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Research Article

Design of an Intelligent Hybrid Machine Learning Model for Early Prediction of Cardiovascular Disease

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ABSTRACT

Cardiovascular disease continues to be a leading cause of mortality across the globe, highlighting the urgent need for accurate, efficient, and non-invasive diagnostic tools. This thesis offers the expansion of a novel machine learning-based framework designed to predict heart disease from "Electrocardiogram (ECG)" image data. The present study leverages the strengths of deep learning by integrating "Convolutional Neural Networks (CNN)" for spatial feature extraction and "Long Short-Term Memory (LSTM)" networks for capturing temporal dependencies in ECG signals. The hybrid CNN–LSTM architecture is complemented with robust preprocessing techniques and intelligent feature selection mechanisms to enhance predictive accuracy and generalization capabilities.

The research was conducted from publicly available ECG image dataset from Kaggle, containing multiple classes of heart conditions, including normal rhythms, myocardial infarction, and other abnormalities. To improve model robustness and mitigate overfitting, various "image augmentation techniques such as rotation, flipping, scaling, brightness modification, and Gaussian noise" were applied. These operations ensured diversity in the training data while preserving the diagnostic integrity of the ECG waveforms. Preprocessing steps like normalization and noise reduction were used to standardize input quality and align it with the requirements of the deep learning model.

During the study, metaheuristic algorithms-specifically, the "Ant Lion Optimization (ALO)" and "Bat-Inspired Algorithm (BIA)"-for effective feature selection was used. These optimization methods reduce computational complexity by identifying the most relevant features, thereby enhancing the model's performance without compromising on accuracy. The selected features are passed through the CNN–LSTM model, where CNN layers detect spatial patterns within the ECG images, and LSTM layers process the sequential nature of heartbeats to capture temporal irregularities often associated with cardiac conditions.

The dataset is divided into 70% training and 30% testing groups using stratified sampling to guarantee fairness and effective learning. Although solo CNN models fail miserably when presented with sequential data, the findings show that, achieving only 49% accuracy, and LSTM models achieve 94% accuracy, the hybrid CNN–LSTM architecture offers a more balanced and powerful solution. It achieves 94% accuracy, 95% precision, 94% recall, and an F1-score of 94%, confirming its superior diagnostic capability. The present work contributes meaningfully to the intersection of healthcare and artificial intelligence, paving the way for more advanced, accessible, and automated diagnostic systems in cardiology.

Keyword: CVD Prediction, ECG Image dataset, CNN–LSTM Hybrid, Deep Learning, Ant Lion Optimization, Bat-Inspired Algorithm, Medical AI

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1. Introduction

Heart disease more commonly known as cardiovascular diseases (CVD) heart disease, is the leading cause of death worldwide, accounting for approximately 17.9 million deaths each year according to the World Health Organization (WHO) [1,2]. A large number of deaths can be attributed to late diagnosis and poor prognostic estimation, mainly from silent onset and the limits of traditional diagnostic tools. With the increasing global burden of CVD, efficient, accurate, and timely diagnosis solutions are now extremely important [3]. The recent evolution of "Machine Learning (ML)" and "Artificial Intelligence (AI)" has created new possibilities in health care particularly in identifying and diagnosing heart disease healthcare outcomes. They also allow computerized systems to manage large amounts of medical data, offer hidden uncovered patterns, and assist in clinical decision-making with efficiency, accuracy, and on fewer resources than traditional methods [4]. This study will develop a hybrid machine learning model that incorporates various algorithms to intelligently predict early heart disease progression, which facilitates preventive treatment and timeliness in intervention.

Early prediction of heart disease requires complex and multivariate data inputs including age, sex, blood pressure, cholesterol, and ECG values, types of chest pain, blood glucose levels, and lifestyle factors. These inputs tend to be non-linearly correlated and interdependent, and hence difficult for individual ML algorithms to predict with consistency [5, 6]. Therefore, the use of multiple algorithms combined in a hybrid system has been found useful in enhancing diagnostic accuracy [7]. Hybrid approaches merge the best of various machine learning methods—namely, the classification capabilities of "Long Short-Term Memory (LSTM)", the ability to recognize patterns of "Convolutional Neural Networks (CNNs)"[8]. With this background, the study offers a new hybrid model that combines LSTM and CNN for increased performance, with a deep learning backbone as the feature extractor, and makes use of optimization algorithms like "Ant Lion Optimization (ALO)" or "Bat-Inspired Algorithm (BIA)" to optimize hyper parameters for the best results. This achieves the dual objective of not only delivering high accuracy but also generalizing well on new, unseen patient data [9]. Classic models, though helpful, tend to fall short with issues including data imbalance, over-fitting, generalization errors, and lack of interpretability, which reduce their real-world application in medical contexts [10]. Figure 1 summarizes these challenges as the key factors that should be optimized in the creation of strong, smart data-driven models.

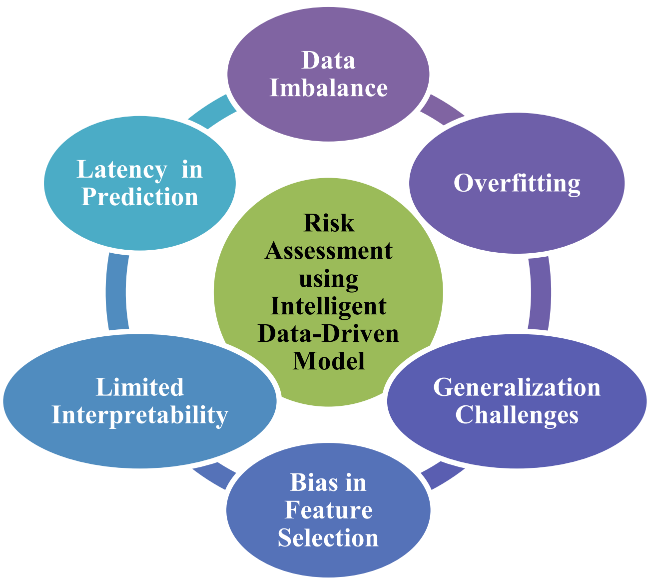

Figure 1: Risk Assessment for Heart Disease Prediction.

