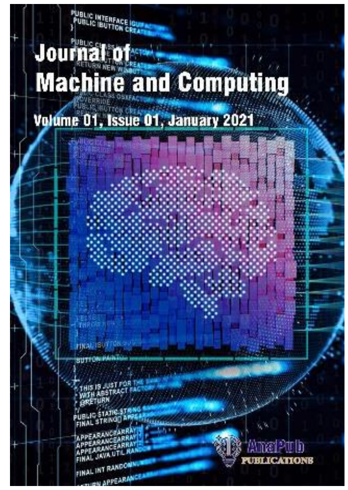
Journal Pre-proof

A Novel Computational Model to Predict Healthcare Problems Through Machine Optimization and Hyperparameter Tuning Logic



Vinitha R, Viji Vinod, Sharmila K P and Kavithavarshini G S

DOI: 10.53759/7669/jmc202505171

Reference: JMC202505171

Journal: Journal of Machine and Computing.

Received 08 May 2025

Revised from 23 July 2025

Accepted 28 July 2025

Please cite this article as: Vinitha R, Viji Vinod, Sharmila K P and Kavithavarshini G S, "A Novel Computational Model to Predict Healthcare Problems Through Machine Optimization and Hyperparameter Tuning Logic", Journal of Machine and Computing. (2025). Doi: https:// doi.org/10.53759/7669/jmc202505171.

A Novel Computational Model to Predict Healthcare Problems Through Machine Optimization and Hyperparameter Tuning Logic

[1] Vinitha R*,[2] Viji Vinod,[3] Dr Sharmila K P, [4]Kavithavarshini GS

[1]Research scholar, Department of Computer Science, Dr.M.G.R. Educational and Research Institute, Chennai

[2]Professor, Faculty of Computer Applications, Dr.M.G.R. Educational and Research Institute, Chennai

[3]Professor, Department of Electronics and Communication Engineering, CMR Institute of Technology, Bengaluru

[4]Research scholar, Department of Computer Applications, Dr.M.G.R.Educational and Research Institute, Chennai
vinitharajan2701@gmail.com, vijivinod.mca@drmgrdu.ac.in, sharmila.kp@cmrit.ac.in, kavithakamalee@gmail.com

*Corresponding Author: Vinitha R

Abstract

Heart disease (HD) remains one of the leading causes of mortality in the world and there are pressing needs to develop effective predictive models of HD at the early stages of development. The given research suggests a new type of computational framework combining optimization-based machine learning with innovative preprocessing and optimization approaches to the design of models predicting the presence of heart disease. It is an analysis of the data collection having clinically meaningful patient attributes. First, the dataset is cleaned with the help of the Discrete Wavelet Transform (DWT) to minimize noise and normalize signals to provide data of the necessary quality and make them more ready to use in a model. In feature extraction, Principal Component Analysis (PCA) algorithm is used to diminish dimensions and maintain most important variables in the realm of heart disease decision. After feature extraction, the data undergoes a Neural Network model which is optimized by Real-Parameter Numerical Optimization Algorithm (ROA). Since ROA has a high convergence rate and stability in locating global solutions, it is selected. As a way of enhancing the model, hyperparameter tuning- Bayesian optimization, is used to increase the overall predictive accuracy. Key performance indicators of the model include accuracy 97%, precision 95%, Sensitivity 94% and specificity92% .The provided system shows good performance in all of them, which proves its potential in achieving robust and early prediction of heart diseases. The proposed neural network model optimized by ROA has greater gains as compared to other algorithms like a Hippopotamus Optimization (HO) and Puma Optimization (PO) algorithms.

Keywords: HD prediction; Optimization algorithms; ROA; HO Algorithm; PO Algorithm; DWT; external parameter tuning; Statistical analysis

1. Introduction

Detecting HD has undergone transformative evolution, influenced by advancements in health technology and scientific computing. Basically, in history, diagnostic approaches relied on fundamental tools such as ECG and echo, providing core insights into cardiac function and structure. In the mid-20th century saw the introduction of heart ultrasound, transforming diagnostics by enabling non-invasive imaging of the heart's chambers, valves, and blood flow dynamics through ultrasound waves. This innovation marked a significant leap in cardiac care, facilitating more precise assessments and earlier detection of structural abnormalities and functional impairments. As cardiovascular science progressed, nuclear imaging techniques like single-photon emission computed tomography (SPECT) and positron emission tomography (PET) emerged as pivotal tools for evaluating myocardial perfusion, metabolism, and tissue viability. These modalities offer critical functional insights, aiding in the diagnosis and management of coronary artery disease (CAD), myocardial infarction, and other complex cardiac conditions by visualizing blood flow patterns and identifying areas of ischemia or infarction. In contemporary practice, the diagnostic landscape for HD encompasses a multifaceted approach integrating clinical evaluation, advanced imaging modalities, laboratory tests, and computational analyses. Electrocardiography remains fundamental for assessing electrical activity of the heart, diagnosing arrhythmias, and detecting signs of myocardial ischemia indicative of coronary artery disease. Moreover, stress testing, whether through exercise treadmill tests or pharmacological stress tests, evaluates cardiac response to exertion or induced stress, providing valuable insights into exercise tolerance and coronary artery function. Cardiac catheterization and heart angiography, albeit invasive, offer unparalleled precision in diagnosing and treating coronary artery disease. By directly saw a coronary artery and measuring pressures within the heart chambers, these procedures are enabled by interventional cardiologists to perform therapeutic interventions like angioplasty, stent placement, or even coronary artery bypass grafting (CABG) when necessary. Such interventions are critical way to restore the blood flow to the heart muscle and mitigating the risks associated with obstructive coronary artery disease. Beyond structural assessments, biochemical markers like troponin, crate, kinase-MB (CK-MB), and lipid profiles provide crucial insights into myocardial injury, heart function, and overall cardiovascular risk. These biomarkers play a pivotal role in diagnosing acute coronary syndromes and monitoring disease progression, guiding curative decisions and optimizing patient care strategies.

Despite significant advancements, challenges persist in the realm of HD detection. Early identification remains a cornerstone of effective management, yet subtle symptoms and variable presentations often delay diagnosis until disease progression has occurred. Moreover, the accuracy and specificity of diagnostic tests can vary, leading to false positives or negatives that impact clinical decision-making and patient outcomes. Accessibility to advanced diagnostic technologies also poses a challenge, particularly in underserved regions or healthcare settings with limited resources. Looking ahead, the future of HD detection holds promise through innovative technologies and research strive. Artificial intelligence (AI) and data driven model are poised to revolutionize cardiac diagnostics by consider vast datasets from ECGs, imaging studies, and patient records, enhancing diagnostic accuracy and predicting cardiovascular risk with unprecedented precision. Telemedicine platforms and remote monitoring devices enable real-time assessment of cardiac parameters, facilitating early detection of irregular heartbeats, heart failure exacerbations, and other cardiac events. Genomics and personalized medicine are undoing the genetic underpinnings of cardiovascular diseases, paving the way for tailored treatment approaches based on individual genetic predispositions and molecular profiles. Wearable devices equipped with ECG monitors and activity trackers offer continuous monitoring of heart rhythm and physical activity, providing valuable insights into cardiac health and enabling timely intervention. Non-invasive imaging innovations, including magnetic resonance imaging (MRI) and advanced echocardiography techniques, continue to evolve, offering higher resolution imaging and greater detail in assessing cardiac structure and function. These advancements are instrumental in early detection, disease monitoring, and guiding therapeutic strategies to optimize outcomes for patients with HD.

The ongoing evolution of HD detection reflects a dynamic interplay between technological innovation, scientific discovery, and clinical practice. By leveraging these advancements, healthcare providers can enhance early detection, personalize treatment approaches, and improve outcomes for individuals at risk of or living with HD. Through continued research and collaborative efforts, the pursuit of more effective diagnostic strategies promises to reduce cardiovascular morbidity and mortality, ultimately advancing global cardiovascular health initiatives.

