A Hybrid Deep Learning Model for Heart Disease Risk Assessment

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ABSTRACT

Heart diseases remains a leading cause of mortality worldwide, necessitating effective risk assessment methodologies. In this study, we propose a comprehensive approach utilizing both clinical data and electrocardiogram (ECG) images to assess heart disease risk. Our dataset comprises clinical variables such as age, gender, blood pressure, cholesterol levels, along with ECG images depicting various cardiac arrhythmias including ventricular fibrillation (VFib), premature atrial contractions (PAC), premature ventricular contractions (PVC), left bundle branch block (LBBB), and right bundle branch block (RBBB). We employ various Machine Learning models and deep learning architectures, a hybrid model. For the analysis of ECG images, we leverage the power of convolutional neural networks (CNNs) with EfficientNetB0 architecture, known for its efficiency and effectiveness in image classification tasks. Through experimentation and evaluation, we demonstrate the performance of these models in predicting heart disease risk. This project provides insights into the potential of integrating clinical data and ECG images for enhanced risk assessment, contributing to the development of more accurate and personalized diagnostic tools in cardiology.

Keyword: - *Heart Disease, ECG, Arrythmia, EfficientNetB0, Hybrid deep learning.*

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1. INTRODUCTION

Cardiovascular diseases (CVDs) remain a predominant global health concern, contributing significantly to morbidity and mortality rates. Accurate risk assessment plays a pivotal role in early detection, prevention, and management of these conditions. Traditional risk assessment approaches often rely on clinical variables such as age, gender, blood pressure, and cholesterol levels. However, integrating advanced technologies such as electrocardiogram (ECG) analysis into risk assessment frameworks offers a promising avenue for more precise and personalized diagnostics.

In this study, we embark on a comprehensive heart disease risk assessment project, leveraging both clinical data and ECG images. The clinical dataset encompasses a range of pertinent variables, while the ECG image dataset features diverse cardiac arrhythmias including ventricular fibrillation (VFib), premature atrial contractions (PAC), premature ventricular contractions (PVC), left bundle branch block (LBBB), and right bundle branch block (RBBB). By combining these datasets, we aim to capture a holistic view of heart disease risk factors, encompassing both physiological and electrical abnormalities. Our methodology incorporates a diverse set of machine learning models tailored to handle different aspects of the data. Logistic regression (LR), k-nearest neighbors (KNN), and random forests (RF) are employed for the analysis of clinical variables, while deep learning techniques, specifically convolutional neural networks (CNNs), are applied to interpret ECG images. In particular, we utilize the EfficientNetB0 architecture known for its efficiency and effectiveness in image classification tasks.

2. RELATED WORK

Research in the field of cardiovascular disease (CVD) prediction has increased due to the pressing need to address the global burden of heart failure, which is the world's leading cause of death. Scientists have used a plethora of machine learning (ML) and deep learning (DL) methodologies to construct prediction models that can recognize people who are susceptible to heart failure. Alqahtani et al. [1] presented a novel ensemble learning strategy for the diagnosis of cardiovascular illness in this context. Their work showed that merging several ML and DL models effectively yielded an accuracy of 88.7%, and it was published in Computational Intelligence and Neuroscience. The researchers used DL models like DNN and KDNN together with ML models like KNN, Decision Tree, and XGB, using a dataset of 70,000 records with 13 characteristics.

In a similar vein, Rindhe et al. [2] used machine learning techniques to investigate the prediction of cardiac disease. They investigated the use of SVM, Neural Network, and Random Forest classifier models on a dataset of 303 records in their research, which was published in the Heart Disease journal. The results showed that SVM produced the best accuracy of 84.0%, highlighting the usefulness of machine learning methods in cardiovascular health prediction analytics. Singh and Kumar [3] made contributions to the subject by using ML algorithms to study the prediction of cardiac disease. The study they conducted involves evaluating a dataset of 303 records and 14 attributes, which they presented at the 2020 International Conference on Electrical and Electronics Engineering (ICE3). The research demonstrated the effectiveness of KNN, which had the greatest accuracy of 87%, highlighting the promise of machine learning approaches in detecting important heart disease risk factors

In our project, we aim to improve the existing traditional machine learning model, with clinical variables which may not fully capture the complex interplay of factors effecting cardiovascular health. By incorporating deep learning architectures such as Conventional Neural Networks (CNNs), we seek to extract meaningful patterns and features from diverse datasets comprising both clinical information and electrocardiogram (ECG) images with high accuracy.

