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Article

OptiDeepNet: Optimized Deep Network for Efficient Prediction of Heart Disease

D. Deva Hema[1], S. Abirami[2], Mohana Priya P.[3], Srikrithi Santhanam[4], Srinithi Santhanam[5]

[1]SRM Institute of Science and Technology, Ramapuram, Chennai, Tamil Nadu, India.
ORCID: 0000-0002-8211-8453
[2]Department of Computer Science and Engineering, SRM Institute of Science and Technology, Ramapuram, Chennai, Tamil Nadu, India.
ORCID: 0000-0001-9602-2973
[3]Department of Computer Science and Engineering, Vels Institute of Science, Technology and Advanced Studies (VISTAS), Pallavaram, Chennai, Tamil Nadu, India.
[4] HP Inc., Bengaluru, Karnataka, India.
ORCID: 0009-0005-8542-7373
[5] HP Inc., Bengaluru, Karnataka, India.
ORCID: 0009-0001-9572-6781
Corresponding Author: D. Deva Hema

Abstract: The accurate Coronary Heart Disease (CHD) prediction is challenging due to the variety of risk factors and the high diagnostic costs. Several deep learning models have been developed to predict the CHD efficiently. However, the crucial influence of choosing optimal hyper parameters of deep learning model makes it difficult to predict CHD with any degree of accuracy. To address this challenge, this study introduces OptiDeepNet (Optimized Deep Network for Efficient Prediction of Heart Disease), an optimized deep network for efficient prediction of heart disease that integrates Random Forest for feature selection and Enhanced Long Short-Term Memory (ELSTM) for CHD prediction, thereby improving the predictive performance of the system. Specifically, feature selection is conducted using a Random Forest classifier to identify the most informative characteristics features which are significant for predicting CHD. Furthermore, the ELSTM model was proposed where the hyper parameters are optimized utilizing Advanced Cuckoo Search, a meta heuristic optimization algorithm. This optimization step aims to maximize the performance of a model to learn intricate temporal relationships in the Cleveland Heart Disease dataset, thereby enriching the model's overall performance. Extensive experimentation shows that OptiDeepNet achieves a predictive accuracy of 98.3%, providing a promising tool for reliable cardiovascular diagnostics.

Keywords: Optideepnet , LSTM, CHD, Advanced Cuckoo Search

1. Introduction

Cardiovascular diseases are continuously the leading cause of mortality in the world that kills around 17.9 million people each year, which is equal to 31% of the total. An early and accurate diagnosis of CHD is a very important factor for reducing the number of deaths. Conventional medical practice visually assesses the factors including bloodstream thickness, level, and family history for the diagnosis of CHD. Even though these approaches offer critical information, they often miss combinations of risk factors that are not simple and linear which results in imprecise diagnostic accuracy.

Long Short-Term Memory (LSTM) networks have been gaining prominence as a strong solution for analyzing sequential data since it is able to have memory for longer periods of time thus eventually capturing temporal dependencies over long sequences. Thus, they are very effective where the history of a patient, such as ECG readings, arterial blood pressure variations, and other time-dependent variables are the main indicators of heart health. In spite of being considered very good, LSTM models can require a lot of computer power and also can be overfitted, especially when they are trained on very few data or with non-optimized hyper-parameters. According to projections, there will be a significant rise in CHD cases by 2030 [1], which highlights the need for efficient predictive models. Numerous studies[2][3][4][5][6] have examined congestive heart failure and important risk factors such diabetes, hypertension, and smoking. Notably, systolic blood pressure and body mass index (BMI) are important variables that impact hypertension. Other correlations involving age, sex, BMI, heart rate, and hypertension have also been discovered.

Studies that apply statistical and machine learning models [7–9] to medical data, such as electrocardiography signals and echocardiography images, aim to predict critical parameters such as heart rate and axis deviation. Machine learning [10] is a process by which your system continuously enhances its abilities and decision-making capabilities by learning from events and experiences. The Random Forest Classifier is a famous machine learning technique because it can identify intricate relationships in high-dimensional datasets. When compared to conventional machine learning methods, deep learning offers numerous benefits. These advantages include the ability to handle large amounts of complex data, automatically learn features, perform better, handle non-linear correlations, and handle both structured and unstructured data. Convolutional Neural Networks (CNNs) are the epitome of deep learning [11] [12], and they are particularly renowned for their ability to interpret images and identify intricate patterns.

Several deep learning models[13, 14] have been developed to predict the CHD efficiently. However, the crucial influence of choosing optimal hyper parameters of deep learning model makes it difficult to predict CHD with any degree of accuracy. To address this challenge, this study introduces OptiDeepNet, an optimized deep network for efficient prediction of heart disease that integrates Random Forest for feature selection and Enhanced Long Short-Term Memory (ELSTM) with optimized hyper parameters for CHD prediction, thereby improving the predictive performance of the system.

Section 2 describes existing techniques for efficient heart disease prediction. Section 3 presents a detailed description of OptiDeepNet. Section 4 presents thorough analysis and discussion of the results. Section 5 concludes with future enhancements.

2. Literature Survey

To improve CHD prediction and healthcare assistance, a revolutionary approach known as Health Care Big Data Analytics (HCBDA)[15] was unveiled. Using Internet of Things and wireless sensor networks devices, the model keeps an eye on patient's cardiac and anatomical conditions. It accesses, analyzes, and forecasts diseases using the vast amounts of data stored on a data server. Compared with existing approaches, the HCBDA model has higher sickness prediction accuracy of up to 96%. The proposed method generates intelligence and offers medical assistance by utilizing efficient machine learning models and classification techniques.

A brand-new Health Care Big Data Analytics (HCBDA)[16] model that leverages IoT devices and wireless sensor networks to enhance patient healthcare was proposed. The model tracks the bio signals of patients and makes highly accurate disease predictions. The suggested method outperforms current ones, obtaining up to 96% accuracy in disease prediction. A stacked ensemble classifier technique to heart disease prediction[17] was proposed. The authors performed data analysis and preprocessing, including outlier removal, on the data that was gathered from the IEEE Data Port. Training and testing data were separated out of the dataset. Machine learning techniques including ExtraTrees Classifier, Random Forest, and XGBoost are used in the framework. With an accuracy of 92.34%, the findings show that the recommended framework outperforms earlier studies. This framework is contrasted with alternative machine learning models. The authors draw the conclusion that early detection and prediction of cardiovascular illnesses can benefit from their paradigm.

Using data mining techniques [18] to increase patients' chances of survival for heart failure patients is the aim of this research. This study analyzes a dataset of 299 patients using nine classification algorithms to estimate patient survival. It tackles about the imbalance class problem using the Synthetic Minority Oversampling Technique (SMOTE). The results show that tree-based algorithms outperform other models and have a high percentage of accuracy in predicting patient survival.

A Convolutional Neural Network (CNN) [19] architecture was employed to enrich the prediction accuracy of CHD. This study takes into account laboratory data, risk factor variables, and demographic data using data from the NHANES dataset. The CNN design is characterized with convolution layers placed between two fully linked layers. Promising outcomes are seen in the precise classification of people with and without CHD by the given architecture. Additionally, it addresses the drawbacks of misclassification in medical research and suggests using deep networks as a solution. It was shown that a Convolutional Neural Network (CNN) [20] could accurately predict CHD. The study uses the 1999–2016 NHANES dataset, which includes survey, medical, laboratory, and demographic data for 37,079 individuals. The authors come to the conclusion that cardiovascular disorders can be better predicted and diagnosed at early stage.