Problem statement

HD stands as one of the foremost contributors to global mortality rates, underscoring the urgent need for precise and timely prediction methods to enhance interventions and elevate patient outcomes. Existing diagnostic methods frequently exhibit limitations in accuracy, often missing subtle signs of cardiovascular risk. This deficiency emphasizes the critical role of advanced computational models in improving diagnostic precision and prognosis. Central to the challenge is the optimization of algorithms capable of effectively managing the diverse and nuanced data inherent to HD diagnosis. Achieving optimal algorithm performance involves meticulous tuning of model parameters to maximize predictive accuracy across varying patient profiles and medical histories. Furthermore, robust data preparation methods are essential to refine data quality, ensuring that predictive models are built on reliable and informative datasets. Addressing these complexities necessitates collaborative efforts across disciplines, blending expertise in healthcare, data science, and computational technology. Innovations in predictive ideal offer promising avenues to develop dependable tools that empower healthcare. In early profession of individuals are heightened risk of HD. By facilitating proactive and targeted preventive measures, these advancements aim to mitigate the impact of cardiovascular ailments and enhance overall public health outcomes on a global scale.

Contributions

To enhance the HD prediction accuracy: To address the challenge of accurate HD prediction, this study evaluates and optimizes three distinct optimization algorithms—ROA, HO, and performance and refining them through free framework tuning, the study aims to significantly improve the accuracy of predictive models beyond conventional diagnostic methods.

(i) **To integrate advanced preproduction techniques**: The study utilizes the DWT algorithm during the pre-processing phase to enhance the accuracy and relevance of the input data. This approach aids in minimizing noise and extracting essential features, thereby strengthening the reliability of predictive models in identifying subtle markers associated with HD risk.

(ii) **To enable informed healthcare decisions**: Through detailed statistical evaluation and analysis of important performance indicators like sensitivity and specificity, the study equips healthcare practitioners with meaningful insights. This enables more accurate decision-making regarding patient management and intervention approaches based on dependable predictive outcomes.

(iii) **To advance interdisciplinary collaboration**: Through the integration of expertise in healthcare, data science, and computational methods, the study fosters interdisciplinary collaboration. This collaboration is essential for developing and validating reliable predictive models that can effectively assist healthcare providers in early identification and proactive management of HD, thereby improving overall patient outcomes.

2. Literature Survey

In order to identify and screen for congenital HD (CHD), a common and complicated congenital malformation, echocardiography is crucial for assessing cardiac anatomy and function. However, due to instinctive fetal movements, artifacts in ultrasound images, and unique fetal cardiac structures, fetal CHD recognition still faces many challenges. Diabetes has several serious side effects, one of which is HD.In order to tune hyperparameters for early diabetes disease prevention and detection, this work proposed an Optimal Scrutiny Boosted Graph Convolutional LSTM (O-SBGC-LSTM), which is SBGC-LSTM enhanced by the Eurygaster Optimization Algorithm (EOA). Pitch-shifting is one of the data augmentation techniques used in the study to increase the robustness of the model [1-3].

The blood, nutrition, and oxygen are all carried throughout the body by the cardiovascular system. The heart, blood, and blood vessels make up this system. We suggest using the multiscale attention convolutional compression network (MACCN), which is based on the clinical PCG dataset, to achieve effective CVD detection. For even better classification performance, we present a hybrid Convolution-DeiT (ConvDeiT) architecture. Before the DeiT model processes the input features, the Conv-DeiT framework combines a convolutional block with a squeeze-and-excitation (SE) attention mechanism to improve the channel and spatial information [4-7].

Cardiovascular issues have become a major public health concern that negatively affects people of all ages. Machine learning (ML) techniques have been applied in a number of recent research studies to design decision-making systems for the massive amounts of data in the medical field. While these efforts yielded encouraging outcomes, the majority of the research was limited to small datasets. Ten cross-validations are performed on the classifiers to guarantee their robustness and generalizability. Two methods of hyper parameter tuning are used to optimize the model's performance: Randomized SearchCV and GridSearch CV. The best estimator values are sought after by these techniques. Before the deep learning stage of inferring the medical condition, dimensionality was reduced through a transformation to wavelet features. This work presents a novel approach to signal processing and feature extraction for person identification [8-11]. Our goal in this work is to create a novel end-toend technique for classifying and detecting abnormalities in heart sounds that can be applied to various heart sound diagnosis tasks. In particular, we created a Multidimensional Decision Fusion (MDF) module and a Multi-dimensional Feature Extraction (MFE) module to form a Multi-feature Decision Fusion Network (MDFNet). To understand heart sound characteristics from various angles, the MFE module extracted spatial features, multi-level temporal features, and spatial-temporal fusion features. In particular, the ADE module segments the aorta and four heart chambers; as a result, five distance field maps are produced, which encode the distance between the coarsely segmented coronary artery and chamber surfaces. In the meantime, ADE carries out coronary artery detection in order to remove foreground-background imbalance and crop the region of interest [12-13].

Heart rate variability (HRV) is a crucial metric that can be used in many different clinical contexts, including mental health, diabetes mellitus, and cardiovascular diseases. Electrocardiography and photoplethysmography signals may be used to obtain HRV data The acquired data is processed using advanced computational methods such as signal filtering and segmentation to extract heart rate variability (HRV) features. However, inconsistencies in data collection, computational modelling, and physiological variations can lead to signal distortion, affecting the accuracy of HRV analysis. The study highlights that although progress has been made over the past decade, several research gaps remain—particularly regarding attrition bias and strategies for managing missing data. As a result, future investigations should focus on implementing predictive models, enhancing their generalization capabilities, adopting interpretable algorithms, and refining the classification of hospital readmission types [14–15]. This research introduces an innovative approach that processes raw phonocardiogram (PCG) signals using deep learning techniques for cardiac diagnostics. The proposed framework features a custom scalogram-based convolutional recurrent neural network (CS-CRNN). Furthermore, to assess various stages of heart murmur (HM) severity, a novel multi-kernel residual convolutional neural network (MK-RCNN) is developed. Moreover, residual learning (RL) helps to extract pertinent features from deep CNN layers without compromising accuracy of performance. After extracting features from the ECG signals, the best features are chosen using a combination of PSO optimization and feature selection techniques such as FCBF, MrMr, and relief. Lastly, a state-of-the-art and proposed method comparison is given for both small and large datasets [16-18].

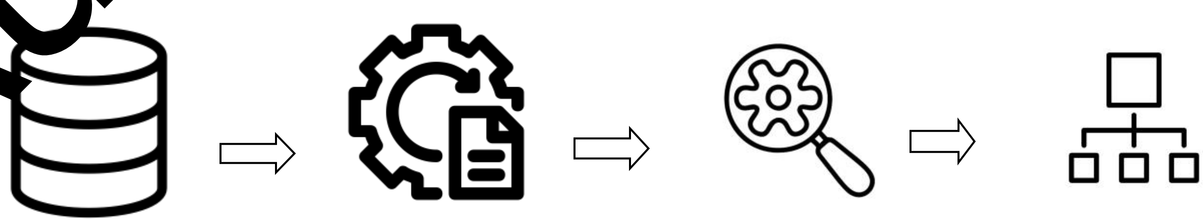
Due to their extreme thinness and flexibility, miniature, ultrathin, and flexible Aluminium Nitride (AlN) piezoelectric MEMS exhibit high sensitivity to minute mechanical deformations. As a result, they can be used to identify skin deformations brought on by cardiac events and provide a variety of biomarkers that are helpful for tracking cardiovascular health and determining the risk of cardiovascular disease. Traditional wearable continuous pulse wave monitoring systems tend to be bulky and dependent on technologies that restrict their applicability. Our network has two parallel branches that are devoted to the simultaneous global localization and fine segmentation of the vessels, utilizing a coarse-fine collaborative strategy. The coarse branch suppresses unnecessary structures and allows for global object localization by utilizing high-level semantic features through the use of a partial decoder. Attention parameterized skip connections are used by the fine branch to enhance boundary information and feature representations. Using widely available laboratory parameters, the transferability of disease progression optimizes examination and treatment strategies and improves patient prognosis. Nevertheless, the thrombus that naturally forms in artificial heart pumps severely restricts the technology's ability to advance. Research on accurately detecting thrombus in artificial heart pumps has become urgent. The high rate of thrombus formation in ventricular assist devices, or VADs, and the possible risks associated with thrombus, such as harm to the human body, are the main subjects of this study [19-22]. Images from invasive coronary angiography (ICA) are regarded as the gold standard for evaluating coronary artery health. Deep learning classification techniques are extensively employed and sophisticated in various domains where medical imaging assessment plays a crucial role because of the advancement of computer-aided diagnosis systems that assist medical professionals in their clinical practices [23-25].

