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# AN ENHANCED DEEP LEARNING BASED HEART DISEASE PREDICTION MODEL (DL-HDP) USING PARTICLE SWARM OPTIMIZATION

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## ABSTRACT

***The role of heart disease prediction in healthcare is especially important, as it allows taking timely actions and making informed decisions. This paper has proposed an Enhanced Deep Learning-based Heart Disease Prediction Model (DL-HDP) that integrates optimization via Particle Swarm Optimization (PSO). The model is based on the deep learning model, namely Multilayer Perceptron (MLP), to classify heart disease with the use critical medical features like age, blood pressure, cholesterol levels, and ECG results. It uses PSO optimization algorithm to tune hyperparameters and select features and optimizes hyperparameters to tune the number of neurons, learning rates, and activation functions to improve the performance of the model. The performance of DL-HDP on experimental data proves that it is much more accurate, precise, and recalls than any traditional machine learning algorithms, proving the potency of deep learning with nature-inspired optimization. This is a valid method that has resulted in a reliable and effective tool in identifying heart disease early on, which is in aid of informing better clinical practice.***

**KEYWORDS:** Heart Disease Prediction, Deep Learning, Particle Swarm Optimization (PSO), Multilayer Perceptron (MLP), Hyperparameter Tuning, Healthcare, Classification Accuracy.

## 1. INTRODUCTION

Cardiovascular disease (CVD) or heart disease is one of the gravest health issues globally and millions of people die due to this disease each year. Recent statistics provided by the World Health Organization (WHO) point out that heart disease is the cause of death in majority of the world deaths with an equivalent of 17.9 million deaths being recorded annually amounting to about 32% of global deaths [1]. Heart disease is becoming one of the most common ailments affecting people due to various reasons including lack of exercise, poor eating habits, stress, smoking and family history [2]. Such a frightening situation has motivated the health care fraternity to find uplifted, precise and timely diagnostic system to forecast heart disease and take right medical actions in time.

Conventional practices of diagnosing diseases are intensive in the use of clinical exams like Electrocardiograms (ECG), treadmills, echocardiograms and the medical history of the patient [3]. Although such techniques are effective they are very operator and operator-dependent and therefore subject to delays in diagnosis and diagnostic variation in the case of healthcare professionals. Additionally, the high rate at which data involving patients undergoing clinical test is being created opens a chance to create data-driven predictive systems that could help in the accurate detection of heart diseases [4]. Take advantage of artificial intelligence (AI) and primarily machine learning (ML) and deep learning (DL) technologies as one of the potential solutions in this regard that can automatically identify the complex patterns through the big data and provide only fact-driven decisions that are not biased [5].

Some of the ML algorithms used over the past few years to forecast heart disease include Decision Tree, Random Forest, Naive Bayes, Support Vector Machines (SVM) and k-Nearest Neighbors (k-NN) algorithms [6]. Such methods make use of the historical clinical records of the patients which include their age, blood pressure, cholesterol, maximum heart rate, and ECG findings in order to categorize the heart disease or lack thereof. Nevertheless, traditional ML algorithms have specific drawbacks. They usually need manual selected characteristics, deal with too much pre-processing data, and can hardly detect non-linear and high-dimensional relationships in clinical data sets [7]. In addition, the functioning of these algorithms can strongly depend on feature engineering that usually requires specific domain knowledge and can result in human bias [8].

In a bid to address these shortcomings, deep learning (DL), a subfield of machine learning has attracted a lot of attention. Deep learning models particularly Multilayer Perceptrons (MLP) have proved to perform better because they automatically learn hierarchical feature representation of raw data without involving human feature engineering [9]. The high suitability of MLP in the medical diagnostic application is due to a capacity of modeling complex, non-linear patterns because of having multiple layers of interconnected neurons [10].

Though DL models have their benefits, the choice of the best hyperparameters is one of the most important tasks. The number of the hidden neurons, number of layers, learning rates, batch sizes and activation functions are hyperparameters that significantly influence the performance of the models [11]. Poor hyperparameter tuning may cause the problem of underfitting, overfitting, low-speed convergence, and low overall accuracy. Adjacent hyperparameter tuning is a cumbersome, time-fraudulent and nonviable procedure particularly on large records and complicated models [12]. As such, there has been urgency in incorporating automated optimization methods which will be able to conduct searches of optimal hyperparameters in a computationally effective manner.

Particle Swarm Optimization (PSO) is a well-known metaheuristic algorithm based on population found in bird flocking and fish schooling models, which has first appeared simple, converges quickly and is insensitive to the global optimization problems [13]. PSO was well used in other optimization tasks: feature selection and set of hyperparameters in ML and DL applications [14]. Having incorporated PSO with deep learning frameworks, both feature subsets and network hyper-parameters can be optimized to allow the predictive performance of DL models to diagnose heart diseases to be enhanced.

