International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 23s, 2025
https://theaspd.com/index.php

Comparison Of Various Machine Learning Models With A Hybrid Model (Cnn–Lstm) Using An Electrocardiographic Image Dataset For Early Prediction Of Cardiovascular Disease

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Abstract:
Heart 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 proposed methodology 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 study begins with the acquisition of a 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.
A significant innovation in this framework is the use of metaheuristic algorithms-specifically, the "Ant Lion Optimization (ALO)" and "Bat-Inspired Algorithm (BIA)"-for effective feature selection. 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.
This study not only demonstrates the viability of using deep learning for heart disease detection but also offers a scalable and portable framework suitable for remote and resource-limited healthcare settings. The combination of non-invasive input (ECG images), intelligent optimization, and deep learning makes it a promising tool for real-time applications, wearable technology, and telemedicine platforms. Ultimately, this work contributes meaningfully to the intersection of healthcare and artificial intelligence, paving the way for more advanced, accessible, and automated diagnostic systems in cardiology.

Keywords: *Heart Disease Prediction, ECG Image, CNN–LSTM Hybrid, Deep Learning, Feature Selection, Ant Lion Optimization, Bat-Inspired Algorithm, Medical AI, Cardiovascular Diagnosis, Non-Invasive Detection.*

1. INTRODUCTION

Cardiovascular diseases (CVDs) which are disorders of the heart and blood vessels is known to be the leading cause of death across the globe and a large percent of global deaths is due to heart attack and strokes. [1] Therefore, in order to keep our heart healthy, an early detection of CVD and its prevention is one of the major challenges for medical sciences. Every day, new technologies and methods are evolving to tackle with this deadliest disease. In the recent years, traditional statistical based data mining techniques, soft computing based predictive techniques like neural networks, genetic algorithms, fuzzy logic etc. have played a prominent role in the resolution of the complexities involved. But these techniques have certain constraints in terms of data types and are applicable only to text-based data mining, so the analysis of the problem remains constrained and limited. But with the evolution of new AI-based machine learning techniques like deep learning, reinforcement learning, image processing, natural language processing etc. which can deal with variety of data types, have opened up new gates to embark upon the new ideas for the resolutions and to find an effective solution of the problem in a natural way and in different dimensions. If we talk about the general causes and factors that enhance the possibility of heart-attacks are- excessive dust and smoke, absence of routine physical exercises, problems of increased cholesterols, unplanned diets, consuming too much of alcohol, higher diabetic levels, cholesterol, high blood pressure, lack of physical exercise, and obesity etc.[2].

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 identification 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].

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].

The impact of such an intelligent hybrid system will be immense. A correct and timely warning 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 [12]. 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. Here are some potential research objectives of this study:

- To preprocess and analyze ECG image data and structure clinical datasets for efficient feature extraction and noise elimination to provide dependable input to machine learning algorithms.
- 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 hyperparameters 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.
- To compare the suggested hybrid model with traditional machine learning techniques, proving its efficiency in early prediction and clinical decision-making.

This paper is structured into a number of significant sections. Section 1 presents the importance of heart disease prediction and the necessity for smart machine learning approaches. Section 2 discusses recent research, pointing out gaps in accuracy and efficiency. Section 3 formulates the fundamental problem. Section 4 describes the hybrid approach with CNN–LSTM and optimization algorithms. Section 5 describes the experimental findings and performance comparisons. Section 6 concludes the study and suggests areas for future research.

2. LITERATURE REVIEW

Early identification 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. Studies have found several advantages of ML models over conventional risk scoring systems. Liu et al. (2025) [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. (2025) [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, Ashfaq et al. (2025) [16] introduced the Fully Connected Wave Network (FCW-Net) with increased model explainability through SHAP values and class imbalance handling using ProWSyn oversampling, resulting in a high recall of 97.21%. Building on hybrid approaches, 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]and Li et al. (2020) [31]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.