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Yet another fundamental goal of this research is to close the gap between data-driven diagnostic models and real diagnostic practice using clever preprocessing methods. Medical datasets tend to be noisy, contain missing values, and redundant features, which can hamper model performance. Thus, the study combines sophisticated data preprocessing operations like normalization and dimensionality reduction. Application of these techniques facilitates improvement in input data quality, a decrease in computational complexity, and interpretability of the model—making it more appropriate for clinical environments [11].

A precise prediction system for heart disease can help doctors in taking timely decisions, decrease the chances of severe cardiac events, and greatly reduce the expense of late-stage interventions. In addition, the system can be integrated into wearable health monitoring devices or cloud applications so it will reach remote or underserved regions. This is aligned with the overall vision of digital healthcare revolution and personalized medicine. Overall, the study hopes to build a strong, smart, and interpretable machine learning model that not only surpasses traditional approaches but also brings us closer to real-time, scalable, and automatic heart disease prediction—a critical step toward decreasing the global health burden and enhancing the quality of life of millions at risk. In light of all these facts the present research was conducted using KAGLE patient image dataset and the present research revolved around these objectives:

- To develop a hybrid machine learning model that integrates Convolutional Neural Networks and "Long Short-Term Memory (LSTM)" architectures for precise heart disease detection and prediction using temporal and spatial features of ECG signals.
- To integrate smart optimization algorithms (e.g., Ant Lion Optimization and Bat-Inspired Algorithm) to optimize the hyper parameters and improve the overall model performance.
- To analyze the performance of the suggested hybrid model utilizing common measures such as accuracy, precision, recall, F1-score, and ROC-AUC on benchmark heart disease data sets.

2. Literature Review

Early prediction of heart disease has emerged as a vital area of research owing to the increasing worldwide mortality rates caused by cardiovascular diseases. Conventional diagnostic techniques, while sure-shot, tend to be inadequate in terms of providing timely interventions, especially in resource-poor or far-flung areas. The recent emergence of ML has introduced smart solutions that facilitate data-driven decision-making, improving the precision and timeliness of heart disease diagnosis. However, independent ML models often tend to come up with the following limitations, such as imbalanced datasets, low generalizability, and poor selection of features. To overcome these challenges, there has been recent research interest in designing hybrid machine learning models that capture the essence and strengths of different algorithms and thus could yield better productivity while enhancing interpretability and clinical applicability. Many Studies have found more advantages of ML models over conventional risk scoring systems**. C. Martín-Isla *et al.* (2020)** in their research **[12]** emphasize on the fact that cardiac imaging is crucial for CVD diagnosis, but big data and machine learning are enabling new opportunities for artificial intelligence tools. This paper reviews recent works and presents machine learning methods for automated, precise, and early diagnosis of most CVDs.

Liu et al.[13] highlighted the importance of comparing ML-based predictions with conventional approaches such as QRISK3 and ASCVD, highlighting how deep learning and Random Forest models obtained better AUCs, even with the high study-level heterogeneity ($I^2 > 99\%$) included.

Building on this, **Mulani et al. [14]** presented a "Machine Learning-enabled Internet of Medical Things (MLIoMT)" framework that combines wearable sensors and ensemble learning approaches to continuously monitor cardiac health, beating state-of-the-art systems by a wide margin on all evaluation measures. **Al-Alshaikh et al. (2024) [15]** also added by introducing the ML-HDPM approach, where genetic algorithms are integrated with feature removal and an optimized deep convolutional neural network, yielding tremendous precision (94.8%) and recall (96.2%). Likewise **Babu et al. (2024) [17]**evaluated "Quantum-Enhanced Machine Learning (QuEML)", which, although yielding slight improvements in accuracy, achieved significant decreases in training time over traditional ML techniques, demonstrating the potential of quantum computing for the future of cardiac diagnostics. Ensemble approaches were also prioritized by **Shrestha et al. (2024) [18]and Bhatt et al. (2023) [19]**, in which methods such as XGBoost, Gradient Boosting, and Soft Voting Ensembles surpassed standalone models, with up to 93.5% accuracy rates. **Mahgoub et al. (2023) [20]** confirmed the stability of neural networks, which proved to be more stable and flexible when dealing with real-world clinical data. **Chandrasekhar et al. (2023) [21]** emphasized that an ensemble of individual classifiers through techniques proved to be more effective than individual models, especially when optimized through Grid Search CV and cross-validation techniques. **Radwan et al. (2023) [22] and Golande et al. (2023) [23]** also provided reinforcement to hybrid frameworks, with Golande's model based on CNN-LSTM recording a superb 99.45% accuracy for classification based on ECG.

