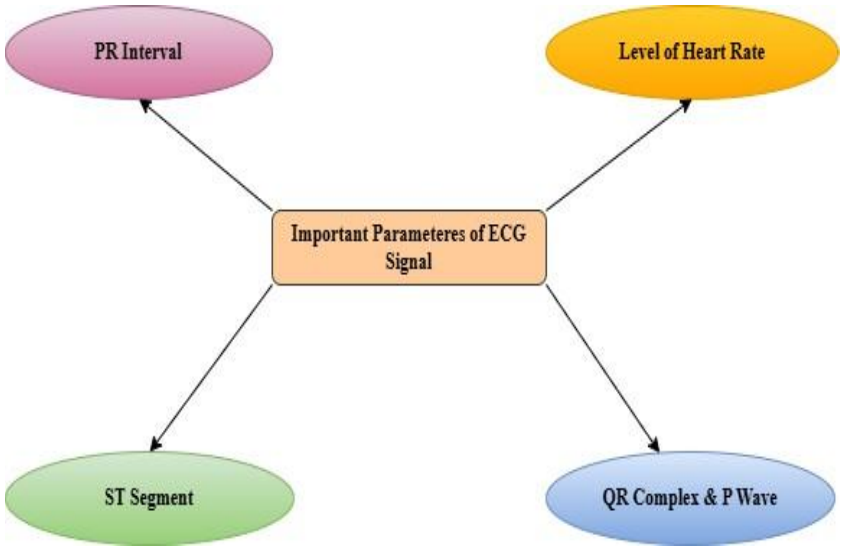

Fig.1. Key Parameters of ECG Signals.

Anuar et al. [1] utilized ML models use ECG data which consists of multiple classes of heart disease cases, as well as normal heart conditions. Then initially ECG signals are processed to remove noise (like artifacts due to muscle movement or electrical interference). then ml classifier is trained on these cleaned data and evaluated by obtaining an accuracy of 93%.

Bertsimas et al. [2] used ECG signal data to build a ml classifier, as part of that signal processing is done to remove noise and then key features like P wave, QRS complex, T wave, and heart rate were extracted from the ECG signals. furthermore, to reduce unwanted features dimensionality reduction is done to retain the most important features. Ensembling techniques is employed as it can handle large datasets efficiently and obtained an accuracy of 94%.

Rath et al. [3] identified challenges in imbalanced ECG datasets where there are fewer examples of one class (e.g., heart disease) than another which often leads to biased models to overcome such things Data Augmentation Techniques were applied to handle the problem of class imbalance. Then CNN model is built to capture the important features of ECG waveforms like P waves, QRS complexes which are important in detecting abnormalities a then trained properly without getting overfitted to obtain an accuracy of 97%.

2 Literature Survey

Heart disease prediction has attracted significant attention in the medical and computer science research communities, with a wide range of machine learning (ML) and deep learning (DL) methods being applied to electrocardiogram (ECG) and related physiological data.

2.1 Machine Learning Approaches

Conventional approaches of ML have been extensively exploited for heart disease detection based on ECG. Initial papers, such as Oresko et al. [16] and Kelly and Hellinger [21] in showed the promise of using feature extraction and statistical segmentation modelling in cardiovascular diagnosis. Bertsimas et al. [2] introduced a real-time ML model using ECG signals, by applying preprocessing and dimension reduction techniques for the purpose of improving the prediction efficiency. Similarly, Anuar et al. [1] and Suhail and Razak [11] used noise cancellation and wavelet transform algorithms for pre-processing the signal and obtained an accuracy of more than 90%.

Arrhythmia detection was also studied by other investigators. Jadhav et al. [25] and Vijayavanan et al. [19] used artificial neural networks and morphological features and Apandi et al. [23] and Islam et al. [26] used the MIT-BIH database for comparison of their classifiers. Ketu and Mishra [20] on the effect of imbalanced ECG data on ML algorithms, and Shorewala [30] on ensemble ML methods for early detection. These techniques highlight the contribution of classical ML in cardiovascular studies, however, their reliance on the handcrafted features serves as a constraint.

2.2 Deep Learning-Based Models

With the development of DL, convolutional neural networks (CNNs) and similar architectures have surpassed conventional ML approaches in complex ECG data processing. Jahmunah et al. [4] presented a GaborCNN, which successfully encoded frequency and orientation characteristics, attaining 99% performance. Abubaker and Babayiğit [5] have also tested ML and DL and concluded that the DL method greatly reduces the manual feature engineering. Mehmood et al. [7] and Karthik et al. [6] CNNs were also proved the effectiveness to extract spatial and temporal information contained in ECG signals, and to improve cardiac diseases classification accuracy.