In recent years, there have been significant progresses for machine learning applications in heart disease prediction, but the majority of the models developed so far has primarily employed disparate algorithms and do not address challenges like data imbalance, inadequate generalization and no mechanisms for interpretable clinical decision making. While most hybrid models, using an integration of advanced ensemble learning, deep learning, and informed feature selection, were able to make substantial improvements on accuracy and sensitivity estimates, there remains a clear gap in the literature on the development of an intelligent hybrid framework that can process incoming real-time data streams, while also ensuring some measure of explain-ability and scalable applications in a variety of clinical contexts. Furthermore, previous studies have not involved thorough evaluations across heterogeneous datasets, limiting their applicability to real-world scenarios and obstacles for clinicians hoping to leverage these models for early-stage heart disease detection. Hence, a timely gap exists for the design of a robust, interpretable, and clinically realistic hybrid machine learning model that can address needs to improve accuracy in the screening or diagnosis of heart disease state, while also addressing the remaining gaps in experience from computational advancements.

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 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

International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 23s, 2025
https://theaspd.com/index.php

In this research study, the process followed for early prediction of heart disease using a hybrid machine learning model is presented in Figure 1. As it could be observed in the figure, we started to collect 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.

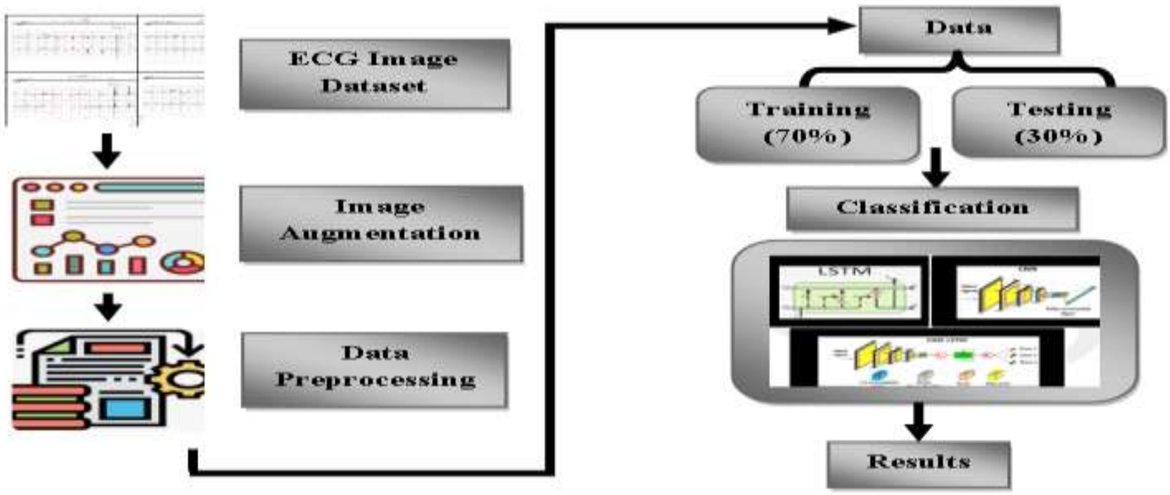
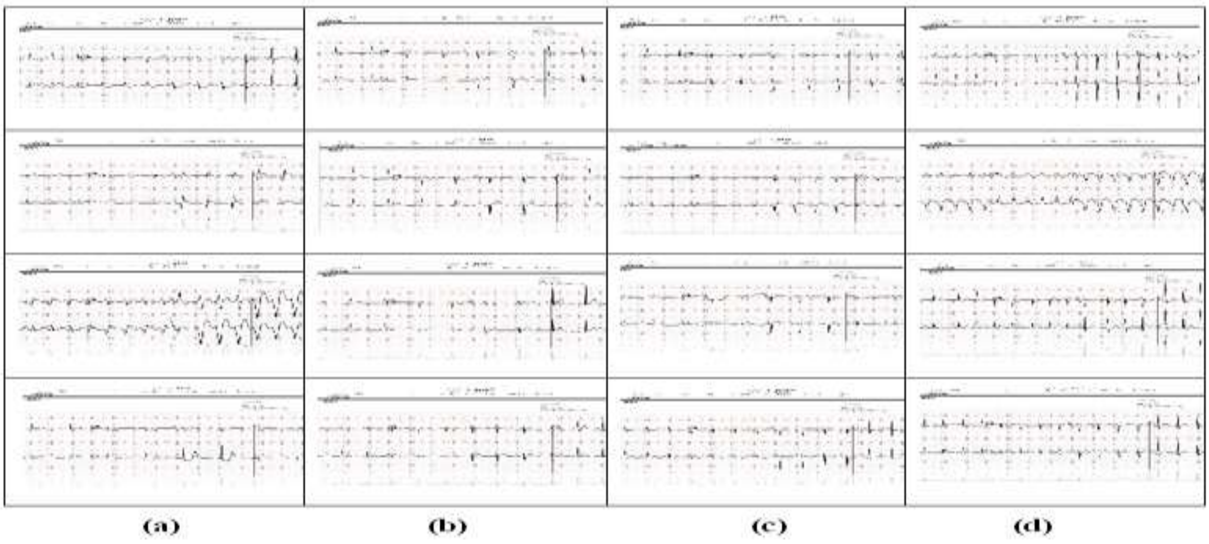