Moreover, several researchers emphasized the importance of feature selection and data preprocessing to enhance model performance. **Khan et al. (2023) [24]** showcased Random Forest's superiority in sensitivity and ROCC values, while **Hossen et al. (2022) [25]** identified Logistic Regression as a simple yet highly accurate method for heart disease prediction. **Chen et al. (2022) [26]** introduced the R-Lookahead-LSTM model, which optimized LSTM networks using advanced algorithms like Rectified Adam, achieving significant improvements in precision and recall. **Rahman et al. (2022) [27]** developed a web-based heart health monitoring tool that integrated multiple ML classifiers (e.g., RF, DT, XGBoost), achieving up to 99% accuracy. Furthermore, studies by **Garg et al. (2021) [28]and Rani et al. (2021) [29]** highlighted how hybrid feature selection methods, such as recursive feature elimination combined with genetic algorithms, significantly improved diagnostic precision, particularly when data imbalance and noise were handled using techniques like SMOTE. **Abdeldjouad et al. (2020) [30]** also focused on developing hybrid classification frameworks by combining fuzzy systems, evolutionary algorithms, and optimal feature selection strategies, demonstrating how such integrations lead to substantial performance enhancements over traditional ML approaches. **E. Naresh *et.al.* (2024) [31]** in their research article have proposed work highlights the importance of testing in machine-learning applications and the ensuing need to increase model quality to decrease the likelihood of errors. . After undergoing feature testing, the application's accuracy ascended to 96.69%, which is a higher percentage than was attained using any alternative method.

While machine learning has made strides in heart disease prediction, current models often fall short in practical clinical settings. The key issues are **data imbalance**, **limited generalization**, and a **lack of interpretability**, which makes it difficult for clinicians to trust these models for decision-making. Some hybrid models that combine ensemble learning, deep learning, and feature selection have improved accuracy and sensitivity but there still there exists a significant gap. Hence, there's a need for a more advanced, intelligent hybrid framework which can:

- Process **real-time data streams**.
- Provide **explainable results** for clinicians.
- Be **scalable** for various clinical contexts.
- Be **thoroughly evaluated** across diverse, real-world datasets.

Ultimately, there is a clear need for a robust, interpretable, and clinically applicable hybrid machine learning model to enhance the early screening and diagnosis of heart disease. This new approach must bridge the gap between computational advancements and practical clinical needs

3. Problem Formulation

Cardiovascular ailments, particularly heart disease, continue to be the leading cause of death worldwide, owing in large part to delayed diagnosis and poor early detection mechanisms. Conventional diagnostic tools, while clinically efficacious, tend to be slow, resource-expensive, and based on specialized interpretation and thus less useful for mass screening or telemedicine settings. Machine learning algorithms have been described as promising mechanisms for automating heart disease diagnostic predictions due to their ability to process complex medical data patterns. However, single ML models are inherently limited with severe obstacles such as imbalanced data, over-fitting, poor generalizability across heterogeneous populations, and limited interpretability for clinical decision-making. While attempts have been made with hybrid ML models to utilize the best features of different algorithms, existing methodological developments are often only centered on accuracy rates, rather than practical limitations that include

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scalability, computational costs, and interpretability and acceptability for clinical practice. Moreover, there is a missed opportunity with respect to the integration of real-time data sources such as wearable sensors and other Internet of Things. Therefore, it is pressing to develop a smart hybrid machine learning model that has not only predictive accuracy, but also robustness, interpretability, and adaptability for the early diagnosis of heart disease. The model must contend with challenges associated with unbalanced data, hyper-parameter tuning, and real-life deployment in heterogeneous clinical conditions allowing for pro-active healthcare to reduce deaths from heart disease.

4. Research Methodology

In this research study, the process followed for early prediction of heart disease using a hybrid machine learning model and data was collected from the ECG image dataset, and we performed dataset augmentation to add variety to the dataset. After the augmented image dataset section, we applied data pre-processing to ensure the dataset as consistent and of quality overall. Then we used 70 % for training and 30% for testing. In our classification task, we used a hybrid deep learning model, which integrates how Convolutional Neural Network as well as Long Short-Term Memory, as it helped taken advantage of the spatial and temporal feature extraction.

4.1 Dataset Description

The ECG Images Dataset of Cardiac Patients on Kaggle [32] is a unique dataset that contains annotated ECG images designed to assist researchers in the development and experimentation of ML models for heart disease diagnostics. This dataset contains more than 1,500 ECG images taken of multiple cardiac conditions, and each ECG image is a visual representation of a patient's heart activity. The images in this dataset encompass many arrangements of ECG leads and the images will differ based on patient variability and recording circumstances, all of which is consistent with actual diagnostic imaging. All ECG images show patterns that are relevant to diagnosing conditions like arrhythmia and ischemia (Figure2). This dataset provides ease of preprocessing, augmentation, and model training and can serve as a valuable resource in designing accurate automated heart disease detection systems.