3. DATASET DESCRIPTION

The dataset, which includes 918 observations, was created by combining data from five different datasets on heart disease: the Stalog (Heart) Data Set (270 observations), the Cleveland (303 observations), the Hungarian (294 observations), the Switzerland (123 observations), the Long Beach VA (200 observations), and the Cleveland (303 observations) sourced from UCI heart disease repository. Following the merger of these datasets, 918 unique observations where the final dataset size after 272 duplicate observations were found and eliminated.

Eleven elements are included in each observation, offering insightful information about possible heart disease occurrences. These characteristics include:

1. Age: The patient's age expressed in years.
2. Sex: The patient's gender (male or female).
3. Type of Chest Pain: The patient's kind of chest pain is classified as either Atypical Angina (ATA), Non-Anginal Pain (NAP), Typical Angina (TA), or Asymptomatic (ASY).
4. RestingBP: Blood pressure at rest, expressed in millimeter-Hg.
5. Cholesterol: mm/dl is the measurement of serum cholesterol.
6. FastingBS: Fasting blood sugar level; values are classified as 0 (otherwise) or 1 (if FastingBS is less than 120 mg/dl).
7. RestingECG: The electrocardiogram's results are classified as Normal, ST (signaling an irregular ST-T wave), or LVH (perhaps or definitely showing left ventricular hypertrophy).
8. MaxHR: The highest heart rate attained, expressed as a number between 60 and 202.
9. ExerciseAngina: Exercise-induced angina is present; it is indicated by a Y (Yes) or N (No).
10. Oldpeak: A numerical assessment of ST depression.
11. ST_Slope: The maximum workout ST segment's slope, which can be either flat, downsloping, or upsloping (down).

The Electrocardiogram (ECG) image dataset consists of more than 22000 images was leveraged from MIT-BH Arrythmia repository. It is a extensive dataset consisting of 6 classes of heartbeats – Normal , Left Bundle Branch

Blocks, Right Bundle Branch Blocks, Premature Atrial Contractions, Premature Ventricular Contractions and Ventricular Fibrillations.