A decision support system that is hybrid in nature[21] was created to aid in the prompt detection of cardiac disorders. By utilizing clinical signs and machine learning techniques, the device may be able to accurately diagnose cardiac issues. To construct the system, the authors incorporate phases of data gathering, preprocessing, and model building. To increase system efficiency, they use strategies including feature selection, multivariate imputation, and class balance. Using the Random Forest classifier, the method obtains a high accuracy of 86.60% when evaluated on the Cleveland Heart Disease dataset.

A deep neural heart disease prediction model [22] was developed for the detection of cardiac disorders. The algorithm makes accurate predictions about the existence or non-existence of the disease by analyzing numerous characteristics using clinical data. This study has made using Cleveland Coronary Disease dataset, which had 14 features and 303 individuals. Using the train-test hold-out strategy, 20% of the data was reserved for testing and the remaining 80% for training. The goal of developing deep neural network models [23] was to increase heart attack prediction efficacy and accuracy. Numerous classification methods, including random forest, logistic regression, K-NN, SVM, Nave Bayes, and hyper-parameter optimization, are contrasted. The results show that hyper-parameter optimization with Talos provides the best accuracy for the heart disease dataset.

Patients with Heart Failure (HF) [24] can now reliably forecast their risk of death with a novel instrument called MARKER-HF. This program evaluates patient data using a machine learning algorithm to pinpoint eight critical characteristics that are highly correlated with the risk of dying. Diastolic blood pressure, albumin, creatinine, hematocrit, platelets, white and red blood cell distribution are some of these characteristics. The risk score produced by MARKER-HF achieves a remarkable area under the curve of 0.87, indicating strong performance in both the training and validation cohorts. Six algorithms were[25] used to predict heart disease: AdaBoost Classifier, Random Forest, K-Nearest Neighbor, gradient boosting, Naïve Bayes and logistic regression. AdaBoost outperformed other models with 90% accuracy on the IEEE dataset, while logistic regression yielded an accuracy rate of 90.26% on the Cleveland dataset. All six algorithms together into a voting ensemble classifier produced results that were 93.46% and 95% accurate for the Cleveland and IEEE Data port datasets, respectively.

A novel technique called Cluster-based Bi-directional Long Short-Term Memory (C-BiLSTM) [26] was used to boost the accuracy of cardiac disease prediction systems. For experimental analysis, the UCI and real-time heart disease datasets are utilized. The C-BiLSTM method is then applied to the prediction of cardiac illness. In terms of better heart disease prediction, the outcome suggests that C-BiLSTM outperforms six conventional approaches with an accuracy of 94.78% and 92.84% on the UCI dataset and the real-time dataset respectively.

A technique for diagnosing CVD that combines a deep learning model (CNN-BILSTM) [27] with Recursive Feature Elimination (RFE) was proposed. It shows that the method has superior predictive efficacy by comparing it to other machine learning classifiers currently in use. The accuracy of the proposed approach is further validated through external verification using additional datasets. 94.51% accuracy was reached in the experimental results of this hybrid deep learning technique, which is in contrast to previous studies of the same kind.

Neural Network with Particle Swarm Optimization [28] was developed for efficient prediction of CHD. It addresses missing data and balances data using cost function. Result shows that it outperforms the existing models. Deva Hema et al., [29] developed InelliDeepNet that uses Improved Extra Tree Classifier (IETC) method for efficient feature selection and CNN with BiLSTM for CHD prediction. IntellideepNet has a superior accuracy rate of 97.67%, comparing to some of the existing CHD prediction systems detailed in the literature.The contribution of proposed model is given below.

1. The OptiDeepNet model is proposed for efficient heart disease prediction that integrates Random Forest and Enhanced Long Short-Term Memory.
2. A Random Forest classifier is used for feature selection in order to find the most informative features that are pertinent to the prediction of CHD.
3. To increase the effectiveness of the CHD prediction system ELSTM model was developed by optimizing the tunable parameters of LSTM model with an Advanced Cuckoo Search Algorithm.

4. The OptiDeepNet model is assessed and contrasted with other models using the CHD dataset. The outcomes show that it has a higher ability to predict heart disease.

3. Methodology

The OptiDeepNet framework is provided in the Fig. 1. Feature selection is performed using Random Forest classifier. An Enhanced LSTM model is suggested for CHD prediction for boosting the accuracy of the heart disease prediction system. The LSTM hyper parameters in this model are optimized using Advanced Cuckoo Search.