Inferences from literature survey

Echocardiography is critical for evaluating cardiac anatomy and function in CHD diagnosis, despite challenges from fetal movements, ultrasound artifacts, and unique fetal cardiac structures. Diabetes, a serious health condition, can lead to HD. To enhance early diabetes detection, O-SBGC-LSTM, optimized by the EOA and utilizing pitch-shifting data augmentation, is proposed. The cardiovascular system, comprising the heart, blood, and vessels, is vital for bodily functions. For effective CAD detection, MACCN and a hybrid Conv-DeiT model with enhanced channel and spatial information are recommended. Cardiovascular diseases pose significant public health issues, prompting the application of ML for decision-making systems in medical data analysis. Studies using small datasets have shown promising results, with robust model performance ensured through ten cross-validations and hyper parameter tuning methods like Randomized SearchCV and GridSearchCV. Dimensionality reduction to wavelet features precedes deep learning stages in medical condition inference. A novel MDFNet with MFE and MDF modules is introduced for heart sound classification and abnormality detection. ADE module aids in aorta and heart chamber segmentation and coronary artery detection. HRV analysis, crucial for various clinical contexts, faces challenges from data collection uncertainties and model limitations. Future research should focus on model generalization, interpretability, and handling missing data. Innovative deep learning methods like CS-CRNN and MK-RCNN improve cardiac problem diagnosis and severity classification. Advanced feature selection techniques combined with PSO enhance ECG signal analysis. Ultrathin, flexible AlN piezoelectric MEMS detect cardiac event-induced skin deformations, offering biomarkers for cardiovascular health monitoring. Traditional wearable systems' limitations necessitate new designs with parallel branches for global localization and fine vessel segmentation. The detection of thrombus in VADs is crucial due to associated risks, while ICA remains the gold standard for coronary artery health assessment. Computer-aided diagnosis systems using DL classification techniques significantly aid medical professionals in clinical practices.

3. Proposed Methodology

The research on heart disease prediction that was proposed is organized into a number of major stages in order to achieve adequate accuracy, robustness, and clinical significance of the process. The dataset used in the first step is the data collection that comprises valuable patient data on heart-health-related issues. This is followed by data preprocessing where data is de-noised and normalized by the use of Discrete Wavelet Transform (DWT) to improve its quality in terms of modelling. Thereafter, Principal Component Analysis (PCA) is run after the feature extraction dimension-reduction technique in order to preserve maximum variables that affect the outcomes of heart diseases. The accomplished features are next fed into a Neural Network model that functions as the principal classifier of the scheme. Neural network weights are optimized via the Real-Parameter Numerical Optimization Algorithm (ROA) to increase the convergence and the efficiency of the model. ROA is selected due to the high accuracy, global search ability and stability on optimization landscapes with irregularity. Moreover, there is hyperparameter tuning of the model via Bayesian Optimization which finds the optimal set of hyperparameters to improve predictive performance further. The last system is tested with the use of standard measures of performance, such as accuracy, precision, recall, F1-score, specificity. Experimental evidences demonstrate that the ROA optimized neural network is superior to other comparative algorithms like the Hippopotamus Optimization (HO) and Puma Optimization (PO) algorithms. This validates the accuracy and the potential of the proposed computational framework that will be able to predict heart disease early and accurately.



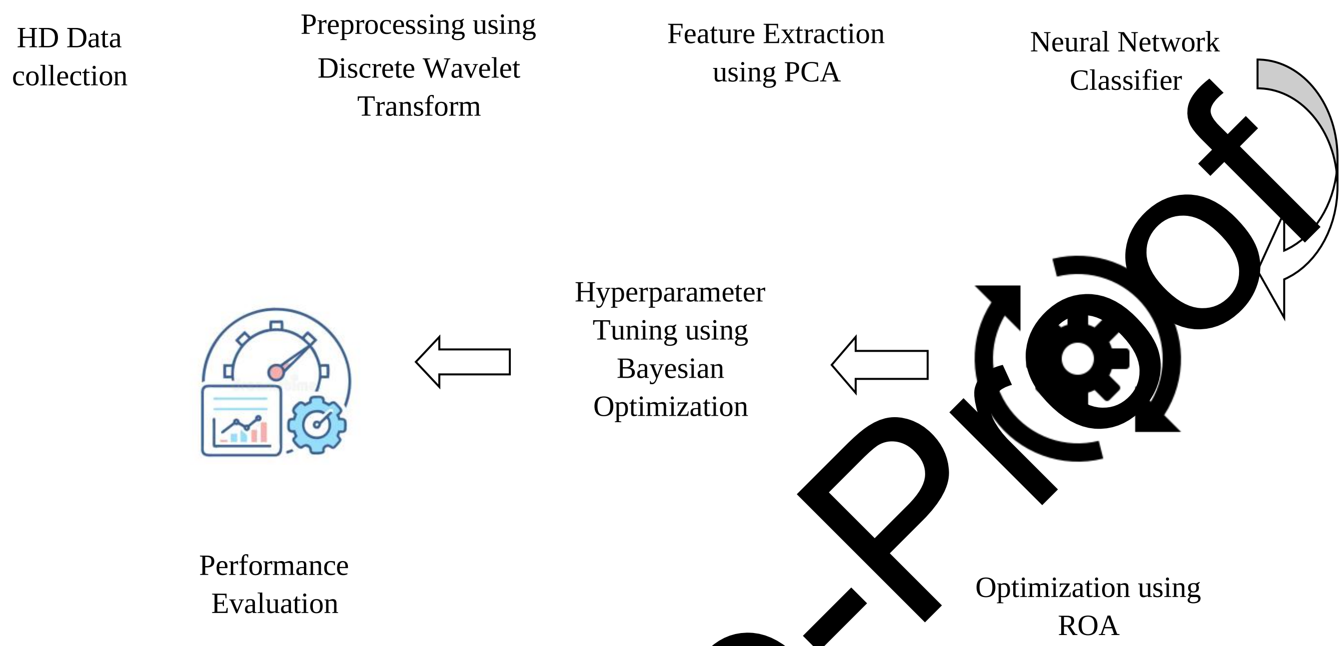


Fig 1 Proposed Block Diagram

3.1 Data Collection

In the case of predicting heart disease, clinical data was obtained over patient health records with necessary medical parameters that usually accompanied heart disease. The data collection aspect entailed collection of numerical and categorical variables related to heart health data within the diagnostic centres as well as hospitals using the right ethical standards. The data obtained comprises the demographic data of the patient including age, gender and medically important data such as the type of chest pain, the resting blood pressure, the cholesterol level, the fasting blood sugar, electrocardiogram, the highest heart rate.