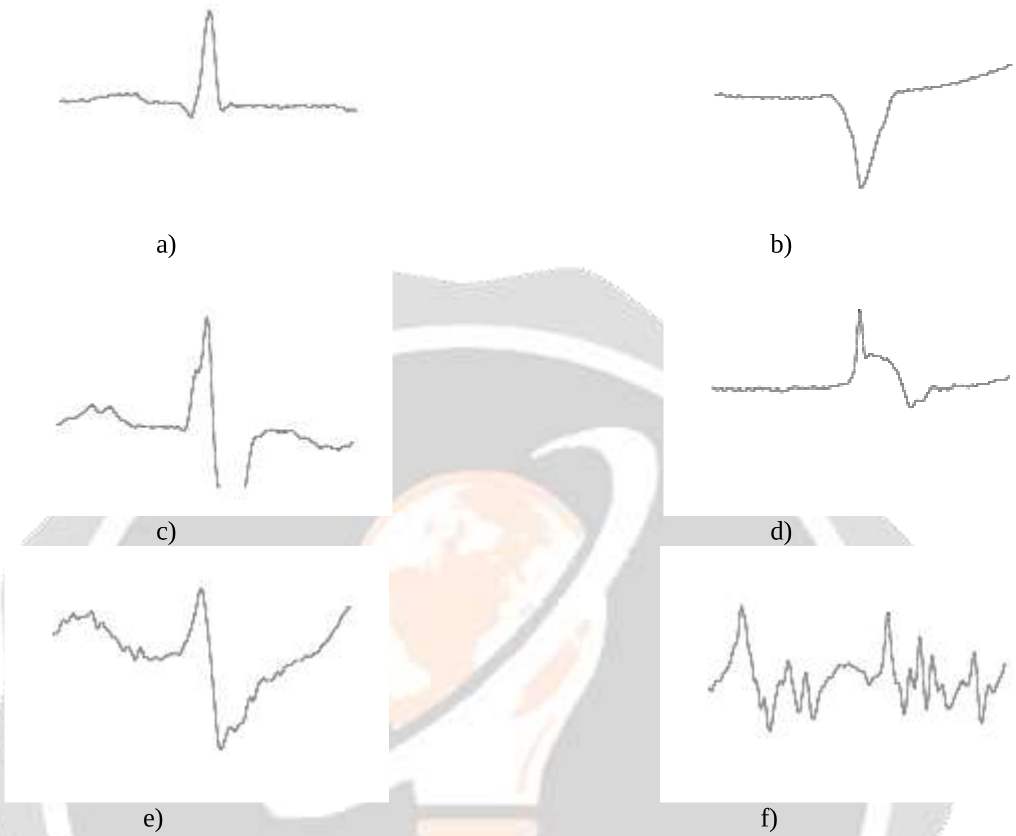

Fig 1: Categories of ECG images a) Normal b) Left Bundle Branch Block c) Right Bundle Branch Block d) Premature Atrial Contraction e)Premature Ventricular Contraction f)Ventricular Fibrillation

4. PROPOSED MODEL

Our proposed model entails a dual-pronged approach, leveraging both traditional machine learning (ML) algorithms and state-of-the-art deep learning techniques for heart disease risk assessment. This entails the utilization of ML algorithms such as logistic regression (LR), k-nearest neighbors (KNN), and random forests (RF) for heart disease prediction based on clinical variables. Concurrently, we employ the CNN EfficientNetB0 algorithm for ECG image analysis, enabling the detection of various cardiac arrhythmias.

The heart disease prediction module utilizes ML algorithms trained on a dataset comprising clinical variables associated with cardiovascular health. Hyperparameter optimization ensures the optimal performance of each ML algorithm, enhancing the accuracy of heart disease risk prediction. Similarly, the ECG image analysis module utilizes the EfficientNetB0 CNN architecture trained on a dataset of ECG images depicting different cardiac arrhythmias. Fine-tuning of hyperparameters ensures that the model effectively captures relevant features from ECG images for accurate arrhythmia detection.

In the final phase of our model, the outputs from both prediction modules are combined to provide a comprehensive heart disease risk assessment. Integration mechanisms are employed to reconcile the predictions from ML algorithms and CNN models, ensuring a holistic evaluation of an individual's cardiovascular health status.