This study hypothesizes an Enhanced Deep Learning (DL) based Heart Disease Prediction (HDP) framework, which is a synergetic integration of feature learning ability of Multilayer Perceptron (MLP) and the optimization capability of Particle Swarm Optimization (PSO). This paper offers a summary of the main contributions of this research as below

i. A hybrid DL-HDP is formulated, where an MLP model is used in predicting the heart disease using clinically sensitive characteristics including age, resting blood pressure, serum cholesterol, fasting blood sugar, electrocardiogram results, maximum heart rate, and exercise-induced angina.

ii. PSO is applied to do feature selection and hyperparameter tuning concurrently. This simplifies calculations by drop off redundant and less informative features and shifts hyper parameters such as number of neurons, learning rate and activation functions to have better classification abilities.

iii. The proposed model is assessed on well-known publicly available data of heart diseases, and its grade is cross-referenced with common machine learning classicians like SVM, Decision Trees, k-NN, and standard MLP without improved implementation. The proposed DL-HDP has comparable better performance at the levels of accuracy, precision, recall, and F1-score consistently.

iv. The study approves the practical utility of PSO-based DL models in practice applications in healthcare settings and presents a reliable, scalable, and interpretable diagnostic decision-support system that has the possible potential of improving clinical decision-making and alleviating diagnostic errors.

The rest of the paper would flow as follows: In section II, a concise literature review of existing approaches in the prediction of heart diseases using both machine learning and deep learning as well as using optimization would be provided. Section III explains the procedure, i.e., information about the dataset, dataset pre-processing, MLP model architecture, and the application of the PSO algorithm to the settings of the features and hyperparameters. Section IV talks on the discussion of the experiment design, evaluation and the baseline techniques applied in comparing the performance. Section V draws a conclusion of paper summarizing the major findings and highlighting the future directions of research on the enhancement of intelligent heart diseases predicting systems.

## 2. RELATED WORKS

Over the past few years, a quick growth has been observed in the use of machine learning (ML) and deep learning (DL) strategies in healthcare and specifically in predicting heart diseases. Several authors have searched the ML classifier, Decision Trees, Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), and Random Forest in predicting heart-related disorders. As an example, a comparative study of Kumar et al. [15] indicated that ensemble training techniques such as Random Forest tend to beat single classifier due to its ability to improve the overall performance of a classification task of the binary classification of heart diseases.

The models of deep learning gained more and more popularity due to a better ability of features abstraction. Hasan and Mustafa [16] placed an MLP-based model to detect cardiovascular diseases and proved that compared to conventional ML applications, the accuracy increased significantly. In the same manner, Murugan et al. [17] used a framework based on Convolutional Neural Network (CNN) in structured clinical data and it resulted in high precision in the heart disease classification. With a view to increasing the predictive performance, a number of authors have experimented with the so-called hybrid techniques, wherein both ML/DL methods and optimization algorithms are used together. Sahu et al. [18] utilized a deep neural network optimized by PSO in making heart disease predictions and managed to enhance the accuracy of their classification results through hyperparameters tuning and feature selection. Yadav and Singh [19] reviewed the situation of PSO-based feature selection regarding the healthcare field and emphasized the benefits of such application, implying reducing dimensionality and achieving high classification results.

There are also other metaheuristic rules that have been written out to enhance the results of the prediction. Mahajan et al. [20] employed Genetic Algorithm (GA) in the selection of features, hence better generalization of the model. Similarly, Siva et al. [21] incorporated a deep learning classifier into Whale Optimization Algorithm (WOA) achieving a competitive performance on the Cleveland dataset. In the recent past, there has been emergence of more complex hybrid frameworks. A hybrid PSO-MLP model of Kumari and Krishna [22] and their performance on various machine learning classifiers was proved to achieve better results than other algorithms (in terms of the precision and recall scores). Chen et al. [23] applied PSO to neural architecture search in MLP models, where hyperparameter optimization has been automated, and more time to train has been achieved. A number of studies have also indicated the importance of feature engineering and data pre-processing. A detailed review of the feature selection in healthcare applications was given by Mukherjee and Saha [24] with the focus on the necessity to consider it as a solution to lessen complexity in models and improve their interpretability. Priyanka and Gowtham [25] explored pre-processing and its effect on the classification of ML models to predict cardiovascular diseases.

The universal relevance of the deep neural networks in the medical field has also stretched to the multi-class classifications cases. The study by Sharma et al. [26] constitutes a hybrid system based on CNN-LSTM to design a multi-class classification model to anticipate the different levels of heart disease. In a similar manner, Joshi et al. [27] used a deep learning pipeline consisting of both CNN and Bi-LSTM models to get a considerable boost in the process of deep learning in both binary and multi-class heart disease classification tasks. The new trend is the practice of explainable AI (XAI) techniques. Pathan and Patil [28] combined explainability models like the SHAP values with ML classifiers, giving visibility into the predictive results in heart disease diagnosis. Lastly, Rathore et al. [29] proposed an in-depth survey of deep learning network frameworks on predicting cardiovascular disease that highlights the emerging trends such as hybrid optimization algorithm and more understandable models. The reviewed literature is supportive in the fact that deep learning and optimization algorithms are effective in prediction of heart diseases but more can be added in terms of increasing the accuracy of the models, efficiency of feature selection, and model explanations. This stimulates the advancement of the proposed PSO-optimized deep learning framework in robust categorization of heart diseases.