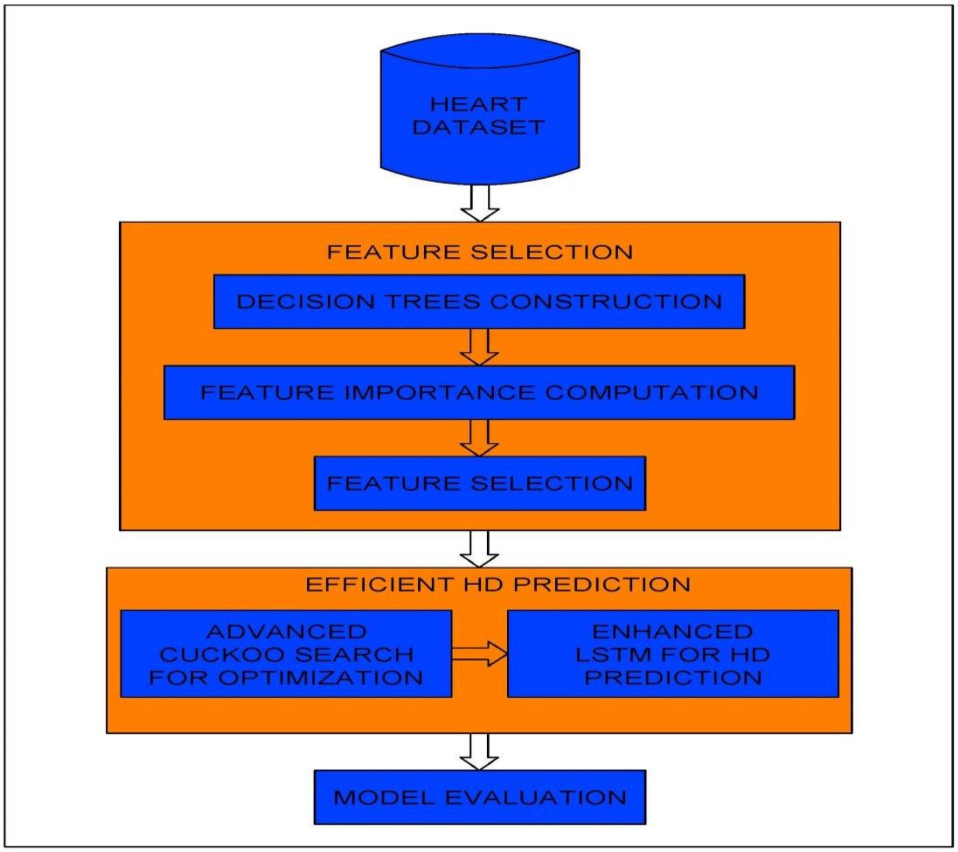

Fig. 1 OptiDeepNet Framework

3.1 The CHD dataset

The Cleveland Heart Disease dataset, which comes from the UCI Machine Learning Repository, is one of the most widely used datasets for cardiovascular health predictive modeling. It encompasses a broad spectrum of clinical and demographic traits that are critical for predicting the heart disease. This dataset contains vital data such as age, gender, type of chest pain, serum cholesterol levels, resting blood pressure, fasting blood sugar, and resting electrocardiogram (ECG) measurements. The ECG-related features in this dataset are derived metrics rather than raw ECG signal data. They represent key indicators extracted from the ECG readings, which are crucial in diagnosing heart health. These features provide important insights into the electrical activity of the heart and its response to stress, aiding in the prediction of CHD. Additionally, it offers details on the maximum heart rate that can be attained while exercising, whether exercise can cause angina, whether exercise causes ST depression, and the degree of severity of the peak activity ST segment.

Notable characteristics also include the kind of thalassemia, which can be classified as normal, fixed defect, or reversible defect, and the number of major vessels that show fluoroscopic coloration, which suggests possible blockages or abnormalities. One "target" variable in the labeled dataset indicates whether cardiac disease is present (1) or absent (0). By using this dataset, medical researchers and practitioners want to improve healthcare research and medical diagnostics by creating machine learning models that support the early detection and evaluation of cardiovascular diseases.

3.2Feature Selection

The method used for feature selection is Random Forest. By dividing the training samples into ever purer subgroups, a decision tree is progressively generated recursively. The samples within a node are divided into multiple subsets (child nodes) at each recursive step, according to the feature that may reduce the impurity of the child nodes. When the node reaches a certain purity or impurity level, the splitting process will end, and the node will be given a class label. An ensemble of decision trees is called a Random Forest (RF) [25]. Due to its excellent generalization and stability, radiofrequency (RF) has several uses [26–28]. Algorithm 1 contains the Random Forest algorithm. The following steps make up the standard RF building process. Initially, the training dataset is subjected to bagging [29] in order to generate several subsets (with variations). A decision tree is then built using each subset. Each node's splitting during tree growth is determined by the feature that is picked from a pool of candidates that are chosen at random from all of the features. All trees grow naturally and serve as base classifiers when left unpruned. These tree classifiers are all incorporated at the end. When cultivating a random forest, there are two key random features. Whereas the other generates the node splitting candidates at random, the first one uses random sampling.

The fact that RF produces a crucial factor of feature importance, commonly referred to as the Gini Importance (IG) of features, is another noteworthy characteristic of RF [32].

$$I_G(\theta) = \sum_T \sum_\tau \Delta i_\theta \,(\tau, T) \tag{1}$$

When calculating the Gini significance, a certain attribute represented by θ is used. The reduction in Gini impurity is represented by Δi_θ (τ, T) at each node τ in the binary tree T. This decrease indicates the frequency with which a certain characteristic is selected for a split, providing information about the features relative importance.

Algorithm 1 Random Forest

```
Inputs: Features
Step 1: At each node of the tree, choose m variables at random from a set of M input variables to find the result.
Step 2: Choose n instances across all N training examples available to make a bootstrap sample from the training set. The accuracy of the tree is estimated by predicting the classes using the remaining instances.
Step 3. Compute the optimal split with respect to the given m variables.
Step 4. Develop all the trees and unprune the same .
Step 5. To make a forecast, a new sample is pushed down the tree. When it reaches the terminal node, it is given the label of the training sample.
Step 6. Repeat steps 1 through 5 for each tree in the ensemble that is being evaluated.
Step 7: Determine the average vote of each tree that is used to make predictions using a random forest.
Results: Selected Elements
```

3.3 Efficient HD Prediction System

The LSTM's hyper parameters are adjusted using Advanced Cuckoo Search to enhance the heart disease prediction system's functionality.

3.3.1 The Basic Cuckoo Search Algorithm

Cuckoo bird’s reproductive habits [30] serve as an inspiration for the cuckoo search algorithm. The idea behind Clockwork Oranges algorithms[31, 32] is to link possible solutions to them. Similar to how cuckoos lay their fertilized eggs in other cuckoos’ nests, the algorithm trades and evaluate potential solutions between different nests. The CS algorithm is discussed based on three ideal needs to fully understand the cuckoo's behavior. (1) Cuckoo eggs are laid in the ideal nest for them: (2) Preserve the best bird nest once the optimum solution has been established: (3) The population size is regulated by a predefined number of nests, which we create in accordance with the algorithm's specifications. The probability of discovery (p_a) is the likelihood of a foreign bird being discovered by a nest bird. It has a value between 0 and 1. When the principal bird of the nest finds a cuckoo egg, the cuckoo deems the nest's position to really be invalid. In CS, the p_a parameter controls the balance of global and local searches. The global searching is represented as given below:

$$X_i^{n+1} = X_i^{n} + \alpha * Levy(\lambda) \tag{2}$$

where X_i^n denotes the position of the ith bird's nest at the iteration ‘n’ where i=1,2,3….. d, X_i^{n+1} describes the position of ith nest of birds in (n+1)th iteration, α is scaling factor which is set as 1 and λ is set as 1.5 (Yang and Suash Deb 2009). The Lévy distribution function is represented by Levy(). The Lévy distribution is used to compute step lengths in Lévy flights, which are random walks. The Lévy distribution is used to calculate step lengths. Lévy flights are still more effective than conventional random walks in researching large size search areas. Several academics utilize Lévy flying to emulate bird flight because the Lévy flight function mimics a bird flight path (Viswanathan et al., 1996). $Levy(\lambda)$ is represented as given below:

$$Levy(\lambda) = \left| \frac{\Gamma(1+\lambda) \times \sin(\pi\lambda/2)}{\Gamma[(1+\lambda)/2] \times \lambda \times 2^{(\lambda-1)/2}} \right|^{1/\lambda} \tag{3}$$

Γ denotes the gamma function. A few nests would be discarded following the Lévy flight due to the probability of discovery, pa. The location of the discarded nest would be changed as represented below (local searching):

$$X_i^n = X_i^n + rand(X_i^n - X_j^n) \tag{4}$$

Where rand is scaling factor and is between [0,1], X_i^n and X_j^n are two solutions chosen at random during the nth generation. The CS algorithm steps are described as given below:

Step 1: Build a new population at random and then evaluate each individual's fitness depending on evaluation criteria.

Step 2: Generate all of the individuals based on Lévy flight equation as given in Eqn.2.

Step 3: Random walks are utilized to produce new nests, as shown in Eqn.3, after discarding a part of the nest based on the probability of discovery.

Step 4: Examine whether the maximum number of iterations has been reached. If needed, return to step 2; otherwise, output would be global optimum.