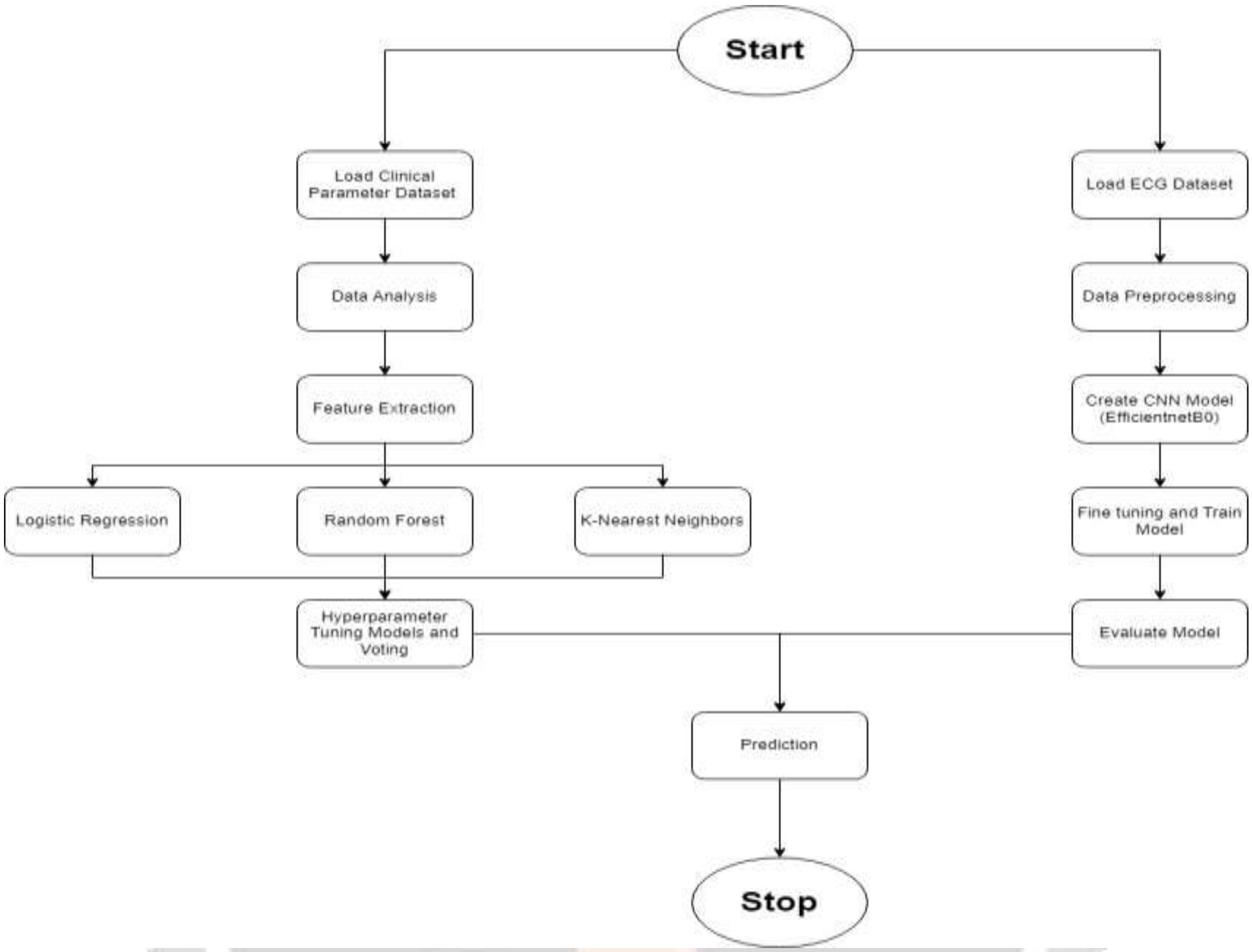

Fig 2: Block Diagram

5. METHODOLOGY

5.1 Dataset and Preprocessing:

The datasets were collected from MIT-BH Arrythmia ECG database and UCI Heart Disease database. The study implemented rigorous quality assurance measures and expert categorization protocols to distinguish between different types of cardiac arrhythmias within the ECG image dataset. Standardizing the ECG images to a consistent size of 64x64 pixels ensured uniformity across models and facilitated seamless interchangeability. Additionally, normalizing the pixel values to a range of 0 to 1 promoted model convergence and minimized the impact of variations in image intensity and contrast. By employing image data generators, the process of batch loading and preprocessing was streamlined, simplifying model training and evaluation procedures for ECG image classification tasks. For UCI dataset, Firstly, to ensure uniformity and enhance model convergence, the features underwent normalization and standardization. The 'MinMaxScaler' was applied for normalization, which scales the features to a range of [0, 1]. Meanwhile, standardization was carried out using the 'StandardScaler', which transforms the features to have a mean of 0 and a standard deviation of 1. Feature selection techniques were employed to identify the most relevant features for predicting 'HeartDisease'. The 'SelectKBest' method was utilized with both chi-squared and ANOVA F-value scoring functions for categorical and numerical features, respectively.

5.2 Model Architecture:

In ECG analysis, we've chosen to employ the pre-trained EfficientNetB0 model as the foundation for our work. This model offers a solid starting point, benefiting from pre-training on a diverse dataset of images, which equips it with the ability to recognize a wide range of image features. Given our task of detecting arrythmia from ECG images, this pretrained model is well-suited for the job. To ensure compatibility with our dataset, we've configured the input shape to 64x64 pixels, reflecting the smaller size of our images. Additionally, we've augmented the model with supplementary layers to further enhance its architecture.