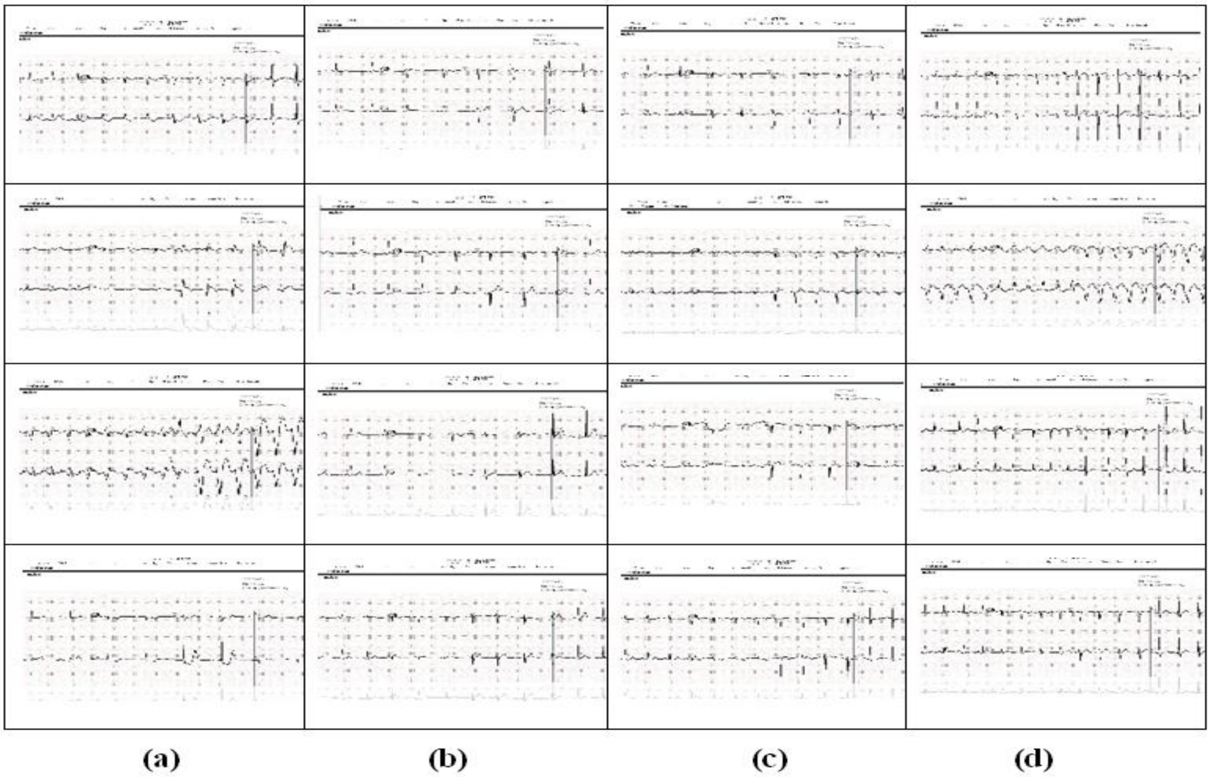

Figure 2: The ECG image dataset comprises four distinct categories: (a) ECG images of myocardial infarction patients, (b) normal person ECG images, (c) ECG images of patients with a history of myocardial infarction, and (d) ECG images of patients exhibiting abnormal heartbeats.

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4.2 Image Augmentation

Image augmentation increases the variability of ECG datasets by creating variant versions of original images by applying controlled image transformations, overcoming dataset sparsity and avoiding over fitting for heart disease prediction models. Scanner-, movement-, and environment-induced variations are replicated by augmentation to make the models learn invariant diagnostic patterns. Image augmentation techniques used are:

- **Rotation**: Limited-angle rotations (±10°–15°) mimic small tilts at acquisition. The applied rotation matrix is:

$$R(\theta) = \begin{bmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{bmatrix} \quad (1)$$

- **Flipping**: Horizontal and vertical flipping reflects lead positions or scanning directions, increasing spatial pattern recognition without sacrificing signal directionality.
- **Scaling/Zooming**: Scaling (±5%–15%) simulates resolution changes; zooming changes focus to learn scale-invariant features.
- **Translation**: Horizontal/vertical shifts (5%–10%) simulate signal misalignments. Translation formula:

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} x & + & \Delta x \\ y & + & \Delta y \end{bmatrix} \quad (2)$$

- **Brightness/Contrast Adjustment**: Changes pixel intensity to simulate scanner or lighting variations, improving illumination invariance.
- **Gaussian Noise Injection**: Injects random noise to simulate real-world signal interference$I' = I + N(0, \sigma^2)$ (3)

4.3 Data Preprocessing

The role of data preprocessing is to clean the raw clinical and imaging data and transform it into an analytical dataset that can support predictive modeling. It may involve many data preparation steps, comprising data cleaning, handling missing values, normalization, image resize, and feature extraction. Data preprocessing fosters consistency, completeness, and noise-free data which improves the performance and dependability of machine learning-based methods for early heart disease identification.

- **Data Cleaning**

Data cleaning encompasses the processes of recognizing and fixing errors, inconsistencies, inaccuracies, and irrelevant data within the dataset to improve data quality and trustworthiness. Within the context of heart disease classification, it refers to fixing misassigned or incorrectly assigned patient records, removing duplicated or incomplete ECG images, and ensuring that only acceptable quality clinical data are used in the training phase of the model. This process also helps to eliminate noise and mitigates bias from the model predictions, allowing for improved accuracy and validity of predictions.

Noise Reduction: $\hat{x_i} = \frac{1}{2k+1}\sum_{j=i-k}^{i+k} x_j$

where k is the window size for smoothing, and $\hat{x_i}$ is the smoothed value.

- **Image Resizing**

ECG images and other cardiac imaging information are resized to a consistent dimension, typically 224×224 pixels, to ensure uniformity throughout the dataset. Uniform image sizes minimize computational load, improve training efficiency, and guarantee compatibility with deep learning architectures such as CNNs, allowing efficient and consistent feature extraction from different imaging sources.

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- ### Data Normalization

Normalization rescales the pixel intensity values of ECG images and numerical clinical data into a unified range, usually [0, 1], making model training stable and converging faster. By this process, consistency in data representation is ensured, and the robustness and accuracy of heart disease models for detection are increased by reducing the effect of data variability. Formula employed for normalization is: $\mathbf{x}_i' = \frac{x_i - x_{min}}{x_{max} - x_{min}}$

where x_{min} and x_{max} are the minimum and maximum values of the feature.

4.4 Feature Extraction using Metaheuristic-Based Optimized Algorithms

To make accurate predictions about heart disease, it is crucial that robust feature extraction is done to convert raw ECG images or structured clinical data into meaningfully inputs into classifiers. Deep learning models like CNNs extract features automatically but will benefit from selecting only the features that provide the most discrimination, as it leads to more computation efficiency and reduces the risk of overfitting. This study will include two metaheuristic algorithms to facilitate optimized feature extraction: Ant Lion Optimization (ALO) and Bat Inspired Algorithm (BIA).