A few studies have attempted to improve DL performance by using data augmentation to deal with class imbalance. Rath et al. [3] and Kumar et al. [8] implemented CNN-based models in combination with synthetic samples generation and obtained a robust accuracy of 97–98%. Ramprakash et al. [14] proposed DNN architecture that could capture complex features and Ullah et al. [27] and Khan and Kim [28] proposed LSTM -based architectures to capture time dependencies in arrhythmia detection.

Li et al. [10] Other studies include who used Empirical Mode Decomposition (EMD) for feature extraction, and Elias et al. [13], who applied DL for detection of left valvular heart disease. Yu et al. [9] fused ECG and photoplethysmogram (PPG) modalities for the multimodal disease prediction and Fradi et al. [24] used CNN variants in the optimizer domain for classification of arrhythmia. Overall, these results collectively demonstrate DL’s ability in automatically learning features and performing better than ML in terms of accuracy and generalization.

2.3 Hybrid and Ensemble Approaches

Combination models combining ML and DL have also been considered to enhance the prediction accuracy. Bharti et al. [12] used a hybrid solution of DL feature extraction and ML classification to obtain 98% accuracy. Ensemble techniques have also been extensively recognized. Rath et al. [3] and Baccouche et al. [15] concluded that several DL classifiers enhances the model's robustness with respect to the variability of the training data. Similarly, Aamir et al. [22] used ensemble ML for ventricular arrhythmia categorization and Hammad et al. [17] and Haleem et al. [18] presented ECG-based cardiovascular detection by using adaptive ensemble models.

2.4 Review Studies and Trends

Several systematic reviews provide comprehensive insights into the field. Singhal and Kumar [29] discussed challenges and opportunities in AI-based arrhythmia diagnosis, emphasizing data imbalance, interpretability, and clinical deployment issues. Hammad et al. [17] and Haleem et al. [18] also highlighted adaptive feature extraction techniques for improving DL-based models. These reviews, along with experimental validations, reveal a clear trend towards DL architectures, hybrid methods, and multimodal data integration to achieve higher predictive performance in heart disease detection.

From the literature, it is evident that ML techniques established the foundation for ECG-based heart disease prediction, but deep learning models now dominate due to their superior feature extraction and classification capabilities. Hybrid and ensemble approaches further enhance prediction reliability, while emerging trends focus on addressing challenges such as data imbalance, generalization, and real-time clinical applicability.

3 Methodology

3.1 Dataset Details

ECG Arrhythmia Image Dataset is an assembly of two dataset, it has 114000 samples images of both without and with heart disease patients whose ECG were streaming. As the larger dataset, the data processing is considered to better train a deep neural network. Specialized set of ECG signal images, the ECG Arrhythmia Image Database is used to diagnose and classify various types of Arrhythmias (Heartbeat disorders). Typically, deflocculated ECG signal data are employed for the above described illustrations, with its waveforms for better comprehension. The dataset may contain several types of arrhythmias, such as atrial fibrillation, normal sinus rhythm and ventricular tachycardia. It is a dataset that researchers commonly use as the foundation dataset to both train and test deep learning (DL) and machine learning (ML) models; especially those of convolutional neural networks (CNNs) which excel in handling visual data. The data is critical to the development of automated diagnostic tools that could help early identification of heart defects. Thanks to the structured nature of this dataset, it has been easier to design models achieving better accuracy. Sample ECG signal as shown in Fig 2.

3.2 Data Enhancement

As part of this process many methods were done all of them are to ensure counting total number of data samples which ensures an overview of the data, giving labels which is done to make the data sparser, pixels are converted to a similar range where pixel ranging values from 0-255 are converted to fixed range which makes the model good fit for training

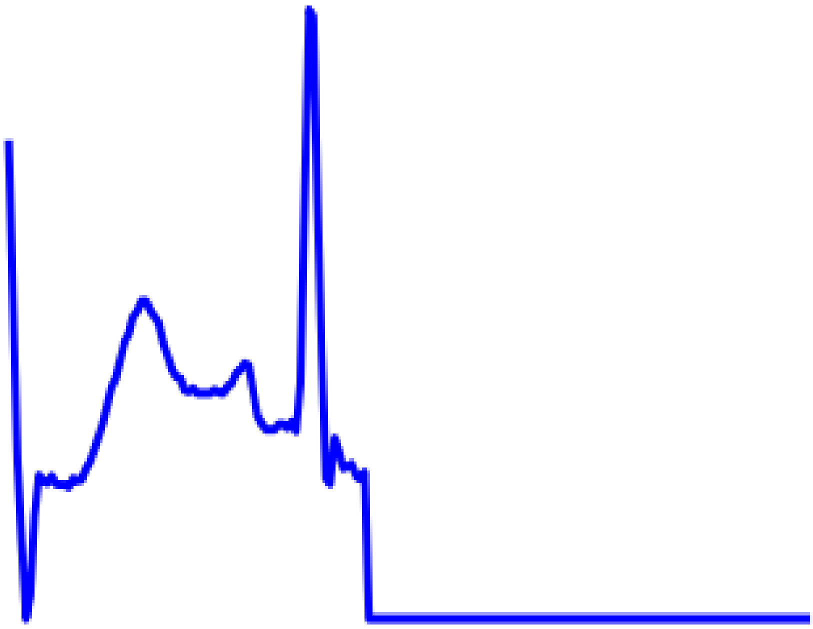

Fig.2. Sample ECG signal.