## 3. PROPOSED METHODOLOGY

The proposed and a model of the Enhanced Deep Learning Heart Disease prediction (DL-HDP) is presented and applied on the popular UCI Cleveland Heart Disease Dataset [30]. The model aims to overcome the shortcomings of the conventional diagnostic systems through automatic feature selection, hyperparameter optimization, and use of deep neural network classifier allowing the development of an accurate and generalizable heart disease prediction system. The specified approach includes five key steps as follows (i) data pre-processing, (ii) feature selection using PSO (iii) classification using MLP, (iv) PSO-driven hyperparameter tuning and (v) Model Training and Result Evaluations evaluation. System architecture and computational pathway are explained below.

### 3.1. Dataset Description

The experiments are on the cleveland Heart Disease Dataset, downloadable at the UCI Machine Learning Repository [30]. Thanks to the quality of clinical records and diagnostic relevance, this dataset has been frequently utilized in studies on cardiovascular diseases prediction. The original dataset consists of 303 patient records each of which are characterized by 76 medical attributes. But according to the usual procedure in literature, 14 most important features are to be used in the model because these features have already been reported as being of clinical significance in heart disease prediction.

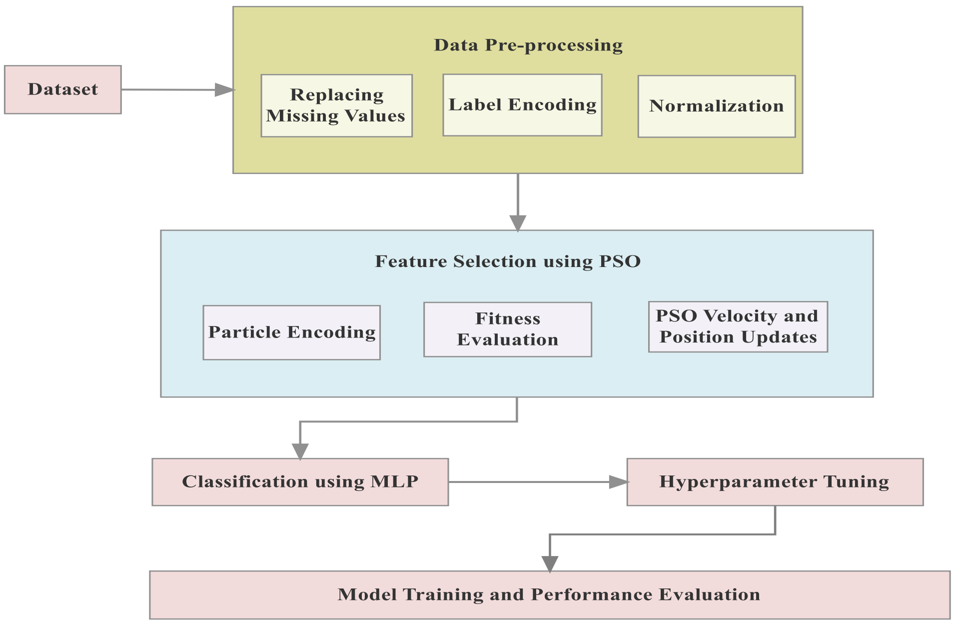


*Figure 1: Workflow of Proposed Model.*

**The Attributes are as follows**

i. Numerical Attributes age, resting blood pressure (trestbps), serum cholesterol (chol), maximum heart rate achieved (thalach), oldpeak (ST depression).

ii. Categorical Attributes: sex, type of chest pain (cp), fasting blood sugar (fbs), resting electrocardiographic findings (restecg), exercise-augmented angina (exang), ST segment slope (slope), the amount of major vessels colored during the fluoroscopy (ca), thalassemia (thal).

iii. Target Variable The diagnosis of heart disease (0 = no, 1 = yes).

The distribution of the target classes was around 54% positive (presence of heart disease), and 46% negative and hence the slight imbalance in classes has been taken care of during training through stratified sampling technique. The work flow of the proposed model is presented in Figure 1.