4.4.1 Ant Lion Optimization (ALO)

This optimization is modeled after the predatory behavior of ant lions. ALO uses a random walk methodology to model the ant's movement toward the trap established by an ant lion [33]. The fitness can be determined by the trap dimensions and how deep the trap is. As a result, the solution quality improves [34]. The iteration of the ant was updated as follows:

$$Antliontj = Ant\text{tj if } f(Ant\text{tj}) > f(Antlion\text{tj}) \quad (4)$$

where *it* is the iteration index, and *f* denotes the fitness function.

4.4.2 Bat Inspired Algorithm (BIA)

BIA is based on bats' echolocation abilities, adjusting position, velocity, and frequency to locate global optima. The algorithm updates parameters as:

$$f = fmin + (fmax - fmin).\beta \quad (5)$$

$$v^{t+1} = v^t + (x^t - x).fi \quad (6)$$

$$x^{t+1} = x^t + v^{t+1} \quad (7)$$

where x is position, v is velocity, f is frequency, and x^t is the best global solution. BIA is known for its fast convergence and broad application in optimization tasks [35].

Both algorithms improve the efficiency of feature selection, which improves the total accuracy of classification and reduces overall complexity.

4.5 Dataset Spitting

This dataset was divided into training (70%) and testing (30%) using stratified sampling to ensure class balance between heart disease positive and heart disease negative cases. Stratified sampling was employed to deliver unbiased training, maintain proportions of representation for classes, and provide the model with improved accuracy, stability, consistency, and generalizability for clinical deployment. Table 1 shows the distribution of proposed CNN–LSTM hybrid model's dataset shown on the training and test ECG image set of four classes: myocardial infarction, history of myocardial infarction, abnormal heart beat, and normal ECGs.

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Table 1: Distribution of Heart Disease Dataset

Disease Classes	Total Samples	Training Samples (70%)	Test Samples (30%)
Normal Person ECG Images	859	601	258
ECG Images of Myocardial Infarction Patients	74	52	22
ECG Images of Patients with a History of Myocardial Infarction	203	142	61
ECG Images of Patients with Abnormal Heartbeat	546	382	164

4.6 Heart Disease Prediction Classifier

Classification is a primitive machine learning method that categorizes datasets into pre-designed classes according to input features. In heart disease prediction, classification models are critical in identifying patients with and without CVD to facilitate early detection and timely treatment. As ECG signals are very complicated and demanding representations that require models that can learn both spatial and temporal patterns, this study evaluates three types of neural network-based architectures - Long Short-Term Memory, Convolution Neural Networks, and a Hybrid CNN-LSTM Model developed so that it can make use of the advantages of each of them to ensure maximum predictive accuracy.

4.6.1 Long Short-Term Memory (LSTM)

LSTM networks are a complex version of "Recurrent Neural Networks (RNNs)" which have been designed specifically for sequential data and dealing with long term dependencies. Normal RNNs are subjected to the vanishing or exploding gradients problem whereas LSTMs apply gated methods to control data through memory cells (input, forget, output gate) [36]. The gates allow the network to intentionally remember or forget information, which is important in modelling for the temporal patterns of ECG signals as patterns evolve in the time dimension.

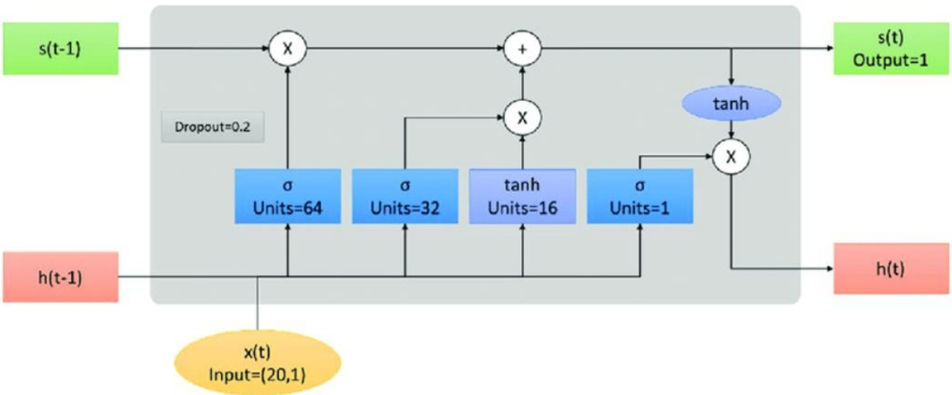

Figure 3: Block diagram of the LSTM prediction model [37]

Mathematically, the forget gate activation in an LSTM cell is defined as:

$$f_p = \propto (W[x_p, h_{p-1}, C_{p-1}] + b_p) \tag{8}$$

where x_p is the input at time step p, h_{p-1} and C_{p-1} represent the previous hidden and cell states, respectively, W andb_p are learnable weights and biases, and σ is the sigmoid activation function. LSTMs are effective in retaining essential signal characteristics over time, making them valuable for sequence-based ECG classification tasks [38].

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4.6.2 Convolutional Neural Networks (CNNs)

CNNs are a type of machine learning models that are well-suited for processing spatial data, in particular, images. They consist of several layers such as convolutional layers for feature extraction, activation layers (typically ReLU) for nonlinearities, pooling layers for dimensionality reduction, and fully connected layers for the actual decision-making process (**Figure 4**) [39, 40].