3.3.2 Advanced CS Algorithm

The Advanced Cuckoo Search (ACS) concept includes the CS and the Circle map for chaos. Chaos[33–35] is used to achieve quicker searches. The conventional cuckoo search algorithm's global search capability is diminished by randomly initializing host nest location, causing the standard cuckoo search method's convergence to deteriorate. Therefore, it rapidly falls on a local optimal solution. To overcome this limitation, chaotic sequences are constructed using a circle map function to determine the location of the host nest. Algorithm2 provides the Advanced CS Algorithm. The flow chart of the Advanced CS algorithm has been depicted in Fig.2.

The chaotic function is used to initialize the host nest's position. Chaos is a deterministic nonlinear system with the potential to generate randomness. Therefore, it can perform simple searches more quickly than stochastic searches. Therefore, it can perform simple searches more quickly than stochastic searches. In the optimization discipline, there are various forms of chaotic maps. In comparison to other test routines, the circular map excels them all. The circle map formula is given as follows:

$$X_{inew} = X_i + b - \left(\frac{c}{2\pi}\right)\sin(2\pi X_i)\,\mathrm{mod}(1) \tag{5}$$

Where b and c represent control parameters, X_{inew} denotes chaotic sequence generated by the circle map function where $i_{new}=1,2,3\ldots d$. It is assumed that c and b have respective values of 0.5 and 0.2.

Algorithm 2 .The Advanced CS Algorithm

```
Determine the new population of host nest using chaotic sequence
Set the maximum number of iteration and Pa
if (iter<Maxiter)
    Generate new positions of ith and jth cuckoo randomly using Eqn. 2
    Test the fitness function Fi and Fj
Choose kth host nests randomly and evaluate fitness function Fk
Select the best function among Fi , Fj and Fk
Discard a tiny fraction of the worst nests
Create new nests at random to replace lost nests using Eqn.2.
Evaluate the new nest's fitness and keep the best one
```

The chaotic numbers created will fall between 0 and 1. After setting parameters, new positions will be generated based on levy's flight. The Eqn. 2 and Eqn. 3 can be rewritten after applying circle map function as given below:

$$X_{inew}^{n+1} = X_{inew}^{n} + \alpha * Levy(\lambda) \tag{6}$$

$$X_{inew}^{n} = X_{inew}^{n} + rand(X_{inew}^{n} - X_{jnew}^{n}) \tag{7}$$

Random walks are utilized to produce new nests, as shown in Eqn. 2, after discarding a part of the nest based on the probability of discovery. Until the maximum number of repetitions has been achieved, the same process is repeated.

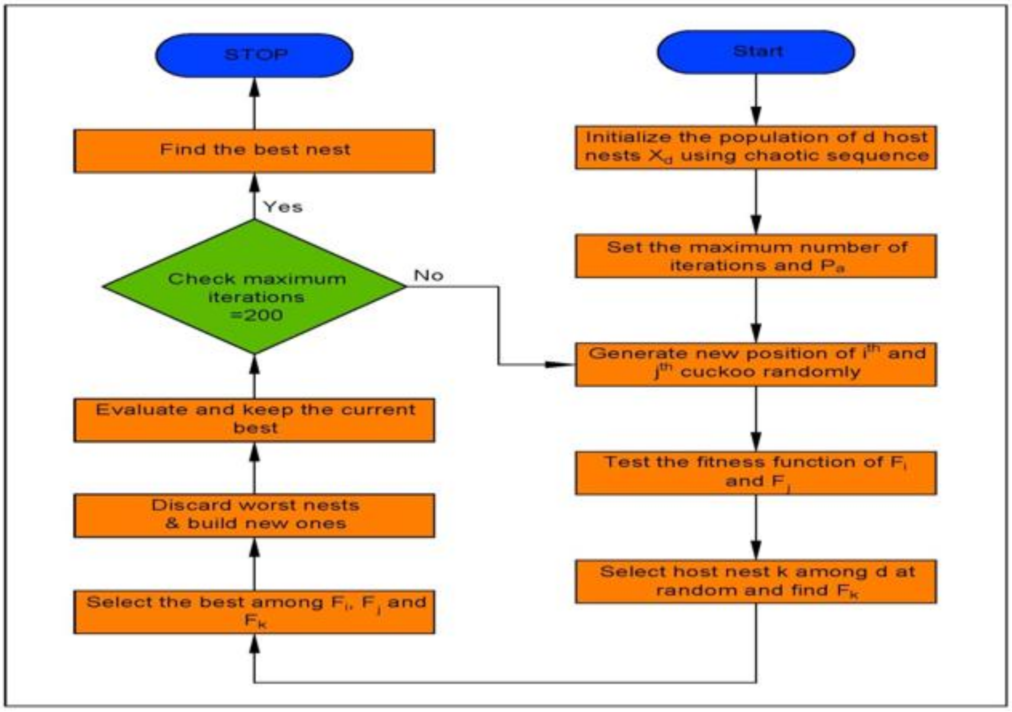

Fig. 2 An Advanced CS Algorithm Flowchart

3.3.3 ELSTM based Heart Disease Prediction

An ELSTM model based deep network is used to forecast cardiac illness. The ELSTM model has solved the Vanishing Gradient issue in Back Propagation Neural Networks. Memory blocks connect the nodes in the LSTM network [36] . Figure 3 shows the LSTM Cell. Long-term dependencies are captured by LSTM when sequential data is learned. At every time step, the LSTM model predicts the risk. The gates are composed of forget, output, and input gates. The variables X(t), st(t), and hn(t) represent the input, internal state, and hidden state output at time t. The input gate 'gt' determines how much update is needed for each unit. The unwanted information in each unit is eliminated by the forget gate (ft). Internal memory is determined by the output gate 'qt'. The following is a description of $ft_i^{(t)}$:

$$ft_i^{(t)} = \sigma\left(b_i^f + \sum_j IU_{i,j}^f X_j^{(t)} + \sum_j WT_{i,j}^f hn_j^{(t-1)}\right) \quad (8)$$

The input vector at time step t is denoted by $X_j^{(t)}$ the layer that is hidden vector at time step (t-1) is represented by $hn_j^{(t-1)}$and the input weight, bias, and weight for the unit i are indicated by (t-1), b_i^f ,$IU_{i,j}^f$ and $WT_{i,j}^f$ respectively. Input gate, $gt_i^{(t)}$is explained as follows:

$$gt_i^{(t)} = \sigma\left(b_i^g + \sum_j IU_{i,j}^g X_J^{(T)} + \sum_j WT_{i,j}^g hn_j^{(t-1)}\right) \quad (9)$$

Each time, an internal state update is carried out, which is explained as follows:

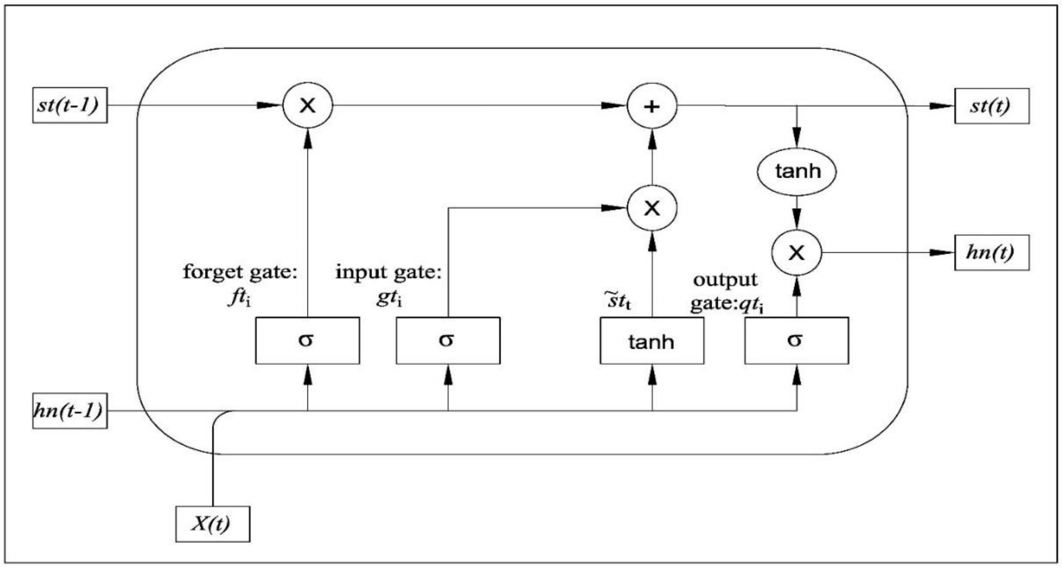

Fig 3 LSTM cell

$$st_i^{(t)} = ft_i^{(t)} st_i^{(t-1)} + g_{ti}^{(t)} \sigma\left(b_i^f + \sum_j IU_{i,j}^f X_j^{(t)} + \sum_j WT_{i,j}^f hn_j^{(t-1)}\right) \quad (10)$$

The LSTM cell output $hn_i^{(t)}$ and equations for output gate $qt_i^{(t)}$ are provided below:

$$qt_i^{(t)} = \sigma\left(b_i^o + \sum_j IU_{i,j}^o x_j^{(t)} + \sum_j WT_{i,j}^o hn_j^{(t-1)}\right) \quad (11)$$

$$hn_i^{(t)} = \tanh(st_i^t) qt_i^{(t)} \quad (12)$$

The output layer forecasts the likelihood of a heat-related risk. Every LSTM layer converts an input vector to a hidden vector over a period of N iterations. The LSTM model and Advanced CS are coupled to generate the optimal prediction result. Algorithm 3 provides the Enhanced LSTM model algorithm. After receiving the input values, each LSTM cell's unique gate value is determined. Values for the hidden state and the current internal state are created. Ultimately, the heart disease is predicted by the Enhanced LSTM model. The chaotic function is used to initialize the host nest's position. The generated chaotic numbers will range from 0 to 1. New positions will be created based on Levy's flight after the parameters have been selected. The process of creating new nests involves using random walks following the removal of a portion of the nest according to its likelihood of being found. Until the maximum number of repetitions has been achieved, the same process is repeated.

Algorithm 3: The Proposed ELSTM Algorithm

```
Divide the test and training sets.
Determine the values of each cell
    Determine the new population of host nest using chaotic sequence. Set the maximum number of iteration and Pa
    if (iter<Maxiter)
        Generate new position and test the test function
    Choose $k^{th}$ host nests randomly and evaluate fitness function Fk
    Select the best host function and discard a tiny fraction of the worst nest.
    Create new nests at random to replace lost nests
```

```
            Evaluate the new nest's fitness and keep the best one
            Calculate the Gate values
            Find the value of current internal state
            Find the value of current hidden state
        End
        Obtain the final output
```

3.4 Model Evaluation:

A confusion matrix [36] is utilised to assess the effectiveness of the suggested methodology. Dangerous cases are indicated by genuine affirmative cases, which also show collision warnings. Safe cases are indicated by true negative cases, which do not exhibit a warning.

Accuracy: The percentage of precise forecasts to samples.

Precision: It pertains to the precise identification of genuine positive results.
Recall: The proportion of true positives to the sum of false negatives as well as true positives
F1 Score: This score integrates recall and precision.

$$Acc = (T_{rp} + T_{rn}) / (T_{rp} + T_{rn} + F_{ap} + F_{an}) \quad (13)$$

$$\mathrm{P}_n = (T_{rp} / (T_{rp} + F_{ap})) \quad (14)$$

$$\mathrm{R}_{call} = (T_{rp} / (T_{rp} + F_{an}) \quad (15)$$

$$F1 - Measure = (2 * \mathrm{R}_{call} * \mathrm{P}_n) / (\mathrm{R}_{call} * \mathrm{P}_n) \quad (16)$$

where F_{ap} stands for false positive, F_{an} for false negative, T_{rp} for true positive, and T_{rn} for true negative. R_{call} stands for recall, and P_n for precision. A true positive indicates accurate predictions of potentially harmful cases. True Negative indicates accurate and safe scenario estimates. In accurate assessments of safe and hazardous circumstances are referred to as false negative and false positive cases, respectively.

4. Results and Discussion

The OptiDeepNet is a novel technique to boost the accuracy of ELSTM-based prediction models for CHD risk assessment. To be more precise, an ELSTM model whose hyper parameters are tuned with the help of Advanced Cuckoo Search (ACS), was developed. This produces a very effective system for predicting cardiac illness, with an astounding accuracy of 98.3%. We assess our model's performance by contrasting it with a number of cutting-edge techniques for CHD prediction. The effectiveness of the ELSTM model-optimized Advanced Cuckoo Search is used to measure the performance of the OptiDeepNet-based CHD prediction model. The ELSTM model optimized with Advanced Cuckoo Search (ACS) architecture comprises a multi-layered structure, each layer contributing uniquely to the model's predictive prowess. Random Forest Classifier is used for selecting model features.

Transitioning to the LSTM layers, the model incorporates two Long Short-Term Memory (LSTM) layers, each comprising 64 memory cells. These LSTM units, equipped with input, output, and forget gates, facilitate the retention and utilization of sequential information vital for CHD prediction. The number of neurons within each LSTM layer is meticulously chosen to strike a balance between model expressiveness and computational efficiency, ensuring optimal performance. In tandem with the architectural components, the Advanced Cuckoo Search optimization algorithm introduces a dynamic element to model refinement. The algorithm generates a set of candidate solutions, with a population size of 50 cuckoos exploring the parameter space during the exploration phase. These candidates, representing various configurations of weights, biases, and learning rates, undergo iterative refinement during the exploitation phase. Here, the algorithm employs a combination of randomization and deterministic search strategies to iteratively enhance model performance.

Throughout the optimization process, ACS vigilantly tracks the global best solution, updating it as superior candidates emerge. This global best solution serves as a guiding beacon, steering the optimization process towards promising regions of the parameter space. By seamlessly integrating RF and LSTM layers with Advanced Cuckoo Search optimization, the proposed model not only captures the intricate spatial and temporal dynamics of CHD data but also dynamically adjusts model parameters to achieve optimal predictive performance. The optimized LSTM parameters are provided in Table 1.