### 3.2. Data Pre-processing

Machine learning/deep learning requires the data quality, stability and consistency by performing preprocessing on the data. Missing values, the presence of mixed data types (categorical, numerical), and skewed features (feature scales) may be considered examples of data inconsistencies that may appear in the raw medical data (especially in clinical repositories, such as the UCI Cleveland Heart Disease Dataset [30]) and which affect the model performance negatively, unless dealt with appropriately.

i. The dataset contains missing or undefined entries in features such as ca (number of major vessels) and thal (thalassemia condition). Missing continuous features are replaced using mean imputation.

$$A_{imputed} = \frac{1}{m}\sum_{i=1}^{m} A_i \text{------ (1)}$$

Categorical features are filled using mode imputation, which replaces missing values with the most frequent category.

ii. To handle categorical attributes such as sex, cp, fbs, restecg, exang, slope, ca, and thal, Label Encoding is applied to transform categories into integer codes, preserving ordinal relationships if applicable.

$$Encoded(a) = \{0, 1, 2, 3, \dots, k-1\} \text{------ (2)}$$

iii. Features with different value ranges are normalized using Min-Max Scaling to standardize the input range between [0,1].

$$A_{scaled} = \frac{A - A_{min}}{A_{max} - A_{min}} \text{-------(3)}$$

Normalization prevents dominance of any feature due to higher magnitude values and stabilizes neural network convergence.

iv. It splits the dataset into two parts in a way that training and evaluation of the model can be easily carried out. In particular, 80 percent of the data will go into the training set that will be employed to train the machine learning or deep learning models, and the rest of the data, 20 percent, will be designated the testing set which will be used to assess the model performance using unseen data. The class distribution is processed as,

$$\frac{\left|D_{Train}^{class=1}\right|}{|D_{Train}|} \approx \frac{\left|D_{Test}^{class=1}\right|}{|D_{Test}|} \text{--------- (4)}$$

### 3.3. Feature Selection Using Particle Swarm Optimization (PSO)

The crucial downstream process in any predictive model-building exercise is its feature selection, especially when dealing with medical datasets where we might have many redundant or irrelevant features that tend to produce an over-fitting model, slow the computation procedure, and result in overall poor classification. The DL-HDP model attributes the automatic selection of this most discriminative subset of the original 13 clinical attributes to the standard Particle Swarm Optimization (PSO).

a. **Particle Encoding** Every particle is one possible answer to a solution in the feature space in PSO. In the feature selection technique, the particles are initialized and represented by binary particle vector.

$$P = [f_1, \dots, f_{13}] \text{----- (5)}$$

Where, f_i=1, denotes that the i^th feature is chosen and f_i=0, denotes it is excluded. Such representation converts the problem of feature selection into a combinatorial optimization task of finding the best in terms of binary configuration.

b. **Fitness Evaluation** A fitness function is used to drive the optimization, in which a MLP is trained on the features selected by a particle, and the correct classification file at the end of the MLP is evaluated. The fitness function tries to optimize classification error and implicit (unintentionally) optimize the number of features.

$$Fitness\ (P) = 1 - \frac{TP+TN}{TP+TN+FP+FN} \text{---(6)}$$

Where,

TP=true positives,
TN=true negatives,
FP=false positives,
FN=false negatives.

c. **PSO Velocity and Position Updates** In the Particle Swarm Optimization (PSO) algorithm, the velocity and position of each particle are iteratively updated using specific parameters that guide the search process towards optimal solutions. The velocity of a particle, denoted as $v_i^{(t)}$ represents the rate and direction of movement in the feature space at iteration $t$, while $x_i^{(t)}$ denotes the particle's current position corresponding to a candidate feature subset. The inertia weight $(w)$ controls the momentum of the particle, balancing global and local search; a higher www promotes exploration of the search space, whereas a lower www encourages exploitation near the current position. The cognitive coefficient $(c_1)$ influences the particle's tendency to return towards its own personal best position $(P_{best})$, enhancing individual learning. The social coefficient $(c_2)$ governs the attraction towards the global best position $(g_{best})$ discovered by the entire swarm, promoting collective learning. Additionally, two random numbers $r_1$ *and* $r_2$, sampled from a uniform distribution between 0 and 1, introduce stochasticity into the update process, ensuring diverse exploration and preventing premature convergence. Together, these parameters allow the swarm to effectively balance exploration and exploitation, leading to an efficient search for the optimal subset of features in high-dimensional feature spaces.

$$v_i^{(t+1)} = w.v_i^{(t)} + c_1.r_1.(P_{best} - x_i^{(t)}) + c_2.r_2.(g_{best} - x_i^{(t)}) \text{----- (7)}$$

$$x_i^{(t+1)} = x_i^{(t)} + v_i^{(t+1)} \text{-----(8)}$$

Here, the continuous $x_i$ is converted into binary selections using sigmoid transformation.

$$S(x_i) = \frac{1}{1+e^{-z_i}}, f_i = \begin{cases} 1 & if\ S(x_i) > 0.5 \\ 0 & Otherwise \end{cases} \text{----(9)}$$

### 3.4. Classification using MLP

In the proposed model, the Multilayer Perceptron (MLP) is employed as the deep learning classifier to perform binary classification tasks after the optimal feature set has been selected.