3.2 Preprocessing using Discrete Wavelet Transform

DWT is a mathematical tool used for signal analysis, data compression, and feature extraction. Unlike the Fourier Transform, which provides frequency information but loses time localization, DWT offers both time and frequency localization, making it highly effective for analysing non-stationary signals and extracting meaningful features from data. DWT can be applied to each feature in the dataset to extract wavelet coefficients, which capture important patterns and trends.

For a feature xin the dataset, the DWT decomposes x into approximation A and detail D coefficients. This can be mathematically expressed as:

$$x = A + D \tag{1}$$

A −Capture the low-frequency components, while D −capture the high-frequency components.

From the wavelet coefficients, extract features that are significant for HD prediction, such as: Energy: Represents the signal's strength within the wavelet coefficients

$$E = \sum_{i=1}^{n} |A_i|^2 + \sum_{i=1}^{n} |D_i|^2 \tag{2}$$

Entropy: Measures the randomness in the wavelet coefficients.

$$H = 1 \sum_{i=1}^{n} P_i \log(P_i) \tag{3}$$

Here, P_i −represents the probability of the i −coefficient occurring.

When the Discrete Wavelet Transform (DWT) is applied to the heart failure dataset, it helps extract important features that improve the accuracy of heart disease predictions. This method takes advantage of wavelet transforms' ability to uncover hidden patterns within the data.

3.3 Feature Extraction using Principal Component Analysis

Principal Component Analysis (PCA) is the statistical feature extraction method that represents dimensionality reduction. In prediction of heart diseases there can be a large number of features in the dataset in which some of them may be either redundant or irrelevant. PCA converts the initial correlated variables into a new and different set of the variable called principal components. Such elements represent the highest amount of variance in a given dataset and are the most informative and feature-filled without noise and depth in the information. Choosing the best principal components, the model is more effective and precise. This would also work to reduce overfitting and enhancing computational efficiency of machine learning algorithms.

$$C = \frac{1}{n-1} (X - \bar{X})^T (X - \bar{X}) \tag{4}$$

Where

- X Original data matrix
- $\bar{X}$ Original data matrix,
- C Covariance matrix

$$C_{v_i} = \lambda_i v_i \tag{5}$$

Where λ_i Eigenvalue, v_i Eigenvector. These represent the direction (eigenvector) and magnitude (eigenvalue) of the data variance.

$$Z = X.W \tag{6}$$

Where

- W Matrix of top k eigenvectors
- Z Transformed data in reduced dime

3.2. HO Algorithm for HD Prediction

This algorithm is a newer nature-inspired optimization technique that draws inspiration from the behaviour of hippopotamuses. It is designed to find optimal solutions for complex problems by mimicking how hippos move and interact. In this context, the HO algorithm is used to fine-tune the hyper parameters of a machine learning model to maximize its performance on the heart disease dataset. During the optimization process, each solution represented by a hippopotamus—is updated by considering the best solution found so far, along with some random exploration to encourage diversity and avoid local optima.

$$X_i(t+1) = X_i(t) + r_1.\left(X_{best}(t) - X_i(t)\right) + r_2.\left(X_{rand}(t) - X_i(t)\right) \quad (6)$$

At each iteration, the algorithm considers the best solution found so far, as well as a randomly chosen solution from the population. Two random numbers between 0 and 1 are used to help guide the search process, introducing variability that helps the algorithm explore different possibilities.

Table 2 Pseudo Code for the Hippopotamus Optimization (HO) Algorithm

Pseudo code for HO algorithm:
Initialize parameters N = number of hippopotamuses D = number of hyper parameters max_iter = maximum number of iterations #Initialize population of solutions population= initialize_population (N, D) best_solution = None best_fitness = -inf for iter in range (max_iter): # Evaluate fitness of each solution fitness = [] for i in range(N): Model =train_model(population[i])

```
fitness.append(evaluate_model(model))

    # Update best solution
for i in range (N):         if
fitness[i] >best_fitness:
best_fitness = fitness[i]
best_solution = population[i]
# Update positions of solutions
for i in range (N):

        r1, r2 = random (), random ()

new_position = population[i] + r1 * (best_solution - population[i]) + r2 * (random_solution() -
Population[i])
Population[i] = new_position # Return
the best solution and its fitness return
best_solution, best_fitness
```

The table 2 gives the pseudo code of the Hippopotamus Optimization (HO) which is used to while optimizing the hyper-parameters of the heart disease prediction model. The algorithm iteratively modifies a set of solutions, through maturation estimation and the pose auto position road map.

3.3. PO Algorithm for HD Prediction

The PO algorithm is a nature inspired optimization method that imitates the hunting strategies and agility of pumas. It is applied to optimize the hyper parameters of machine learning models, improving their effectiveness in predicting heart disease. The process begins by initializing a population of N pumas, where each puma represents a candidate solution encoded as a vector of hyper parameters:

Where D is the number of hyperparameters.

$$X_i = \{x_{i1}, x_{i2}, \dots \dots x_{iD}\} \quad \text{for} \quad i = 1,2, \dots \dots, N \tag{7}$$

Table 3 Pseudocode for the Puma Optimization Algorithm

Pseudocode for PO Algorithm:
Initialize parameters

```
N = number of solutions

D = number of hyperparametersmax_iter = maximum iterations population = initialize population (N, D) best solution = None best_fitness = -in f # Main optimization loop for iter in range (max_iter):     for i in range (N):

Fitness = evaluate fitness (population[i])
if fitness >best_fitness:          best_fitness = fitness                    best_solution = population[i]     for i in range(N):          r1, r2 = random (), random ()

Population[i] = population[i] + r1 * (best_solution - population[i]) + r2 * (random_solution() - Population[i])

# Return the best solution and its fitness return best_solution, best_fitness

#Functions
definitialize_population(N, D):

   # Initialize N solutions with D hyperparameters return [random_solution(D) for _ in range(N)]
```

The following table 3 contains a step-by-step pseudocode that has been applied in PO algorithm for hyperparameter optimization. It starts by initializing the population and parameters like the size and dimension of population. The fitness of each solution is analysed and the best solution is updated in turn. Solutions are directed to the optimum and a randomized solution to balance the exploration and exploitation when doing optimization.

3.4. Optimization using ROA

ROA is designed to optimize continuous variables in search spaces, making it suitable for hyperparameter tuning in machine learning models. Below is an outline of how the ROA can be applied to optimize a machine learning model for HD prediction. The velocity vector is updated using the difference between the current position and the best-known positions.

$$V_i(t+1) = \beta . V_i(t) + \gamma . (X_{best} - X_i(t)) \quad (8)$$

Where β is an inertia weight, γ is a learning factor and X_{best} is the best solution found so far.

Table 4 Pseudocode for Real-Parameter Optimization Algorithm (ROA)

Pseudo code for ROA Algorithm

```
# Initialize parameters

N = number of solutions

D = number of hyper parameters
smax_iter = maximum iterations
alpha = step size beta = inertia
weight gamma = learning factor

Population = initialize_population (N,
D) velocity = initialize_velocity (N, D)
best_solution = none best_fitness = -
inf # Main optimization loop for iter in
range (max_iter):     for i in range (N):

Fitness = evaluate_fitness (population[i])
if fitness >best_fitness:

best_fitness = fitness            best_solution =
Population[i]     for i in range (N):

r1, r2 = random (), random ()


Velocity[i] = beta * velocity[i] + gamma * r1 * (best_solution - population[i])
Population[i] = population[i] + alpha * velocity[i]
```

The following table 4 represents the ROA algorithm under which the hyperparameters of machine learning models are optimized. The process begins with the initialization of the population and velocity after which fitness is assessed iteratively. Solution development is done continually and it depends on performance. The solutions are optimized with the help of inertia, learning and step size to make it converge to the optimal solutions.