Convolution is the primary operation performed by a CNN, and it is mathematically defined as:

$$y_{i,j} = \sum_m \sum_n x_{i+m,j+n} \cdot \omega_{m,n} + b \quad (9)$$

where x represents the input image patch, w is the filter (kernel), b is the bias, and$y_{i,j}$ is the resultant feature map at position (i, j). CNNs are particularly adept at detecting local spatial patterns such as edges, textures, and specific morphological structures within ECG waveforms, making them highly effective for ECG image classification.

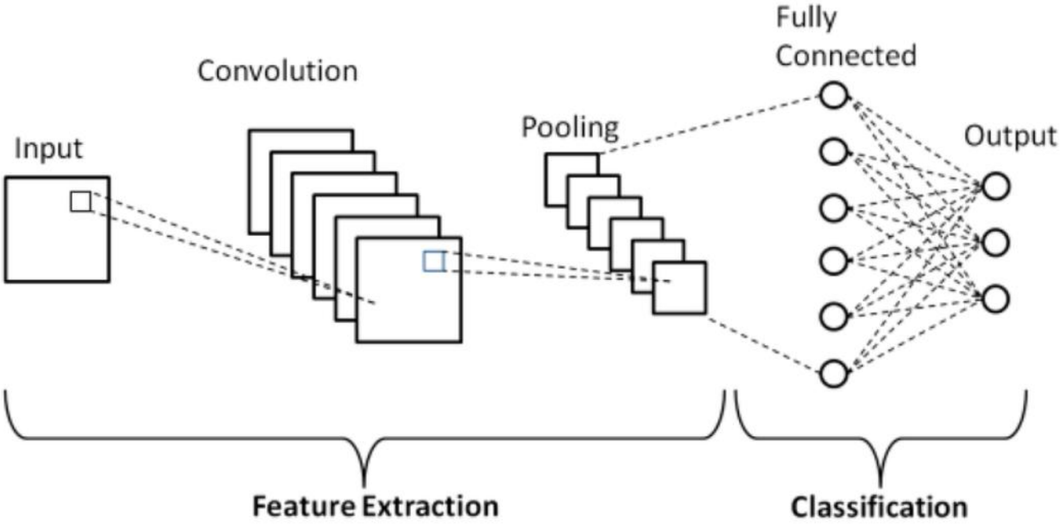

Figure 4: Schematic diagram of a basic CNN architecture [41]

4.6.3 Hybrid CNN-LSTM Model

To better take advantage of both spatial and temporal learning, a hybrid CNN-LSTM model is introduced. In this framework, CNN layers are first used to extract spatial features automatically from ECG images, highlighting key waveform patterns and structural features indicative of heart disease. The CNN-generated feature maps are reshaped into sequences and put into LSTM layers to represent the temporal relationships and dynamics of the sequences between time steps.

This combines some benefits of CNNs recognizing complicated spatial patterns from ECG images with LSTMs learning how those spatial patterns change over time, which also improves the model's ability to make accurate predictions when faced with complex diagnostic cases. Localized feature extraction with CNNs and sequential pattern recognition with LSTMs result in improved classification performance which makes this approach a strong solution for the use of computer-aided detection of heart disease.

4.7 Performance Measures

The use of a variety of evaluation metrics to evaluate the performance of the machine learning models for heart disease prediction was conducted in this research study, including the Confusion Matrix, Accuracy, Precision, Recall, F1-Score, ROC-AUC, Learning Curve, and Precision-Recall Curve.

• **Confusion Matrix**: A tabular representation of model predictions, showing "True Positives (TP)", "True Negatives (TN)", "False Positives (FP)", and "False Negatives (FN)". It is the basis for computing various performance metrics [42].

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (10)$$

$$Precision = \frac{TP}{TP+FP} \quad (11)$$

$$Recall = \frac{TP}{TP+FN} \quad (12)$$

$$F1\ Score = 2 \times \frac{Precision \times Recall}{Precision+Recall} \quad (13)$$

• **ROC Curve and AUC**: ROC plots True Positive Rate (TPR) vs. False Positive Rate (FPR), where:

$$FPR = \frac{FP}{FP+TN} \quad (14)$$

\AUC represents the classifier's ability to distinguish between classes, with values closer to 1 indicating better performance.

• **Learning Curve**: Shows the model's performance improvement as the training data size increases, helping identify under-fitting or over-fitting.

• **Precision-Recall Curve**: Plots Precision against Recall, particularly informative for datasets with class imbalance, focusing on the trade-off between FP and FN.

Results and Conclusions:

This section defines the experimental results of the proposed machine learning model "CNN-LSTM Hybrid" for predicting heart disease using ECG. The results are evaluated by plotting the training/validation accuracy, and loss curves, later using the precision, recall, F1-scores, and aggregate accuracy for each of the models, making further evaluations using data distributions, feature extraction methods, and per-class performance. The comparative evaluation shows the advantages and disadvantages of each approach along with the overall advantage of using the proposed Hybrid approach.

The "ECG Images of Myocardial Infarction Patients" class holds the largest number of samples (24012 = 2880), with "Normal Person ECG Images" taking a close second at 284×12 = 3408 images. The "ECG Images of Patients with Abnormal Heartbeat" has 233×12 = 2796 samples, while the smallest class, "Patients with a History of MI," has 172×12 = 2064 images.