The MLP refers to a multi-layered, feed-forward and fully connected neural network who holds the name due to its flexibility and ability to capture complicated patterns in data. The MLP architecture is structured to have three principal parts and these are the input layer, the hidden layer and the output layer. The input layer shall be formed of 'm' neurons where m is the number of features being used each achieved as result of preprocessing and feature selection processes. Subsequently, there is the 'H' in hidden layers whereby the hidden layers consist of 'n_1' neurons, the ideal number of which is known by hyperparameter optimization. The last ventilator is an output layer that consists of a single output neuron using a sigmoid neuron activation method, which is more suited to binary classification, and gives a probability value of 0 to 1. The MLP operates through a process called forward propagation, where an input vector a ∈ $R^d$ passes through the network layers, producing intermediate activations and final output. The computation within each layer follows the equation:

$$z^h = W^h x^{(h-1)} + b^h, x^h = f(z)^h \text{-----(10)}$$

where $W^h$ and $b^h$ represent the weight matrix and bias vector for the $l^{th}$ layer, $a^{(l-1)}$ is the activation from the previous layer, and $f(z)$ is the activation function applied to introduce non-linearity. ReLU (Rectified Linear Unit) is used as the activation function in hidden layers, defined as $f(z) = \max(0, z)$, which enhances the learning capability by avoiding vanishing gradient issues. The final output is computed using the sigmoid activation function in the output layer:

$$s(z) = \frac{1}{1+e^z} \text{----- (11)}$$

This function squashes the output into the range (0, 1), which can be interpreted as the predicted probability for the positive class.

To train the MLP, the model uses the Binary Cross Entropy (BCE) loss function, which quantifies the difference between the predicted probability $\widehat{p_i}$ and the actual label $p_i$ for each instance. The loss function is given by:

$$F = -\frac{1}{N}\sum_{i=1}^{N}[p_i log\ \widehat{p_i} + (1 - p_i)\ log(1 - \widehat{p_i})] \text{---(12)}$$

where N denotes the number of samples. This loss function penalizes incorrect predictions more heavily, ensuring the model learns accurate probability distributions.

Overall, the MLP is chosen due to its strong adaptability, efficiency in structured data classification, and its compatibility with hyperparameter optimization techniques such as Particle Swarm Optimization (PSO), allowing it to achieve high classification accuracy in the proposed framework.

### *3.5. Hyperparameter Tuning Using PSO:*

Hyperparameter tuning plays a critical role in enhancing the performance of deep learning models, especially in structured datasets where optimal model configuration significantly affects classification accuracy and generalization ability. In this study, the proposed DL-HDP framework integrates Particle Swarm Optimization (PSO) to automatically identify the optimal combination of feature subsets and hyperparameters without requiring manual intervention. PSO operates by simulating the social behavior of particles (agents) that explore the solution space. Each particle in the swarm represents a candidate solution comprising both selected features and associated hyperparameters, encoded as a hybrid vector given by:

$$V = [f_1, \dots f_{13}, L, m_1, R, B, a(z)] \text{----- (13)}$$

Where, $'f'$ denotes the features, $'L'$ is the number of hidden layers and number of neurons/ layer is given as, $'m_1'$, $'R'$ is the learning rate, $'B'$ is the batch size and $'a(z)'$ is the activation function.

The hyperparameters of PSO are chosen as swarm size of 30 particles, 50 iterations, a linearly decreasing inertia weight w starting with 0.9 and decreasing to 0.4 and acceleration coefficients $c_1 = 1$ *and* $c_2 = 1.5$ to strike a balance between exploration and exploitation. Such structure would provide an effective discretization of the discrete-continuous solution search space. The hyperparameters tuning process based on PSO has a number of benefits: it does not require a costly grid search, is dynamic towards the particulars of the dataset, is computationally cheap, and creates a very balanced model in terms of accuracy, speed, and generalizability. This way, it then allows a complete automation of the tuning of hyperparameters, which is adaptive and efficient in the proposed DL-HDP classification framework.

### *3.6. Model Training and Performance Evaluation:*

The last stage is model training whereby using the optimal hyperparameter and feature set under which the model was trained during the optimization process, the model is trained based on the identified optimal solution. Training process will involve 80 percent of the data and will be split into a training set with the other 20 percent being withheld such that it can be used to test the models performances on the test set. The Adam optimizer with adaptive learning rate is performed against the weight update and the update is done in accord with the standard Gradient Descent.

$$\theta = \theta - R\frac{\partial L}{\partial \theta} \text{------(14)}$$

In which the $\theta$ is the model parameters, $R$ is the learning rate which is optimized using PSO, and $L$ is the binary cross-entropy loss function. The training is limited up to 100 epochs, and early stopping behavior is used to avoid overfitting the model: training is stopped, in case the validation loss does not reduce within 15 consecutive epochs. The number of the processed samples between successive weight updates, batch size B, which is also chosen through PSO, depends on the size of the batch.