Table 1: The LSTM's optimized parameters

Parameter	**Name of the Parameter**	**Value**
L	Learning rate	0.001
H	Total number of hidden layer	2
HU1	Hidden units in the first LSTM unit	16
HU2	Hidden units in the second LSTM unit	32
W	Window size	128

AUC, F1 score, recall, accuracy, and precision are used to assess the performance of the model. Table 2 displays comparative analysis of different prediction models. The OptiDeepNet prediction model has a precision of 98.9% and an accuracy of 98.3%. Fig.4 displays the OptiDeepNet model's training and validation accuracy, with epochs denoting the total number of iterations during the training phase. Because the Advanced Cuckoo Search Algorithm was used to optimize the hyper parameters of the LSTM, the OptiDeepNet model has a high training and validation accuracy. The LSTM model's weights are efficiently optimized using Advanced Cuckoo Search (ACS), which also tackles the nonlinear issues that arise during CHD prediction.

The optimized parameters produced by the ACS approach are crucial in accurately predicting both safe and harmful events. Through this optimisation process, the ability of the model to recognise complex patterns and correlations in the data is improved, which raises the accuracy and dependability of the model's prediction of who is at risk of getting coronary heart disease. Metrics such as precision and recall are crucial for determining if a model can accurately categorize cases of CHD. Fig. 5 shows a comparison of the several models. Among all the models, the OptiDeepNet model has the best accuracy, precision and recall, so we start with it. The OptiDeepNet model outperforms all other models in terms of recall rates and precision, indicating its usefulness for CHD prediction.

The entire accurate identification of cases with a high chance of collision is represented by precision. In order to prevent collisions, the suggested approach has improved the accuracy of identifying problematic scenarios. As demonstrated in Fig.3, the results clearly show that, when compared with IntelliNet, NN-PSO and CNN-BiLSTM, a greater number of safe and risky situations were accurately identified in OptiDeepNet.

Table 2: A Comparative Analysis of CHD prediction Models

Model	**Accuracy**	**Precision**	**Recall**	**F1 Score**
CNN-BiLSTM	0.945	0.950	0.963	0.957
NN with PSO	0.964	0.970	0.962	0.966
IntelliNet	0.976	0.979	0.974	0.976
The proposed Model	**0.983**	**0.989**	**0.982**	**0.985**