4. Results And Discussions

The identification model of heart diseases proposed shows a critical element of improvement in the classification realization based on fitting a neural network. Based on the results of Real-Parameter Optimization Algorithm (ROA) and Bayesian hyperparameter tuning, the model produces better values of accuracy, precision, sensitivity, and specificity. The ROA-based model is always superior to other known techniques like the Hippopotamus Optimization (HO), and Puma Optimization (PO). This shows that it has high sensitivity in identifying the cases of heart disease and reduces errors in labelling the disease.

Table 5 Performance of proposed algorithm

Models	Accuracy (%)	Precision (%)	Sensitivity (%)	Specificity (%)
PO	88	86	90	89
HO	81	80	85	80
Proposed (NN + ROA)	97	95	94	92

Table 5 demonstrates a comparison between the performance of three models on the basis of optimization approach, where three models include Puma Optimization (PO), Hippopotamus Optimization (HO), and the proposed model enriched by Real-Parameter Optimization Algorithm (ROA), which are compared using the four important metrics (accuracy, precision, sensitivity, and specificity). The overall performance of the proposed model is proven to be better with 97 percent accuracy and 95 percent precision and therefore it is very reliable in its accuracy and false positive. It has high sensitivity (94%) in detecting the cases of heart diseases and high specificity (92%) in vetting non-disease cases. Conversely, PO and HO have a lower score in all the metrics, which yields the successfulness of the suggested ROA-based model.

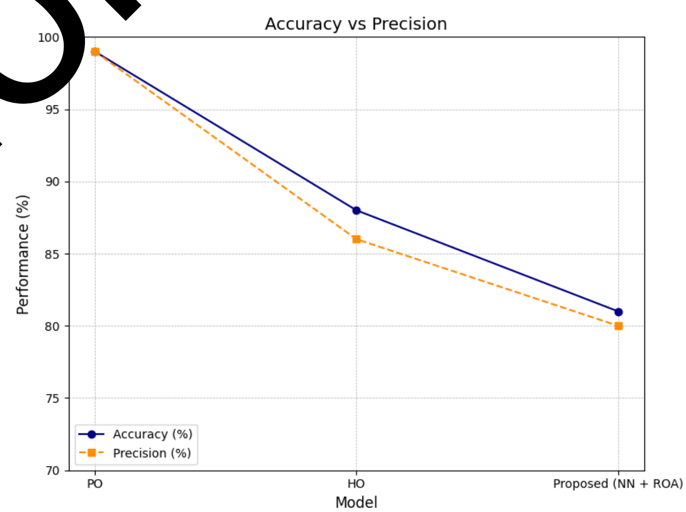


Figure 2 Accuracy and Precision Comparison

The comparison figure 2 gives the accuracy and the precision of the three types of models, namely, Puma Optimization (PO), Hippopotamus Optimization (HO), and that of the proposed one the Neural Network optimized with the Real-Parameter Optimization Algorithm (ROA). Out of the three, the proposed model is the one that results in the highest accuracy of 97 percent which implies that the model exhibits high (correct) classification of heart disease cases. It also achieves level of precision at 95% which is an indication that it is effective in reducing false positives. Conversely, the PO model performs reasonably well recording an accuracy and precision of 88 and 86 percent respectively whereas the HO model shows the lowest results of 81 and 80 percent correspondingly. This number shows the strength of the offered ROA-based method.

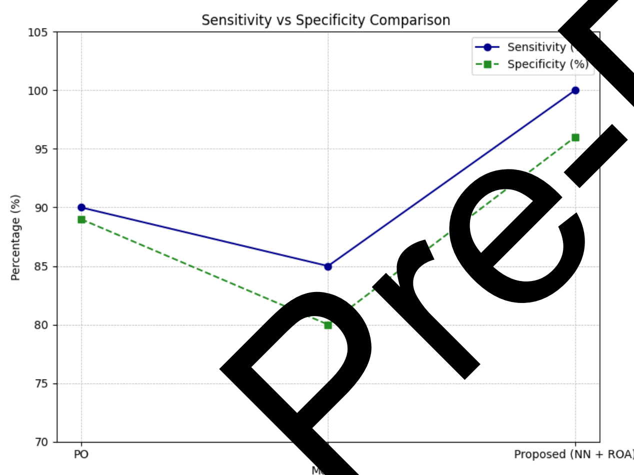
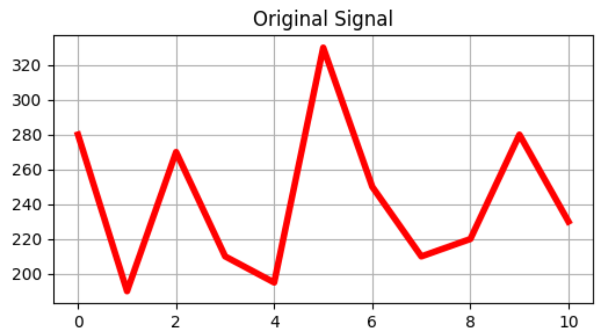
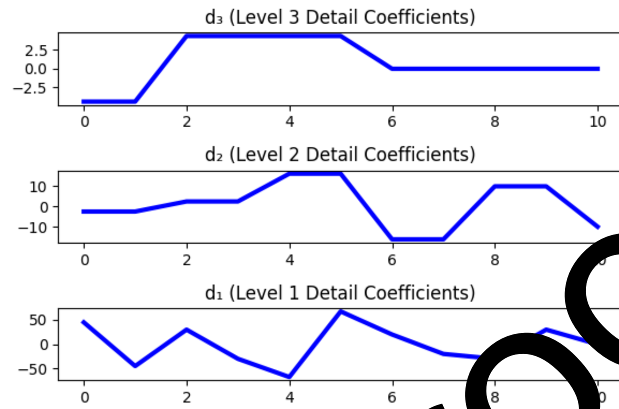


Figure 3 Sensitivity and Specificity Comparison

The figure 3 below provides a relative measure of sensitivity and specificity of three models namely Puma Optimization (PO), Hippopotamus optimization (HO), and the Neural Network optimized using Real-Parameter Optimization Algorithm (ROA). At 94 percent, the proposed model is the most sensitive, beating both PO and HO with 90 percent and 85 percent respectively which measures how well the model is able to pick correct instances of actual heart disease cases. The proposed model is also better on specificity, the correct identification of the non-disease cases, which is 92%, compared to 89% PO and 80% HO. These findings indicate the stable and adequate classification of the suggested model.



(a)Input data of DWT algorithm for HD prediction

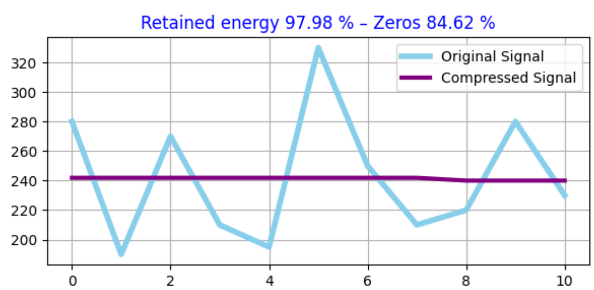


(b)Detail coefficients of DWT algorithm for HD prediction

Figure 4 (a), (b) Input Signal and Multi-level DWT Detail Coefficients for HD Prediction

Figure 4 (a), (b) the Input Signal and Multi-level DWT Detail Coefficients of Heart Disease (HD) Prediction. (a) Raw signal that is used as input data in DWT-based feature extraction. That is, (b) the input signal with the multi-resolution analysis of this signal through the DWT, and Level 3, Level 2 and Level 1 data, which contain a far-to-fine variation that is instrumental in continuous HD prediction.