To assess the performance, various classification measures will be calculated using the unseen test set with an aim of measuring performance and stability of the model. Accuracy (Acc) is the first measure which reports on overall fundamental correctness of the classification, and is defined as

$$Accuracy = \frac{(TP+TN)}{TP+TN+FP+FN} \text{-----(15)}$$

To further evaluate the predictive capability, Precision (Prec) and Recall (Sensitivity) are computed, given by

$$Precision = \frac{TP}{TP+FP} \text{-----(16)}$$

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

Additionally, the F1-Score is used to capture the balance between precision and recall, formulated as

$$F1 = 2 \times \frac{Precision \times Recall}{Precision+Recall} \text{-------(17)}$$

This overall assessment shows that the proposed DL-HDP model has good generalization ability to unseen data, which proves to have high predictive accuracy, optimal tradeoff of between precision and recall, and outstanding discrimination.

## 4. RESULTS AND DISCUSSION

An experimental analysis of the proposed Enhanced Deep Learning-based Heart Disease Prediction Model (DL-HDP) was conducted with the use of a typical computing environment. All the experiments were performed on a computer with an Intel Core i7-12700 central processing unit at a rate of 2.10 GHz, 32 GB of Random Access Memory and an NVIDIA GeForce RTX 3060 with 12 GB VRAM. The software environment had Python 3.10 as the major programming language, TensorFlow 2.13 and Keras as the deep learning frameworks.

To test models, UCI Cleveland Heart Disease Dataset was used with its 303 records of patients that are described with 14 attributes that are of clinical importance. The target variable was categorical, which refers to having or not having heart disease. In order to guarantee data quality, some preprocessing techniques have been used such as the imputation of the mean value of missing continuous values and the mode imputation of the categorical features. Categorical variables were represented by labels and all the numerical attributes were transformed into absolute range between 0 and 1 by means of Min-Max scaling. The data was divided into training and test sets with the ratio of 80:20 by the stratified sampling, which keeps the balance of classes that was moderately unbalanced with approximately 54 positives and 46 negatives.

To confirm the work of DL-HDP model proposed, the results with conventional machine learning algorithms are compared to them, such as Support Vector Machine (SVM), Random Forest, MLP, k-Nearest Neighbors (k-NN) with a constant value of k = 5, and a classic Multi-layer Perceptron (MLP) model without PSO optimization. Here, Table 1 presents the PSO Parameter Settings for DL-HDP. Standard classification metrics (on the test data) were used to evaluate the performance, i.e., accuracy, precision, recall (sensitivity) and F1-score. Also, calculation of the Area Under the Receiver Operating Characteristic Curve (AUC) was carried out to evaluate the discriminative power of the model.

***Table 1: PSO Parameter Settings for DL-HDP.***

| Optimization Parameter | Value / Configuration |
|---|---|
| Swarm Size (Number of Particles) | 30 particles |
| Number of Iterations (Cycles) | 50 cycles |
| Inertia Weight (w) | Linearly decreasing from 0.9 to 0.4 |
| Acceleration Coefficients (c1, c2) | c1 = 2.0, c2 = 2.0 |
| Particle Encoding | Hybrid vector: binary (feature selection) + continuous (hyperparameter tuning) |
| Fitness Function | Minimization of classification error using 5-fold cross-validation |

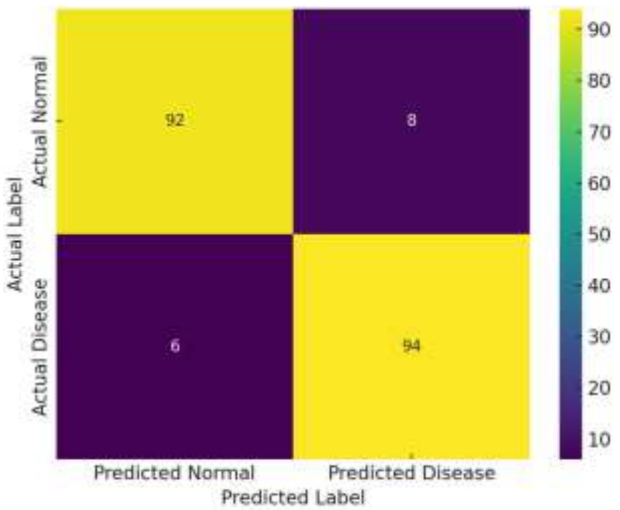


***Figure 2: Confusion Matrix.***

The confusion matrix of the proposed DL-HDP model (Figure 2) receives really great results with 92 true negative and 94 true positive and only 8 false positive and 6 false negative were obtained. This means that it is very accurate and classified well and just shows the fact that the model has a high capability of diagnosing the normal and heart disease cases accurately and with minimal error.