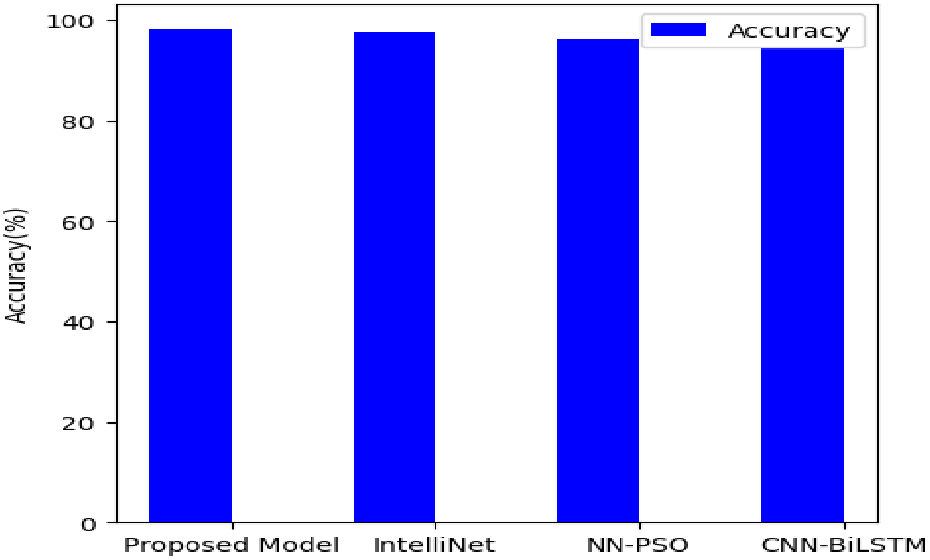

Fig.4 Comparative analysis of different algorithm's accuracy

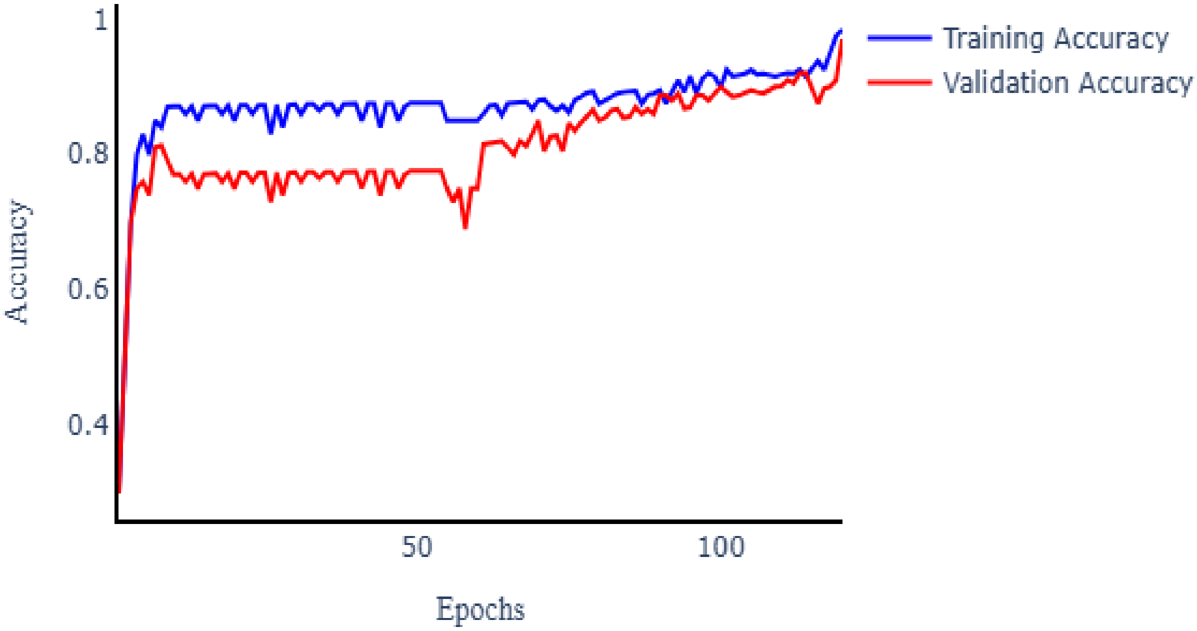

Fig. 5 OptiDeepNet Model's accuracy comparision

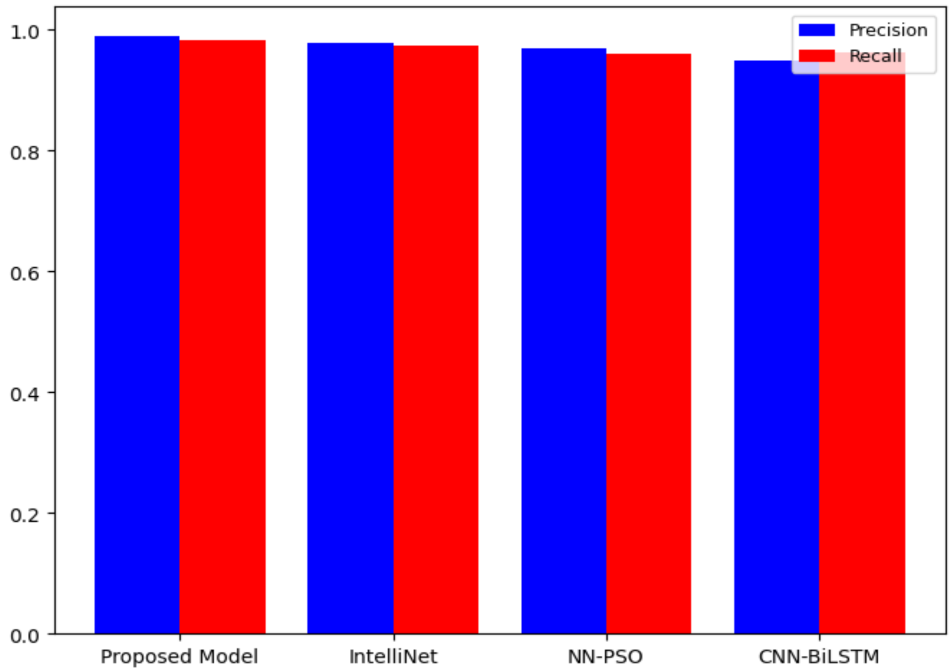

Fig. 6 Performance comparison using Precision and recall

Table 3. Loss Comparison

	The Proposed Model	IntelliNet	NN-PSO	CNN-BiLSTM
MSE	**0.009**	0.1102	0.1115	0.165
Iterations	**120**	140	150	160

As presented in Table 3, IntelliNet, NN-PSO and CNN-BiLSTM require 140, 150 and 160 iterations respectively whereas OptiDeepNet requires 120 iterations that minimizes the Mean Square Error.

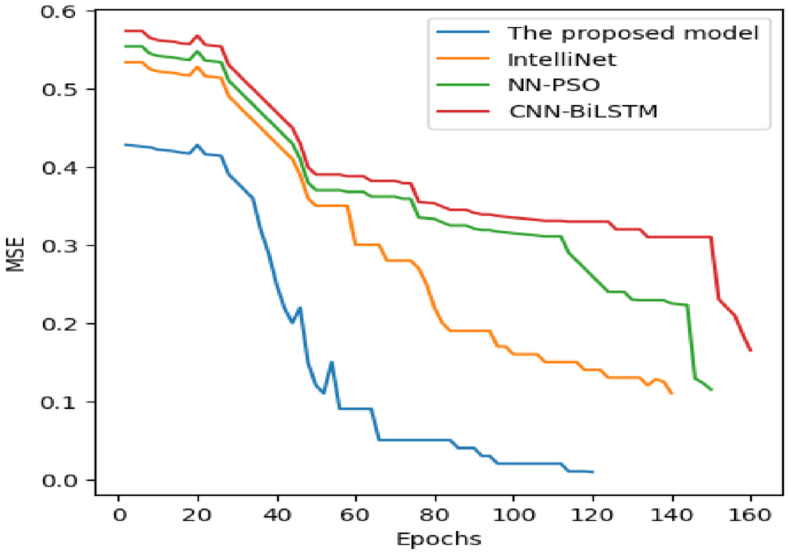

Fig. 7 Comparing the losses of different models

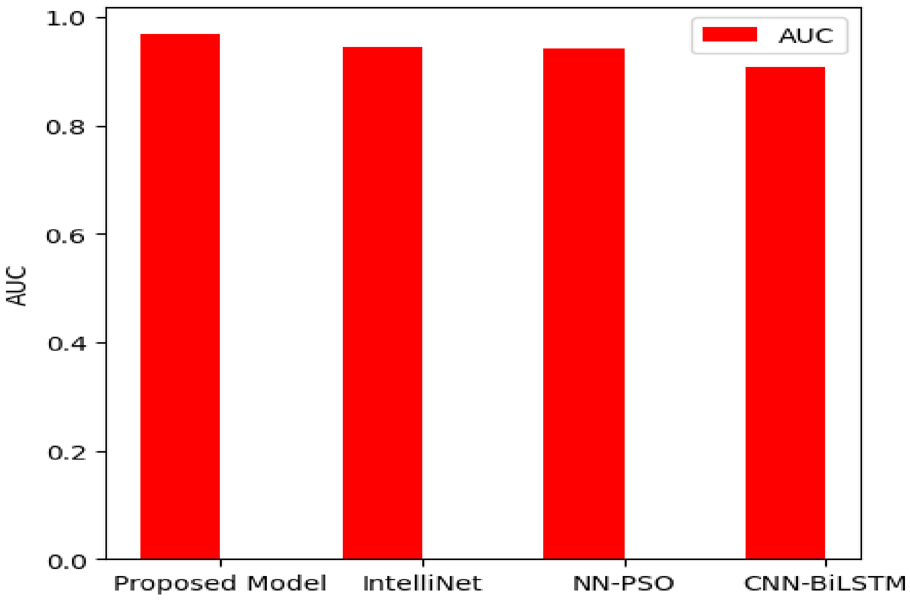

Fig.8 AUC Comparison

The training result demonstrates that OptiDeepNet outperforms other conventional techniques, as illustrated in Fig. 6. AUC makes it clearer how to distinguish a model's capabilities between classes. As shown in Fig. 7, the AUC values of OptiDeepNet, , IntelliNet, NN-PSO and CNN-BiLSTM are 0.97, 0.945, 0.942, and 0.909, respectively. ROC curves unequivocally show that OptiDeepNet performs better than a number of other algorithms. OptiDeepNet model performs better than the current approaches in terms of accuracy, minimum loss, Precision, recall and AUC.

5. Conclusions

This study presented OptiDeepNet which is Optimized Deep Learning network for Efficient Heart Disease Prediction, an ELSTM-based prediction model for Coronary Heart Disease (CHD) risk assessment that is optimized using Advanced Cuckoo Search (ACS). Initially RF is applied for selecting efficient features. Consequently, the LSTM model's hyper parameters are optimized using Advanced Cuckoo Search to make sure it reaches its ideal setup. Fine-tuning hyper parameters like training hidden units and layers, time steps, and learning rate improve the model's overall prediction performance. This approach improves decision-making in emergency situations and raises the predictive value of cardiac disease. The ELSTM model's good generalization to fresh, untested data is ensured by this optimization procedure, which also helps to reduce over fitting. The primary benefit of the suggested approach is that it will improve the heart disease prediction system's performance. In the future, transformer based model could be developed to enhance the prediction performance of the CHD.

Ethical Approval

Not Applicable

Consent to Participate

Consent was obtained from all individual participants involved in the paper.

Consent to Publish

Participants provided written informed consent for publication of the paper.

Data Availability Statement

Not Applicable

Authors Contributions

D.Deva Hema contributed conceptualization, Analysis, Methodology, Software Implementation, Visualization, Investigation, Writing –Original Draft, and Project Administration. S.Abirami, Mohana priya.P, Srikrithi Santhanam and Srinithi Santhanam, contributed Literature Survey, Methodology, Writing – Review and editing.

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Competing Interest

The authors declare that they have no conflicts of interest to disclose.