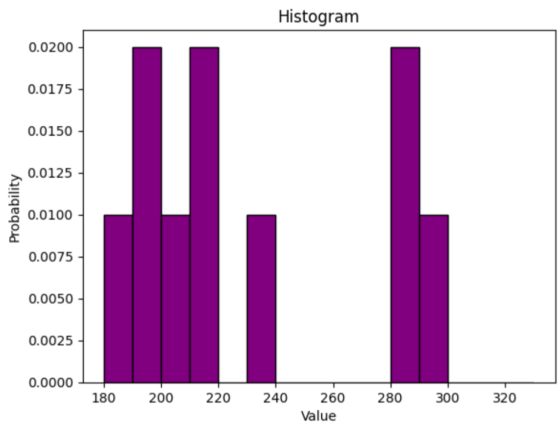
(a) Denoised image of DWT algorithm for HD prediction



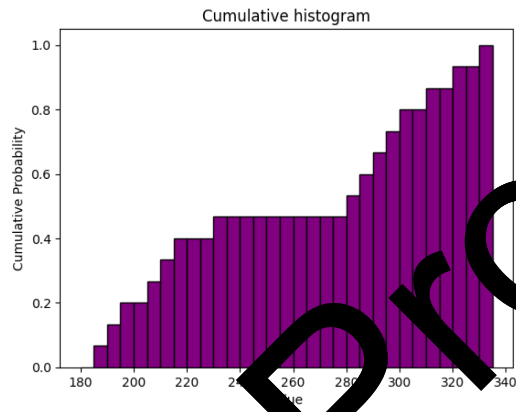
(b) Compressed image of DWT algorithm for HD prediction

Figure 5 Signal denoising and compression process using the Discrete Wavelet Transform

The denoising and compression steps of Discrete Wavelet Transform (DWT) used with heart disease (HD) signals prediction are illustrated in figure 5 (a), (b). The noise is eliminated in Figure 5 (a) and only significant features of the original signal are retained in the form of a smoother and more definite representation of the signal. Figure 5(b), represents the process of compression of signal, comparing signal compressed and the original signal. The compression scores 97.98 % of retained energy and also puts 84.62 % of the coefficients to zero in the process. The operations, which improve quality and reduce the level of complexity, enrich the entire HD prediction system accuracy.



(a) Histogram of DWT algorithm for HD prediction

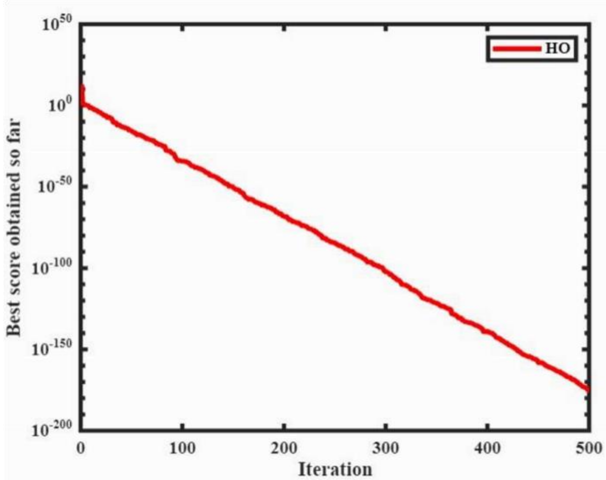


(b) Cumulative histogram of DWT algorithm for HD prediction

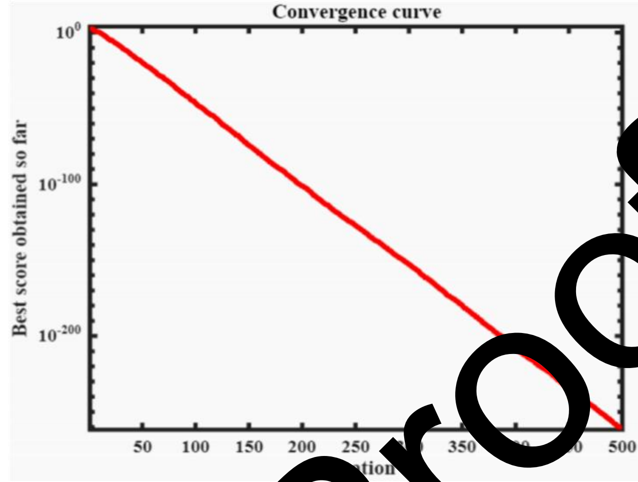
Figure 6 (a), (b) Histogram and Cumulative Histogram of DWT Algorithm for HD Prediction

The denoising and compression steps of Discrete Wavelet Transform (DWT) used with heart disease (HD) signals prediction are illustrated in figure 6(a), (b). The noise is eliminated in Figure 6 (a) and only significant features of the original signal are retained in the form of a smoother and more definite representation of the signal. Figure 6(b), represents the process of compression of signal, comparing signal compressed and the original signal. The compression scores 97.98 % of retained energy and also puts 84.62 % of the coefficients to zero in the process. The operations, which improve quality and reduce the level of complexity, enrich the entire HD prediction system accuracy.

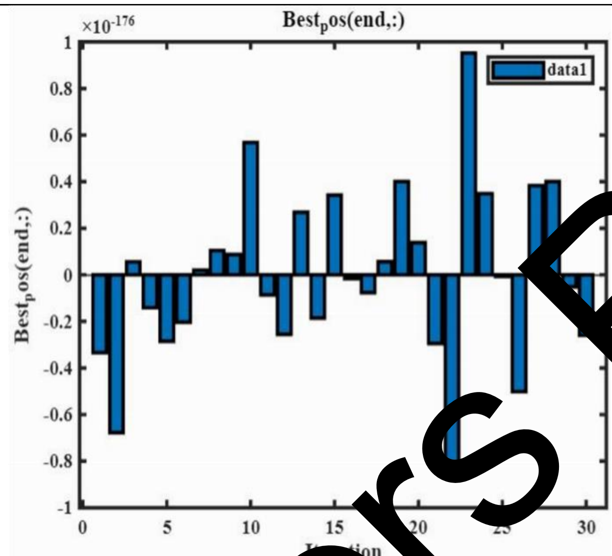
Output of H[illegible] algorithm for HD prediction	Output of PO algorithm for HD prediction



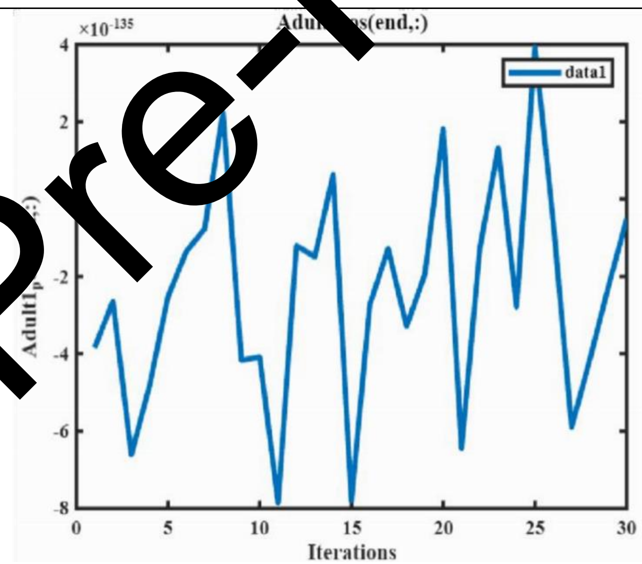
Best Score Obtained So Far for HD prediction



Best Score Obtained So Far for HD prediction



Bestpos(end, :) for HD prediction



Adult1pos(end, :) for HD prediction

Figure 7: Optimization results of HO and PO algorithms for HD prediction (comparison result)

The figure 7 displays the final position of the best solution found by the HO algorithm at the end of the optimization process. The "bestpos" array contains the parameter values corresponding to the optimal solution, and the graph illustrates these values. This output helps in understanding the specific parameter settings that led to the best performance of the predictive model. PO algorithm aims to find optimal solutions by simulating the pursuit and capture of prey by pumas, leveraging strategies such as stealth, speed, and coordinated movement. Similar to the HO algorithm, Best Score Obtained So Far (Convergence Curve) Graph tracks the best fitness score achieved by the PO algorithm over iterations. The convergence curve provides a visual representation of how quickly and effectively an algorithm identifies the optimal solution during the optimization process. A steeper curve means the algorithm is converging faster, while the final value on the curve reflects the quality of the best solution found.