3.3 EfficientNet B0 model

This model is considered as good for efficient feature extraction due to better understanding of complex p- wave, T-wave from ECG waveform which is crucial for diagnosing heart conditions. Makes it suitable for heart related predictions, additionally ability to process large datasets, making it ideal for ECG data where high- resolution features are critical. This kind of CNN has more layers, making it appropriate for big datasets. A balanced model with great precision can be achieved thanks to compound scaling, which increases all three parameters depth, width, and resolution at the same time. Fig 3 Shows the Architecture of the Proposed Model.

3.4 Adam Optimizer

It is for weight adjustment the learning rate gets adjusted in each parameter for past moments. Instead of a fixed learning rate here, and one that is updated accordingly is to help in better and faster convergence. Fig 4 Shows the Accuracy of the Adam Optimiser over different epochs.

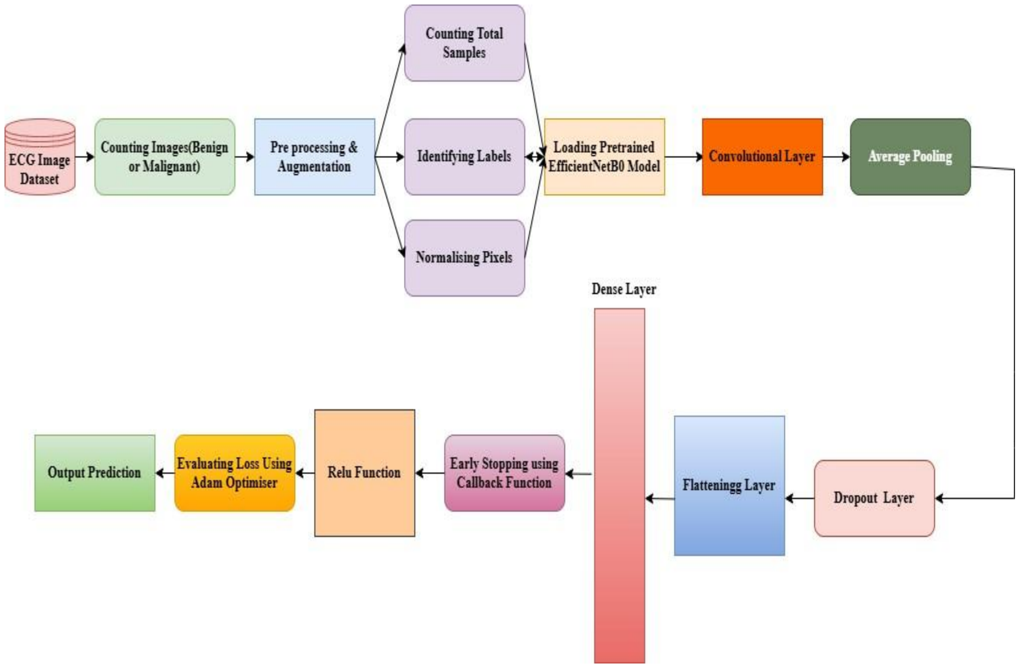

Fig.3. Architecture of the Proposed Model.