In Figure 5, the learning activities of the proposed hybrid model across 22 epochs are illustrated, including the accuracy and loss plots for training and validation datasets. The hybrid model demonstrated an astonishing amount of learning performance from the early epochs, as training accuracy jumped from 50 to above 90 in just a few epochs. In addition, validation accuracy increased sharply to values above 94 and stayed above the value, confirming that the model quickly learned how to extract and interpret spatial and temporal artifacts from ECG images. The small gap between the training and validation accuracy curves indicates great generalization and stability in the model with no clear indications of overfitting and underfitting. The curves stay closely together throughout, demonstrating that the hybrid model is not only good on the training data but also on novel data. Figure 6 dipicts the confusion matrix for the proposed hybrid model under study.

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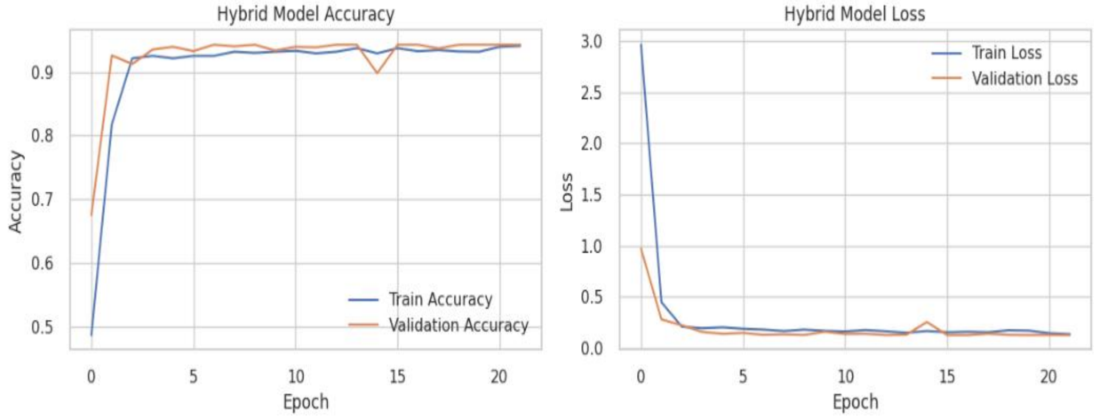

Figure 5: Training and Validation Curves of the Proposed Hybrid Model

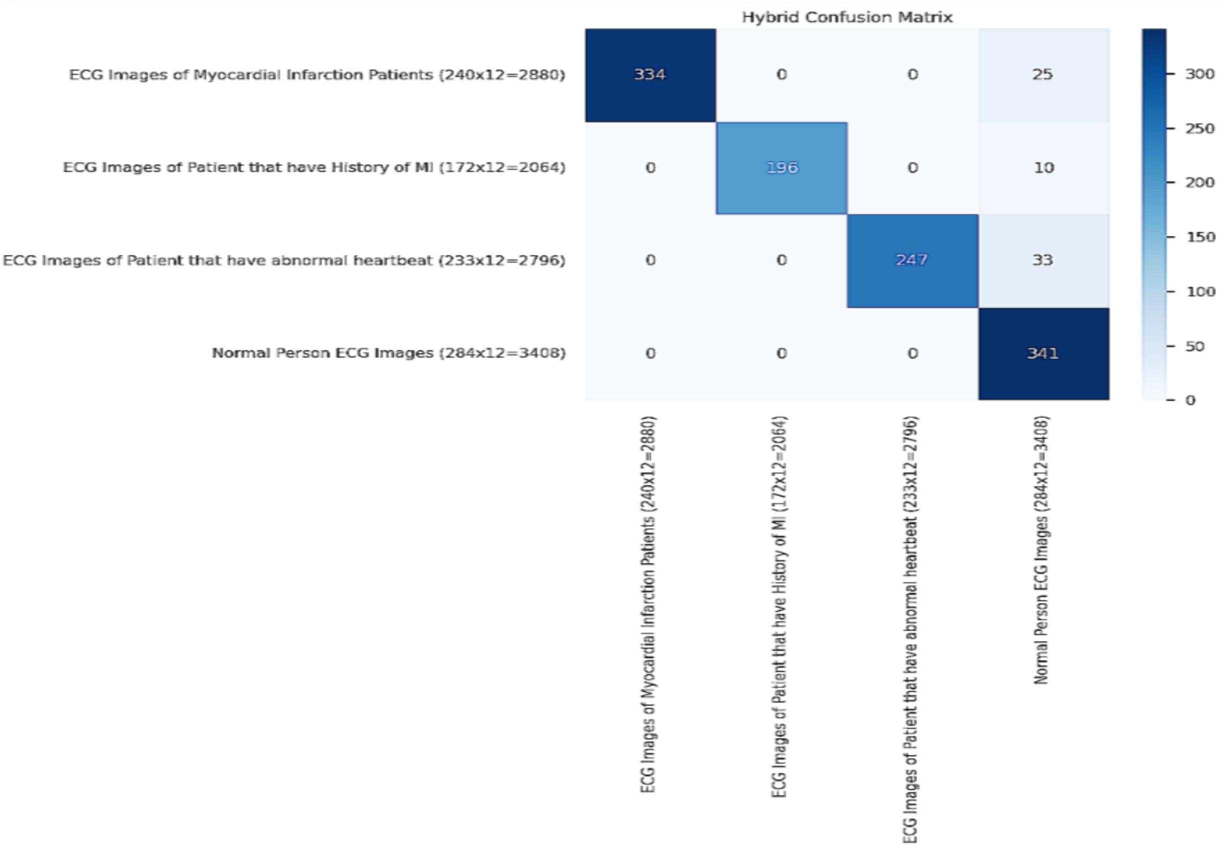

Figure 6: Hybrid Model Confusion Matrix

Table 2: Classification Report of the Hybrid Model on Test ECG Dataset

Class Label	Precision	Recall	F1-Score	Support
ECG Images of Myocardial Infarction Patients (240×12 = 2880)	1.00	0.93	0.96	359
ECG Images of Patients with a History of MI (172×12 = 2064)	1.00	0.95	0.98	206
ECG Images of Patients with Abnormal Heartbeat (233×12 = 2796)	1.00	0.88	0.94	280
Normal Person ECG Images (284×12 = 3408)	0.83	1.00	0.91	341
Overall Accuracy			0.94	1186
Macro Average	0.96	0.94	0.95	1186
Weighted Average	0.95	0.94	0.94	1186