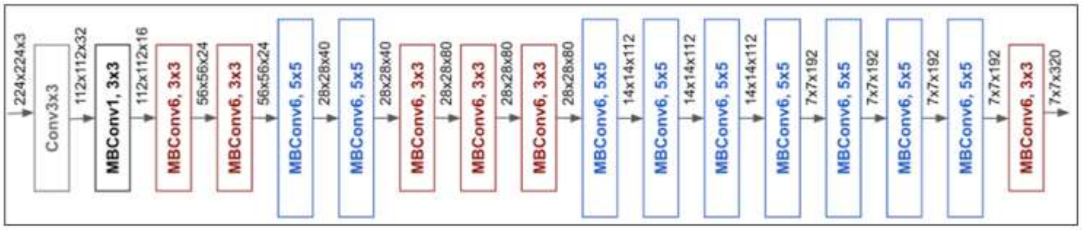

Fig 3: Architecture of baseline EfficientNet-B0 [5]

5.2.1 The EfficientNetB0 is pivotal in our project, serving as the cornerstone upon which we build our tailored model. This pre-trained convolutional neural network (CNN) architecture, refined on the extensive ImageNet dataset, lays the groundwork for our model's framework. By initializing the base model's weights with those pre-trained on ImageNet, we equip our model with a comprehensive comprehension of various visual features, enabling reliable performance across a spectrum of tasks.

5.2.2 **Batch normalization**, for example, assists in smoothing the learning process by adjusting the data before it proceeds to the subsequent layer.

5.2.3 **Dense layers:** serves as the decision-making hub of the model, with the initial dense layer comprising 256 "neurons" and utilizing techniques such as L2 regularization to mitigate overfitting on the training data.

5.2.4 **Dropout layer:** To further mitigate overfitting, a dropout layer has been incorporated, randomly deactivating certain neurons during training to discourage reliance on specific features.

5.2.5 **Output layer:** provide the probability of each image being normal or displaying indications of pneumonia. Model training involved employing the Adamax optimization technique and fine-tuning parameters to ensure effective learning.

In our model, we've opted to utilize three classical machine learning algorithms: RandomForest (RF), Logistic Regression (LR), and k-Nearest Neighbors (KNN), as the cornerstone of our approach for heart disease prediction. These algorithms offer a reliable and interpretable framework for analysing tabular data, making them well-suited for our task. While they may lack the complexity of deep learning models, their effectiveness in handling structured data makes them a pragmatic choice for our heart disease prediction task. We've meticulously pre-processed our dataset, including features such as age, resting blood pressure, cholesterol levels, and maximum heart rate, to ensure their compatibility with the algorithms. Additionally, we've conducted extensive hyperparameter tuning to optimize the performance of each algorithm on our specific dataset. Through this approach, we aim to develop a robust predictive model capable of accurately identifying individuals at risk of heart disease.

5.3 Model Training and Assessment:

During the training phase, our model learns to correlate ECG images with their corresponding diagnostic labels, indicating different types of cardiac arrhythmias or normal heart rhythms. This learning process involves adjusting internal parameters based on the ECG data, aiming to minimize the disparity between predicted diagnoses and the actual labels. Optimization techniques, such as Adamax, assist in gradually refining the model's settings over numerous training epochs. With each epoch, the model enhances its ability to accurately classify ECG images, distinguishing between different cardiac conditions.

We began by manually tuning hyperparameters for k-Nearest Neighbors (KNN), recognizing its sensitivity to parameter settings. For the remaining algorithms, RandomForest (RF) and Logistic Regression (LR), we employed GridSearchCV to systematically explore the hyperparameter space and identify optimal configurations for improved performance metrics. Following hyperparameter tuning, we conducted model training using a comprehensive dataset comprising clinical data. This involved splitting the data into training and testing sets, allowing us to assess each model's performance independently. Finally, to make predictions, we aggregated the outputs of all models and determined the majority decision as the final prediction, ensuring robustness and reliability in our heart disease prediction framework.