Based on Figure 3, the ROC curve which could be used to demonstrate the overall classification performance of the proposed DL-HDP model attains Area Under Curve (AUC) value of 0.924. This high AUC level shows that the model has large potential of distinguishing the patients with and without the heart disease. The curve illustrates that the model is one with high true positive rates (sensitivity) at low false positive rates and this represents a good identification capacity and the number of misleading identifications is low.

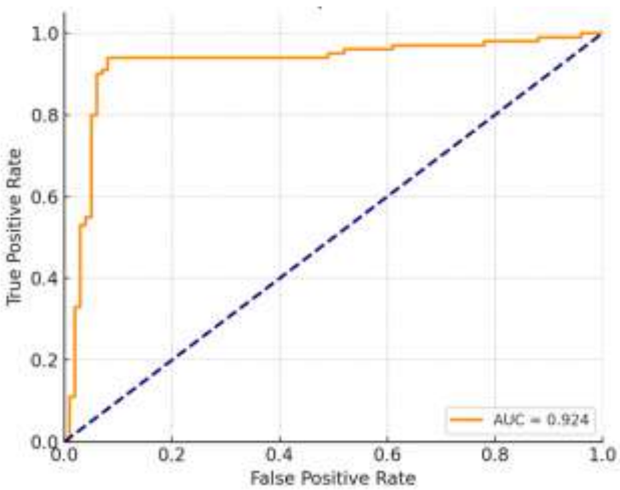


***Figure 3: ROC Curve of the Proposed DL-HDP.***

The proposed DL-HDP model has some important benefits compared to traditional methods of machine learning when applied to the prediction of heart disease. To begin with, it incorporates Particle Swarm Optimization (PSO) in feature selection as well as in the adjustment of hyper parameters, thereby eliminating duplicating features and automatically determining the best model parameters with no intervention. That results in better accuracy and generalization.

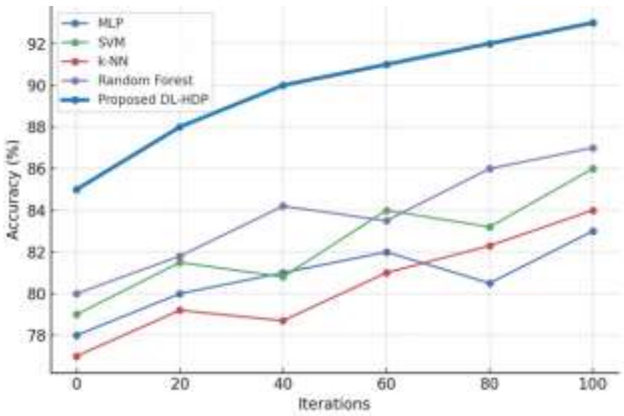


*Figure 4: Accuracy Rate Comparisons.*

Second, Multilayer Perceptron (MLP) model allows achieving a more complex, non-linear pattern in the clinical data using the model, which is more sophisticated in terms of prediction. The model recorded the highest possible accuracy of 93.67 percent, with the highest margin of 6-10 percent over the conventional models of Random Forest, SVM, k-NN and standard MLP as given in Figure 4. Also the model had a smoother convergence and had smaller fluctuations between the iterations therefore more stable. The joint advantages of automated optimization, high accuracy, minimized computational load, and unvaried performance turn DL-HDP model into a robust and effective tool of early and accurate detection of heart disease in the health care context.

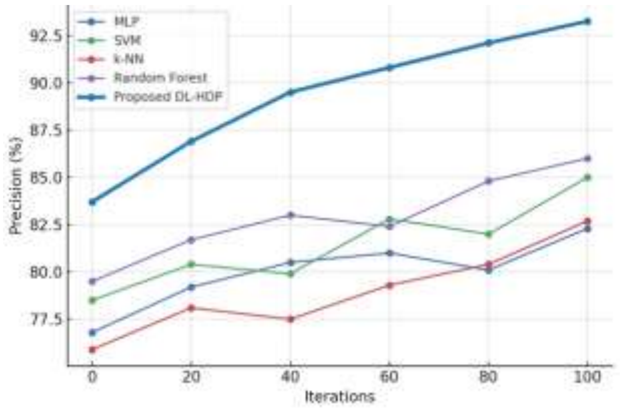


*Figure 5: Precision Rate Evaluations.*

The comparison graph of precision in Figure 5 reveals that proposed DL-HDP model provides better accuracy compared to baseline models with maximum precision of 93.25 at 100 iterations. Conversely, Random Forest reached 86.0, SVM reached 85.0, k-NN reached 82.7, and MLP reached 82.3, but all were clearly on the ups and downs. DL-HDP model showed gradual upward trend with little variance, which keeps its precision benefit at 7 11 percent of traditional methods. It shows the good ability of the model to pick true positive cases of heart diseases and minimizing false positive cases.