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Table 2 shows the hybrid model's classification performance on ECG image data. The model performed with a 94% overall accuracy, manifesting robust predictive power across all four modules. Myocardial infarction and past of MI images were categorized with great accuracy and precision, recording F1-scores of 0.96 and 0.98, correspondingly. Abnormal heartbeat class also recorded outstanding performance with an “F1-score of 0.94” (Figure 7). Normal ECGs were correctly predicted with perfect recall (1.00) and high precision (0.83), suggesting minimal false positives. Macro-average and weighted-average F1-scores of 0.95 further validate consistent performance. This validates the hybrid model in identifying spatial and temporal ECG patterns, thus serving real-world heart disease prediction purposes.

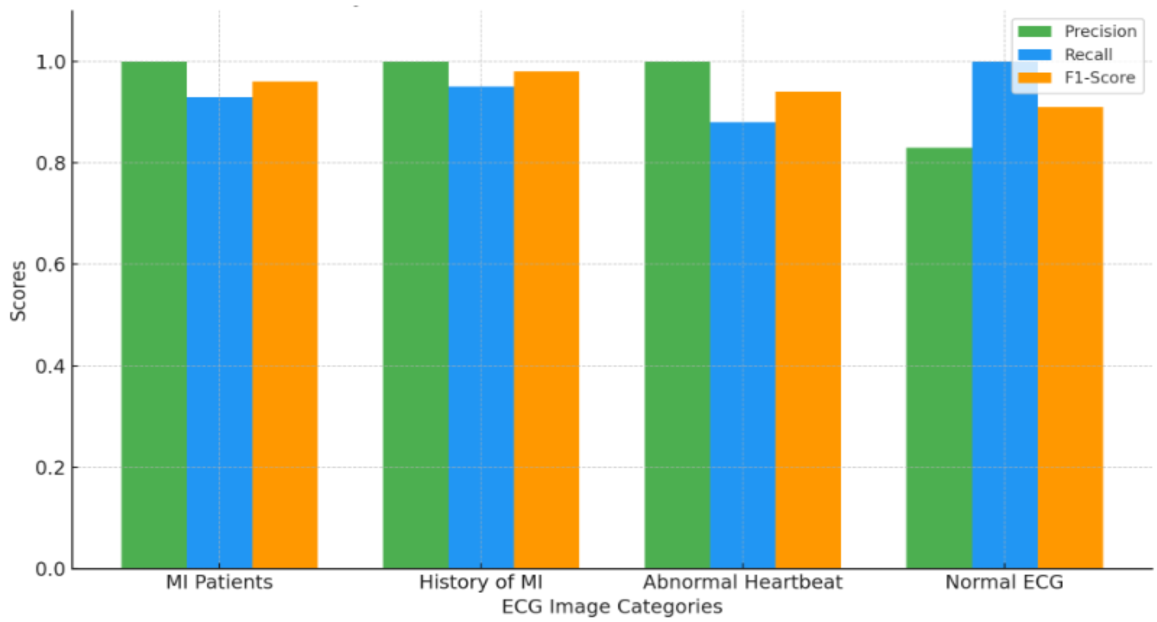

Figure 7: CNN-LSTM Model Performance Metrics for each ECG Class

Conclusions and Summary:

Cardiovascular disease ranks among the most critical global health issues, and it claims a large percentage of premature mortality every year. Early identification and prompt intervention are critical in enhancing patient prognosis and lessening healthcare systems' overall workload. Classic diagnostic approaches, although reliable, tend to be associated with invasive measures or subjective clinical evaluations, which may not always be timely or predictive in nature. This research introduced and effectively applied a new machine learning-based model for prediction of heart disease based on ECG image data. Identifying the worldwide prevalence of cardiovascular disease and the drawbacks of conventional diagnostic methods, this work aimed to construct an automated, precise, and scalable diagnostic system that takes advantage of the capabilities of image-based deep learning methods. The suggested methodology drew its inspiration from a holistic pipeline with several stages, from extensive image enhancement and smart feature extraction to a hybrid deep model using “Convolutional Neural Networks (CNN)” and “Long Short-Term Memory (LSTM)” networks. These features collaborated to provide both spatial and temporal features of ECG images, allowing the model to efficiently identify intricate patterns and anomalies related to heart disease like myocardial infarction and arrhythmias. Use of meta-heuristic optimization algorithms such as “Ant Lion Optimization (ALO)” and “Bat Inspired Algorithm (BIA)” further improved the feature set for increased computational efficiency without any loss in prediction accuracy.

The hybrid model showed high generalization performance across different patient classes, as verified by stable performance in stratified cross-validation. Additionally, the application of wavelet-transformed inputs and class probability visualizations infused robustness and interpretability into the outcomes, strengthening the model's clinical usefulness. In summary, the proposed framework provides an effective and non-invasive diagnostic device for the detection of early heart disease, revealing great promise for application in real-time clinical decision-support systems.

It not only minimizes the necessity for cardiologists to manually interpret ECGs but also makes cardiac diagnosis more accessible, particularly to developing regions. Future research can address real-time deployment, integration with multi-modal data, and additional validation on more comprehensive and diversified datasets to increase the system's reliability and scope.

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