6. EXPERIMENTAL RESULTS:

The ECG detection model, trained over 10 epochs, achieved high accuracy and minimal loss in classifying training data, demonstrating its potential for real-world application in healthcare settings, particularly in arrythmia classification.

Values	**Training**	**Validation**	**Testing**
Accuracy	97.39%	98.32%	98.45%
Loss	0.2681	0.1378	0.1442

Table 2: Accuracy and Losses across three sets

The Machine Learning models include Logistic Regression, Random Forest and K Nearest Neighbors Classifier were given better metrics after hyper tuning, showing its efficacy in predicting CVD based on clinical parameters.

Model	**Precision**	**Recall**	**F1- Score**	**Accuracy**
Logistic Regression	0.88	0.85	0.87	0.875
Random Forest	0.83	0.88	0.86	0.842
K Nearest Neighbors	0.82	0.89	0.85	0.858

Table 3: Evaluation Metrics

Fig 4: Confusion Matrix

7. OUTPUT

Presenting the output derived from our hybrid model's predictions, taking inputs of clinical parameters and their ECG image, to provide a comprehensive overview of a patient's cardiovascular health.

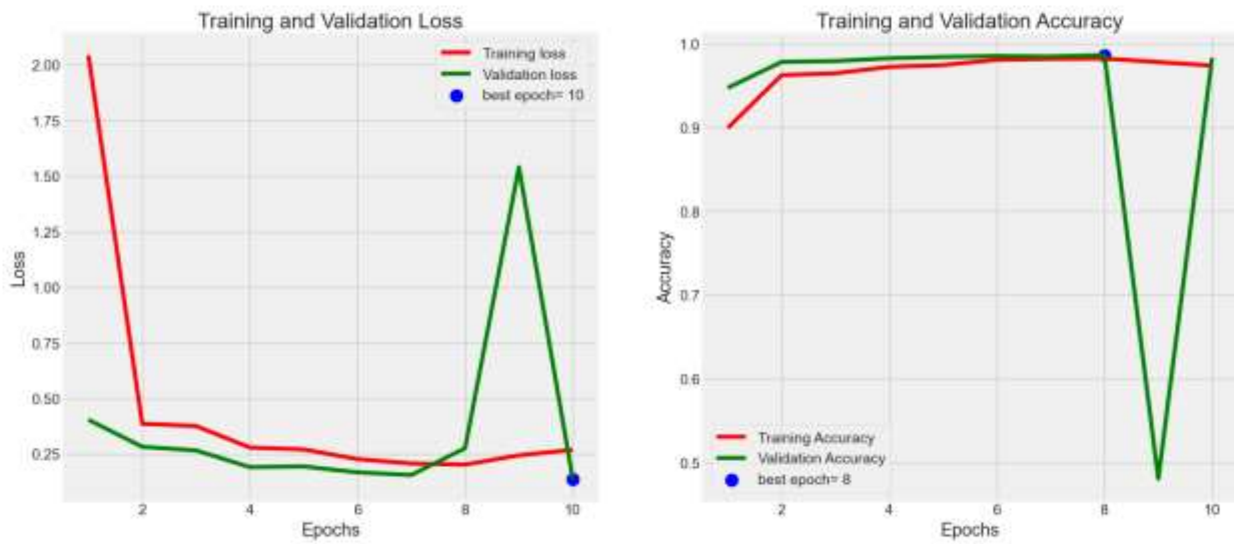

Fig 4: Loss Chart Accuracy Chart

8. CONCLUSION

In conclusion, this project has provided a comprehensive heart disease detection scheme that employs both machine learning and deep learning techniques. With the integration of clinical data and ECG analysis, our project has successfully developed a robust model for predicting heart disease. Leveraging comprehensive datasets and advanced machine learning techniques, we have achieved impressive accuracy and performance metrics in discerning between individuals with and without heart disease. Through rigorous experimentation and validation, we have validated the reliability and generalizability of our model, laying the groundwork for its practical application in real-world healthcare scenarios. Looking forward, further refinement and expansion of the model hold promise for improving diagnostic accuracy and facilitating early intervention, thereby advancing patient care in the realm of cardiovascular health.

9. REFERENCES

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