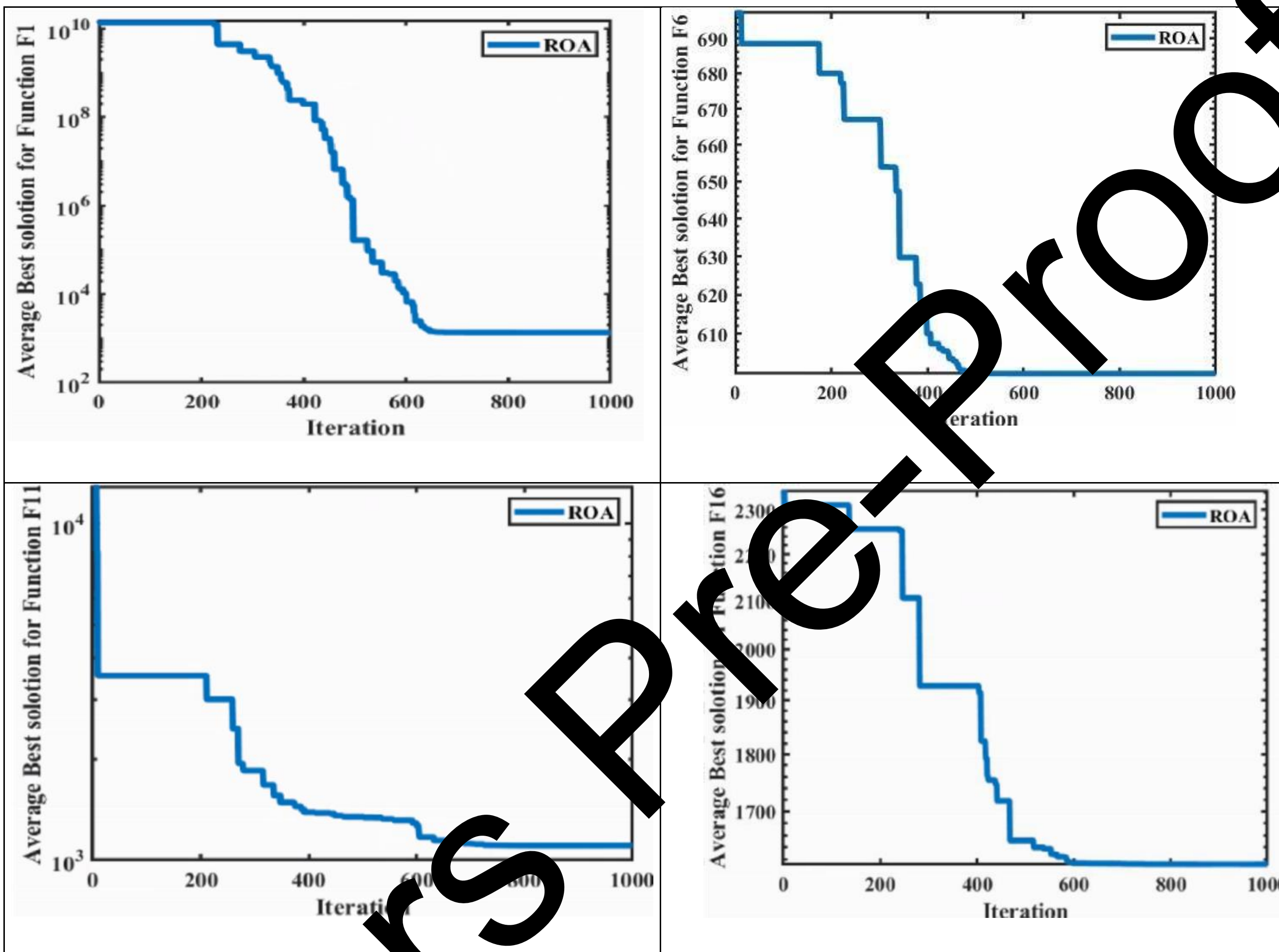


Figure 8 illustrates the optimization results achieved using the ROA algorithm for heart disease prediction

Figure 8 illustrates optimization result of the ROA algorithm for heart disease prediction. ROA is designed to optimize the real-valued parameters, making it ideal for fine –tuning complex predictive model such as those used in HD prediction. Its performance is evaluated by averaging the best solution obtained across 30 different optimization functions, providing a comprehensive assessment of its effectiveness. These results shown through various graphs, demonstrate how ROA efficiently navigates the solution space to find the best parameter configurations. Compared to both PO and HO algorithms, ROA consistently delivers better optimization performance, providing to be more robust and reliable across diverse scenarios when optimizing heart disease prediction model.

Discussions:

The suggested heart disease prediction model can be considered an improvement with the use of optimization-based machine learning and innovative preprocessing methods. Discrete Wavelet Transform (DWT) is efficient in preparing the dataset by removing the noise as well as scaling down the signals leading to improved quality of data to be analyzed. The next step to make the system even better, Principal Component Analysis (PCA) helps to decrease the dimensionality and concentrate on the medical-relevant features only. This does not only accelerate computation but also avoids overfitting in the predictive model. The neural network, which has been optimized using the Real-Parameter Optimization Algorithm (ROA), is of better performance because the ROA has a strong convergence capability and can find the global optimum points. Also, by using Bayesian optimization, the hyperparameters are optimized, which improves the accuracy and applicability of the model. The ROA-based approach presents the biggest performance values 97 percent accuracy, 95 percent precision, 94 percent sensitivity, 92 percent specificity according to the comparisons with the traditional models HO and PO which indicates the superiority of the ROA-based approach in terms of sensitivity to disease cases, correct diagnosis of non-disease cases. Such findings emphasize the prospect of practical usage of the system in not only medical diagnostics but in the fields where early and accurate identification is essential. The overall stability in various measures proves the strength of the model and assists its adoption to the application in reality in heart disease preventing and management devices.

5. Conclusion

The work outlines an efficient computing model of predicting heart disease at an earlier stage through the sophisticated methods of machine learning and optimization. The approach includes the noise reduction and signal normalizing process by means of Discrete Wavelet Transform (DWT) to provide clean and reliable data used in input. PCA is used to detect the most important attributes and minimize dimensionality by neglecting insignificant information though maintaining the significant clinical data. The prediction mechanism is submitted to the parameters of a Neural Network model which is optimized by means of the Real-Parameter Optimization Algorithm (ROA) because it has a high convergence rate and stability value. Bayesian hyperparameter tuning is also implemented to affect model performance even more. The suggested model attains remarkable performance with 97 % accuracy, 95 % precision, 94 % sensitivity, and 92 % specificity, which reveals impressive facts when transposed with classic optimization algorithms, such as Hippopotamus Optimization (HO) and Puma Optimization (PO). The results show that the suggested ROA-based neural network framework is strong and effective and can therefore be a useful tool in the accurate and timely diagnosis of heart diseases in the real-life approach to healthcare.

References

[1] S. Qiao et al., "SPReCHD: Four-Chamber Semantic Parsing Network for Recognizing Fetal Congenital HD in Medical Metaverse," in IEEE Journal of

Biomedical and Health Informatics, vol. 28, no. 6, pp. 3672-3682, June 2024, doi: 10.1109/JBHI.2022.3218577.