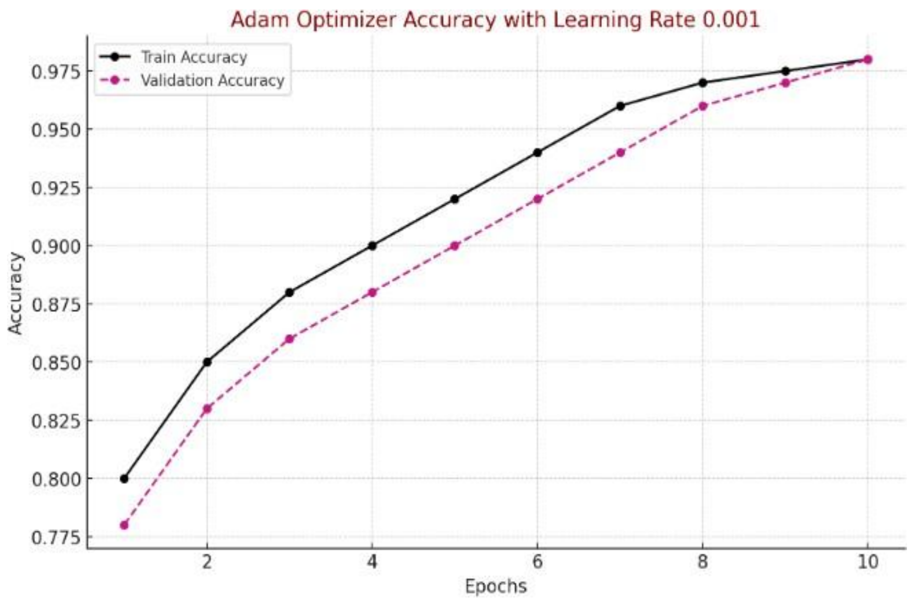

Fig.4. Accuracy of the Adam Optimizer over different epochs.

3.5 Advantages and Disadvantages

Table 1 Represent the Comparison of Research Studies – Advantages and Disadvantages.

Table 1. Comparison of Research Studies – Advantages and Disadvantages.

S.No	Author & Year	Advantages	Disadvantages
1	Oresko et al. [16]	Highly accurate prediction with advanced feature extraction techniques	Need to enhance while handling imbalanced data
2	Hammad et al. [17]	Highly accurate prediction with advanced feature extraction techniques	Need to enhance while handling imbalanced data
3	Haleem et al. [18]	Highly accurate prediction with advanced feature extraction techniques	Need to enhance while handling imbalanced data
4	Vijayavanan et al. [19]	Highly accurate prediction with advanced feature extraction techniques	Need to enhance while handling imbalanced data
5	Ketu & Mishra [20]	Highly accurate prediction with advanced feature extraction techniques	Need to enhance while handling imbalanced data
6	Kelly & Hellinger [21]	Highly accurate prediction with advanced feature extraction techniques	Need to enhance while handling imbalanced data
7	Aamir et al. [22]	Highly accurate prediction with advanced feature extraction techniques	Need to enhance while handling imbalanced data
8	Apandi et al. [23]	Highly accurate prediction with advanced feature extraction techniques	Need to enhance while handling imbalanced data
9	Fradi et al. [24]	Handles long-term data while understanding underlying trend	Better generalization of model is needed
10	Jadhav et al. [25]	Handles long-term data while understanding underlying trend	Better generalization of model is needed

11	Islam et al. [26]	Handles long-term data while understanding underlying trend	Better generalization of model is needed
12	Ullah et al. [27]	Handles long-term data while understanding underlying trend	Better generalization of model is needed
13	Khan & Kim [28]	Handles long-term data while understanding underlying trend	Better generalization of model is needed
14	Singhal & Kumar [29]	Handles long-term data while understanding underlying trend	Better generalization of model is needed

4 Experimental Setup

This experiment uses a python version of 3.8 and the required libraries, listed below, ie numpy, pandas, matplotlib for visualisation. TensorFlow 2.6 or later is suggested. This good environment makes this system eligible for Heart disease detection.

5 Results Discussion

The EfficientNet model performed better than these traditional methods because it effectively learned the complex features using the unique compound scaling. This technique guarantees that the model width, depth, and resolution could all be increased concurrently to improve the learning ability and performance of the model. This blend produced an impressive accuracy of 98% for the model. Additional enhancements could be the use of transfer learning in order to make the model more general and employing optimization methods in order to tune the performance of the model. Furthermore, application of the model to real-time usages would broaden the viable scope of its clinical application. Accuracy Obtained Shown in Fig 5.

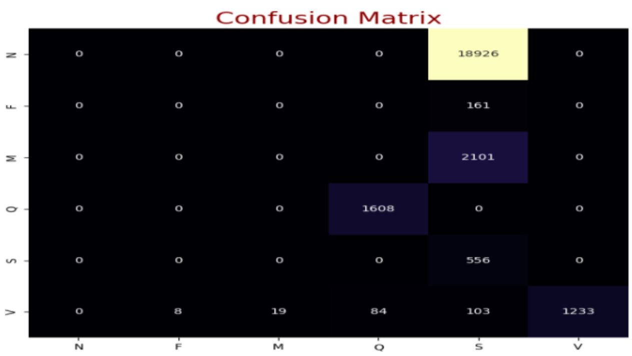

Fig.5. Accuracy Obtained.

6 Conclusion and Future Scope

The EfficientNet model outperformed classic ML models, which is mainly because of the compound scaling. This property guarantees that the width, depth, and resolution of the model is scaled together such that it can learn complex features and we obtain the highest accuracy of 98%. In the future, we will bring this model into cloud platform, and develop a reliable, efficiency and secure scalable environment for ECG prediction. Further tuning of the hyperparameters of model or the architecture could potentially improve the performance. Real time ECG monitoring, and generalization of the model to other health care settings are other possibilities.

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