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References:

1. Roger VL (2010) The heart failure epidemic. International journal of environmental research and public health 7 (4): 1807–1830.
2. Vasan RS, Larson MG, Leip EP et al. (2001) Impact of high-normal blood pressure on the risk of cardiovascular disease. New England journal of medicine 345 (18): 1291–1297.
3. Celermajer DS, Sorensen KE, Georgakopoulos D et al. (1993) Cigarette smoking is associated with dose-related and potentially reversible impairment of endothelium-dependent dilation in healthy young adults. Circulation 88 (5): 2149–2155.
4. Burke AP, Farb A, Malcom GT et al. (1997) Coronary risk factors and plaque morphology in men with coronary disease who died suddenly. New England Journal of Medicine 336 (18): 1276–1282.
5. Hogema, J.H. · Janssen WH (1996) Effects of intelligent cruise control on driving behavior: a simulator study. Soesterberg.
6. Haskell WL, Alderman EL, Fair JM et al. (1994) Effects of intensive multiple risk factor reduction on coronary atherosclerosis and clinical cardiac events in men and women with coronary artery disease. The Stanford Coronary Risk Intervention Project (SCRIP). Circulation 89 (3): 975–990.
7. Jin Z, Sun Y, Cheng AC (2009) Predicting cardiovascular disease from real-time electrocardiographic monitoring: An adaptive machine learning approach on a cell phone. In: 2009 Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. IEEE. pp 6889–6892.
8. Hassan D, Hussein HI, Hassan MM (2023) Heart disease prediction based on pre-trained deep neural networks combined with principal component analysis. Biomedical Signal Processing and Control 79 104019.
9. Nakanishi R, Dey D, Commandeur F et al. (2018) Machine learning in predicting coronary heart disease and cardiovascular disease events: results from the multi-ethnic study of atherosclerosis (mesa). Journal of the American College of Cardiology 71 (11S): A1483–A1483.
10. Goldstein BA, Navar AM, Carter RE (2017) Moving beyond regression techniques in cardiovascular risk prediction: applying machine learning to address analytic challenges. European heart journal 38 (23): 1805–1814.
11. Ambekar S, Phalnikar R (2018) Disease risk prediction by using convolutional neural network. In: 2018 Fourth Int. Conf. Comput. Commun. Control Autom. IEEE. pp 1–5.
12. Hussain S, Nanda SK, Barigidad S et al. (2021) Novel deep learning architecture for predicting heart disease using CNN. In: 2021 19th OITS Int. Conf. Inf. Technol. IEEE. pp 353–357.
13. Yashudas A, Gupta D, Prashant GC et al. (2024) Deep-cardio: Recommendation system for cardiovascular disease prediction using iot network. IEEE Sens. J.
14. Mandava M (2024) MDensNet201-IDRSRNet: Efficient cardiovascular disease prediction system using hybrid deep learning. Biomedical Signal Processing and Control 93 106147.
15. Safa M, Pandian A, Gururaj HL et al. (2023) Real time health care big data analytics model for improved QoS in cardiac disease prediction with IoT devices. Health and Technology 13 (3): 473–483.
16. Tiwari A, Chugh A, Sharma A (2022) Ensemble framework for cardiovascular disease prediction. Computers in Biology and Medicine 146 105624.
17. Latha CBC, Jeeva SC (2019) Improving the accuracy of prediction of heart disease risk based on ensemble classification techniques. Informatics in Medicine Unlocked 16 100203.
18. Ishaq A, Sadiq S, Umer M et al. (2021) Improving the prediction of heart failure patients' survival using SMOTE and effective data mining techniques. IEEE access 9 39707–39716.

19. Mienye ID, Sun Y, Wang Z (2020) An improved ensemble learning approach for the prediction of heart disease risk. Informatics in Medicine Unlocked 20 100402.
20. Dutta A, Batabyal T, Basu M, Acton ST (2020) An efficient convolutional neural network for coronary heart disease prediction. Expert Systems with Applications 159 113408.
21. Rani P, Kumar R, Ahmed NMOS, Jain A (2021) A decision support system for heart disease prediction based upon machine learning. Journal of Reliable Intelligent Environments 7 (3): 263–275.
22. Mohan S, Thirumalai C, Srivastava G (2019) Effective heart disease prediction using hybrid machine learning techniques. IEEE access 7 81542–81554.
23. Sharma S, Parmar M (2020) Heart diseases prediction using deep learning neural network model. International Journal of Innovative Technology and Exploring Engineering (IJITEE) 9 (3): 2244–2248.
24. Adler ED, Voors AA, Klein L et al. (2020) Improving risk prediction in heart failure using machine learning. European journal of heart failure 22 (1): 139–147.
25. Chandrasekhar N, Peddakrishna S (2023) Enhancing heart disease prediction accuracy through machine learning techniques and optimization. Processes 11 (4): 1210.
26. Dileep P, Rao KN, Bodapati P et al. (2023) An automatic heart disease prediction using cluster-based bi-directional LSTM (C-BiLSTM) algorithm. Neural Computing and Applications 35 (10): 7253–7266.
27. Ahmad S, Asghar MZ, Alotaibi FM, Alotaibi YD (2023) Diagnosis of cardiovascular disease using deep learning technique. Soft Computing 27 (13): 8971–8990.
28. Reddy SR, Murthy GV (2025) Cardiovascular Disease Prediction Using Particle Swarm Optimization and Neural Network Based an Integrated Framework. SN Computer Science 6 (2): 186.
29. Deva Hema D RJ (2025) IntelliNet: intelligent deep net architecture for efficient cardiovascular disease prediction. Multimed Tools Appl. doi: https://doi.org/10.1007/s11042-025-20767-5
30. Hema DD, Kumar KA (2024) Novel optimised deep learning approach for an efficient traffic state prediction based on CAE-ICCDCS-GRU model. International Journal of Bio-Inspired Computation 23 (2): 80–98.
31. Yang X-S, Suash Deb (2009) Cuckoo Search via Lévy flights. In: 2009 World Congr. Nat. Biol. Inspired Comput. IEEE. pp 210–214.
32. Viswanathan GM, Afanasyev V, Buldyrev S V. et al. (1996) Lévy flight search patterns of wandering albatrosses. Nature 381 (6581): 413–415. doi: 10.1038/381413a0.
33. Arora S, Singh S (2017) An improved butterfly optimization algorithm with chaos. Journal of Intelligent & Fuzzy Systems 32 (1): 1079–1088. doi: 10.3233/JIFS-16798.
34. Ong P, Zainuddin Z, Sia CK, Zain BAM (2015) Adaptive Cuckoo Search Algorithm with Two-Parent Crossover for Solving Optimization Problems. pp 427–435.
35. Mareli M, Twala B (2018) An adaptive Cuckoo search algorithm for optimisation. Applied Computing and Informatics 14 (2): 107–115. doi: 10.1016/j.aci.2017.09.001.
36. Deva Hema D, Ashok Kumar K (2021) Levenberg–Marquardt –LSTM based Efficient Rear-end Crash Risk Prediction System Optimization. International Journal of Intelligent Transportation Systems Research 20 132–141. doi: https://doi.org/10.1007/s13177-021-00273-2.