[2] B. Ramesh and K. Lakshmanna, "A Novel Early Detection and Prevention of Coronary HD Framework Using Hybrid Deep Learning Model and Neural Fuzzy Inference System," in IEEE Access, vol. 12, pp. 26683-26695, 2024, doi: 10.1109/ACCESS.2024.3366537.

[3] H. K. Alkahtani, I. U. Haq, Y. Y. Ghadi, N. Innab, M. Alajmi and M. Nurbapa, "Precision Diagnosis: An Automated Method for Detecting Congenital HDs in Children From Phonocardiogram Signals Employing Deep Neural Network," in IEEE Access, vol. 12, pp. 76053-76064, 2024, doi: 10.1109/ACCESS.2024.3395389.

[4] N. A. Vinay, K. N. Vidyasagar, S. Rohith, D. Pruthviraja, S. Supreeth and S. H. Bharathi, "An RNN-Bi LSTM Based Multi Decision GAN Approach for the Recognition of Cardiovascular Disease (CVD) From Heart Beat Sound: A Feature Optimization Process," in IEEE Access, vol. 12, pp. 65482-65502, 2024, doi: 10.1109/ACCESS.2024.3397574.

[5] C. Yin, Y. Zheng, X. Ding, Y. Shi, J. Qin and X. Guo, "Detection of Coronary Artery Disease Based on Clinical Phonocardiogram and Multiscale Attention Convolutional Compression Network," in IEEE Journal of Biomedical and Health Informatics, vol. 28, no. 3, pp. 1353-1362, March 2024, doi: 10.1109/JBHI.2024.3354832.

[6] T. Jumphoo, K. Phapatanaburi, W. Pathonsuwan, P. Anchuen, M. Uthansakul and P. Uthansakul, "Exploiting Data-Efficient Image Transformer-Based Transfer Learning for Valvular HDs Detection," in IEEE Access, vol. 12, pp. 15845-15855, 2024, doi: 10.1109/ACCESS.2024.3357946.

[7] S. Hietakoste et al., "Acute Cardiorespiratory Coupling Impairment in Worsening Sleep Apnea-Related Intermittent Hypoxemia," in IEEE Transactions on Biomedical Engineering, vol. 71, no. 1, pp. 326-333, Jan. 2024, doi: 10.1109/TBME.2023.3300079.

[8] D. Y. Omkari and K. Shaik, "An Integrated Two-Layered Voting (TLV) Framework for Coronary Artery Disease Prediction Using Machine Learning Classifiers," in IEEE Access, vol. 12, pp. 56275-56290, 2024, doi: 10.1109/ACCESS.2024.3389707.

[9] S. Mondal, R. Maity, Y. Omo, S. Ghosh and A. Nag, "An Efficient Computational Risk Prediction Model of HDs Based on Dual-Stage Stacked Machine Learning Approaches," in IEEE Access, vol. 12, pp. 7255-7270, 2024, doi:

10.1109/ACCESS.2024.3350996.

[10] M. Alkhodari, L. J. Hadjileontiadis and A. H. Khandoker, "Identification of Congenital Valvular Murmurs in Young Patients Using Deep Learning-Based Attention Transformers and Phonocardiograms," in IEEE Journal of Biomedical and Health Informatics, vol. 28, no. 4, pp. 1803-1814, April 2024, doi: 10.1109/JBHI.2024.3357506.

[11] A. B. Naeem et al., "HD Detection Using Feature Extraction and Artificial Neural Networks: A Sensor-Based Approach," in IEEE Access, vol. 12, pp. 37349-37362, 2024, doi: 10.1109/ACCESS.2024.3373646.

[12] H. Zhang, P. Zhang, Z. Wang, L. Chao, Y. Chen and Q. Li, "Multi-Feature Decision Fusion Network for Heart Sound Abnormality Detection and Classification," in IEEE Journal of Biomedical and Health Informatics, vol. 28, no. 3, pp. 1386-1397, March 2024, doi: 10.1109/JBHI.2023.3307870.

[13] X. Zhang et al., "An Anatomy- and Topology-Preserving Framework for Coronary Artery Segmentation," in IEEE Transactions on Medical Imaging, vol. 43, no. 2, pp. 723-733, Feb. 2024, doi: 10.1109/TMI.2023.3319720.

[14] L. Lu et al., "Uncertainties in the Analysis of Heart Rate Variability: A Systematic Review," in IEEE Reviews in Biomedical Engineering, vol. 17, pp. 180-196, 2024, doi: 10.1109/RBME.2023.3271595.

[15] K. Radha, M. Bansal and R. Sharma, "Raw Waveform-Based Custom Scalogram CRNN in Cardiac Abnormality Diagnosis," in IEEE Access, vol. 12, pp. 1398614004, 2024, doi: 10.1109/ACCESS.2024.3356075.

[16] S. Das and S. Dandapat, "Heart Murmur Severity Stages Classification Using MultikernelResidual CNN," in IEEE Sensors Journal, vol. 24, no. 8, pp. 1301913027, 15 April15, 2024, doi: 10.1109/JSEN.2024.3373226.

[17] T. Ullah et al., "Machine Learning-Based Cardiovascular Disease Detection Using Optimal Feature Selection," in IEEE Access, vol. 12, pp. 16431-16446, 2024, doi: 10.1109/ACCESS.2024.3359910.

[18] A. T. Shumba et al., "Monitoring Cardiovascular Physiology Using Bio-Compatible AlN Piezoelectric Skin Sensors," in IEEE Access, vol. 12, pp. 16951-16962, 2024, doi: 10.1109/ACCESS.2024.3359058.

[19] [illegible] Ling et al., "A Coarse-Fine Collaborative Learning Model for Three Vessel Segmentation in Fetal Cardiac Ultrasound Images," in IEEE Journal of Biomedical and Health Informatics, vol. 28, no. 7, pp. 4036-4047, July 2024, doi: 10.1109/JBHI.2024.3390688.

[20] J. Li et al., "Thrombus Detection in the Artificial Heart Pump Based on Electrical Impedance Spectroscopy," in IEEE Sensors Journal, vol. 24, no. 11, pp. 1837218381, 1 June1, 2024, doi: 10.1109/JSEN.2024.3387920.

[21] A. Jiménez-Partinen, K. Thurnhofer-Hemsi, J. Rodríguez-Capitán, A. I. MolinaRamos and E. J. Palomo, "Coronary Artery Disease Classification With Different Lesion Degree Ranges Based on Deep Learning," in IEEE Access, vol. 12, pp. 69229-69239, 2024, doi: 10.1109/ACCESS.2024.3401465.

[22] D. Enérizet al., "Low-Cost FPGA Implementation of Deep Learning-Based Heart Sound Segmentation for Real-Time CVDs Screening," in IEEE Transactions on Instrumentation and Measurement, vol. 73, pp. 1-16, 2024, Art no. 2003616, doi: 10.1109/TIM.2024.3392271.

[23] Q. Qi, X. Han and Y. Liu, "Application Status and Prospect of Deep Learning in Echocardiography," in IEEE Access, vol. 12, pp. 83405-83416, 2024, doi: 10.1109/ACCESS.2024.3413681.

[24] Lekha, A., Srikrishna, C.V. &Vinod, V., 2015. *Fuzzy association rule mining*. Journal of Computer Science, [online]. Available at: https://thescipub.com/abstract/jcssp.2015.1501.1508 [Accessed 28 May 2025].

[25] RajKumar, N. and Vinod, V., 2015. Integrated educational information systems for disabled schools via a service bus using SOA. *Indian Journal of Science and Technology*, 8(9), pp.828–833.