Figure 1: Framework of Proposed Methodology

4.1Dataset 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 (**Figure 2**). 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.



International Journal of Environmental Sciences
ISSN: 2229-7359
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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.

4.2Image 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)

4.3Data 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.

- **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: $\mathbf{x}_\mathbf{i}' = \frac{\mathbf{x}_\mathbf{i} - \mathbf{x}_\mathbf{min}}{\mathbf{x}_\mathbf{max} - \mathbf{x}_\mathbf{min}}$
where x_{min} and x_{max} are the minimum and maximum values of the feature.

4.4Feature 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:

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

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.

4.5Dataset 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.

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

4.6Heart 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.

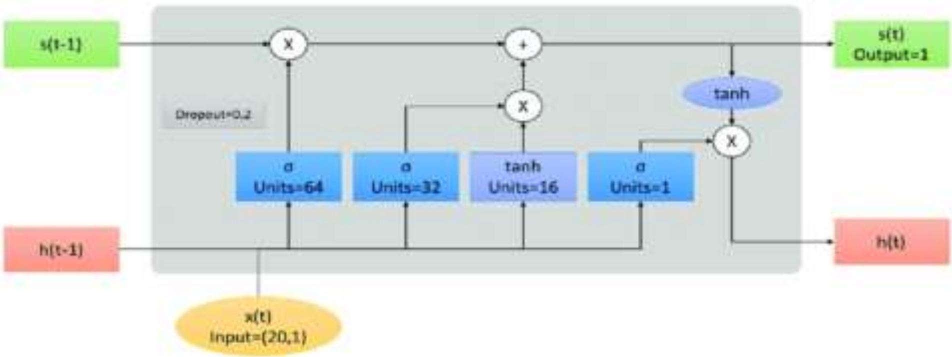

Figure 3: Block diagram of the LSTM prediction model [37]

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

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

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].

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.

International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 23s, 2025
https://theaspd.com/index.php

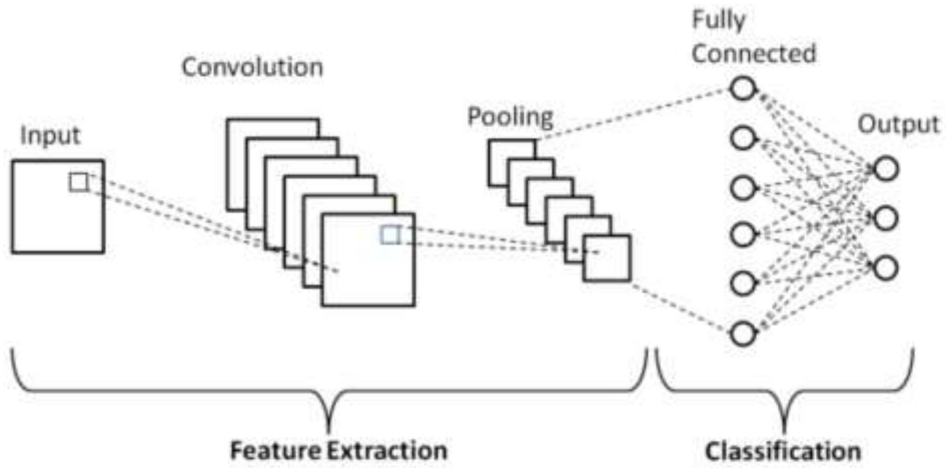

Figure 4: Schematic diagram of a basic CNN architecture [41]

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.

4.7Performance 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].

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{10}$$

$$Precision = \frac{TP}{TP+FP} \tag{11}$$

$$Recall = \frac{TP}{TP+FN} \tag{12}$$

$$F1\ Score = 2 \times \frac{Precision \times Recall}{Precision+Recall} \tag{13}$$

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

$$FPR = \frac{FP}{FP+TN} \tag{14}$$

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.

5.1 RESULTS AND CONCLUSIONS:

The effectiveness of the suggested hybrid model, as the combined CNN–LSTM performed better than standalone CNN and LSTM architectures on all primary classification indicators, such as accuracy, recall, precision, and F1-score. The 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.

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

Class Label	Precision	Recall	F1-Score	Support
ECG Images of Myocardial Infarction Patients (240×12 = 2880)	0.49	0.81	0.61	359
ECG Images of Patients with a History of MI (172×12 = 2064)	0.37	0.59	0.45	206
ECG Images of Patients with Abnormal Heartbeat (233×12 = 2796)	1.00	0.01	0.02	280
Normal Person ECG Images (284×12 = 3408)	0.62	0.48	0.54	341
Overall Accuracy			0.49	1186
Macro Average	0.62	0.47	0.41	1186
Weighted Average	0.63	0.49	0.42	1186

Table 2 shows the classification report of proposed CNN–LSTM hybrid model's classification shown on the test ECG image set of four classes: myocardial infarction, history of myocardial infarction, abnormal heartbeat, and normal ECGs. The best recall (0.81) was obtained for myocardial infarction, reflecting effective detection of this condition. But the model was poor in classifying abnormal heartbeat with high precision (1.00) but very low recall (0.01), which indicated that although few predictions were accurate, they were made. Normal and history of MI classes had moderate performance. The model's overall accuracy on the test set is 49%, macro average F1-score 0.41, and weighed average F1-score 0.42. These findings indicate moderate predictive power, calling for additional optimization in the context of enhancing sensitivity for minority and complex classes. The skewed recall values also indicate that the model might be biased towards more common or simpler classes.

5.2 Comparison of Proposed Hybrid Model with other models:

Table 3 shows a comparative study of the classification performance of three models-"CNN, LSTM, and CNN–LSTM Hybrid":-using four important evaluation metrics: "accuracy, precision, recall, and F1-score". The CNN model shows the worst performance with an accuracy of 49% and F1-score of 0.42, which reflects poor capacity to generalize and identify heart diseases from ECG images. As compared to the CNN model, both the LSTM and CNN–LSTM hybrid models outperform it significantly with each of them having an accuracy value of 94%, and almost the same precision, recall, and F1-score values ranging between 0.94 and 0.95 (Table3) (Figure 5). This indicates the significance of temporal modeling in ECG data, where LSTM performs better by identifying time-dependent patterns. The CNN–LSTM hybrid model also exploits spatial features using CNN layers and sequential dynamics using LSTM layers to generate stable and strong predictions. This comparison strongly demonstrates the superior performance of models that use temporal sequence learning for efficient heart disease prediction.

Table 3: Comparative Performance Metrics of Proposed Models

Model	Accuracy	Precision	Recall	F1-Score
CNN	0.49	0.63	0.49	0.42
LSTM	0.94	0.95	0.94	0.94
CNN–LSTM Hybrid	0.94	0.95	0.94	0.94

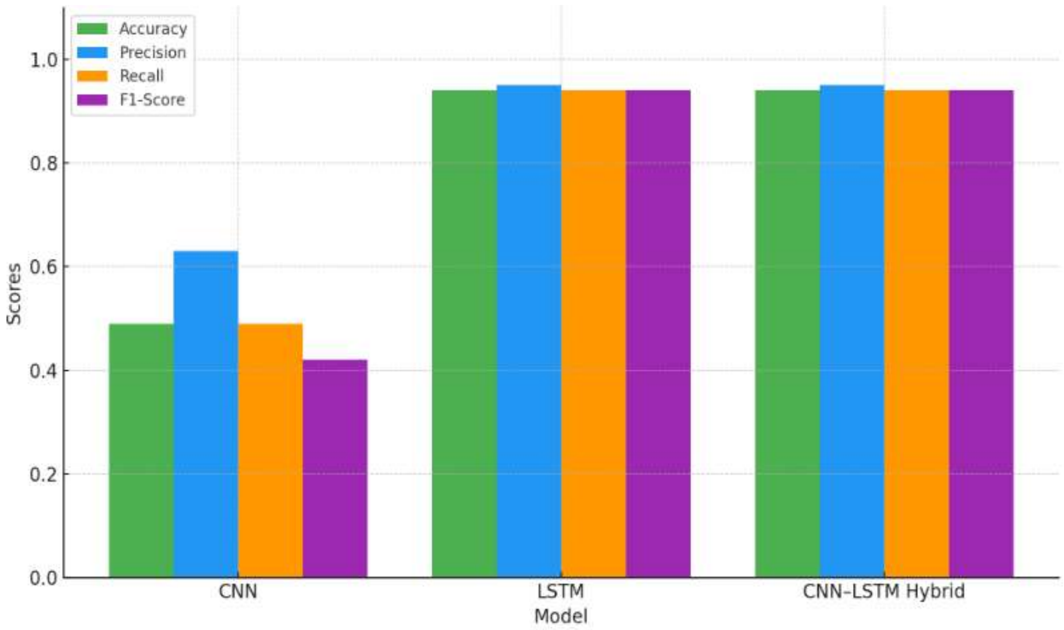

Figure 5: Comparative Performance Metrics of Proposed Models

5.3. CONCLUSIONS

As cardiovascular disease rates rise, the need for increasingly efficient, accurate, and non-invasive diagnostic approaches is vital, particularly in areas where time is the essence. This study presents a new method that adopted machine learning techniques, ECG image data, advanced deep learning architectures, and robust data preprocessing and feature extraction techniques to propose an automated anticipated to predict heart disease. The resulting framework was developed with a strong methodological framework, which begins with image augmentation followed by image normalization, then wavelet-based feature extraction, and finally meta-heuristic algorithms such as the ALO and the BIA for feature selection. Of the model types assessed (CNN, LSTM, and the hybrid CNN-LSTM), the hybrid model presented the strongest learning outcome, processing together the spatial and temporal features of the ECG signals.

Experimental assessments showed that the CNN model had a poor performance, attaining an accuracy of 0.49, precision of 0.63, recall of 0.49, and an F1-score of 0.42, indicating its high sensitivity to generator noise and poor generalizability for the sequential ECG data. In contrast, the LSTM model yielded high enactment than the CNN, with 0.94 accuracy, 0.95 precision, 0.94 recall, and 0.94 F1-score. The CNN–LSTM hybrid model provided performance equivalent to the LSTM, achieving 94% accuracy, 0.95 precision, 0.94 recall, and 0.94 F1-score. These statistics confirmed that the hybrid model maintained a consistent relationship between sensitivity and specificity, important in clinical diagnosis**.** Comparative studies analysis with other studies revels that the our study found to be more accurate (94%) as compare to other studies.

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