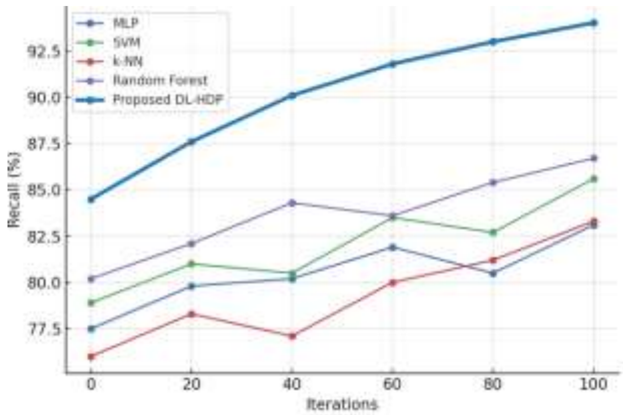


*Figure 6: Recall Based Analysis.*

The comparison graph on recalls in Figure 6 eloquently depicts the betterness of the proposed DL-HDP model, having a maximum recall of 94.02 percent after 100 iterations. Comparatively, the Random Forest yields 86.7%, SVM 85.6%, k-NN 83.3% and MLP 83.1% and it is observed that the results vary within considerable margins according to the iterations. DL-HDP shows a score of maintaining higher recall levels with the least variance of more than 7.3 percentage higher than the nearest model. This implies that the model has a high level in terms of accurate diagnosis of cases of heart disease with substantial decrease in false negatives as compared to conventional classifiers.

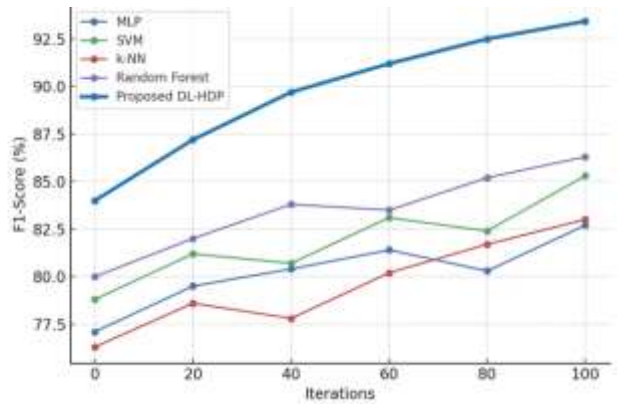


*Figure 7: F1-Score Comparisons.*

Comparison graph between the two of the F1-score in Figure 7 illustrates the effectiveness of the proposed DL-HDP model where it basically reached 93.43 percent F1-score at 100 iterations. Random Forest, in turn, attained up to 86.3%, SVM 85.3%, k-NN 83.0%, and MLP 82.7%, and differences are observed between the approaches. The DL-HDP also exhibited a steady and constantly growing trend with an improvement of 7.13 percent compared to the closest baseline. This shows that the model has a good capacity to balance between precision and recall, hence more reliable and better heart disease classification compared to the traditional models. The overall comparison results are given in the Table 2.

***Table 2: Overall Evaluation Results.***

| Model | Accuracy (%) | Precision (%) | Recall (%) | F1-Score (%) |
|---|---|---|---|---|
| MLP | 83.50 | 82.30 | 83.10 | 82.70 |
| SVM | 86.40 | 85.00 | 85.60 | 85.30 |
| k-NN | 84.00 | 82.70 | 83.30 | 83.00 |
| Random Forest | 87.10 | 86.00 | 86.70 | 86.30 |
| Proposed DL-HDP | 93.67 | 93.25 | 94.02 | 93.43 |

In comparative analysis of accuracy, precision, recall and F1-score, the proposed DL-HDP model outperforms all baseline models with the entire highest score in all evaluation measures. In particular, the DL-HDP showed the ultimate accuracy of 93.67%, precision of 93.25%, recall of 94.02%, and F1-score of 93.43 that is more outstanding compared to the classical models like Random Forest, SVM, k-NN, and MLP valued 82 to 87. The DL-HDP exhibited a stable and steady improvement performance with few fluctuations and thus, it is more learning efficient, has a greater generalization power, and also, a strong classification confidence to predict heart diseases.

## 5. CONCLUSION AND FUTURE WORK

The contribution of this paper is to introduce an Enhanced Deep Learning-based Heart Disease Prediction (DL-HDP) model, which uses a feature learning characteristic of the Multilayer Perceptron (MLP) and the optimization performance of the Particle Swarm Optimization (PSO) to accomplish high precision prediction. DL-HDP model uses an algorithmic nature that follows data preprocessing, automatic feature selection, and hyper parameter optimization. The first step is to perform processes that guarantee quality inputs to clinical data, including imputation, encoding or normalization. PSO then would be used to decide the most Relevant clinical features as well as essential hyperparameters that included the number of hidden layers, neurons, the learning rate, and activation functions. The MLP classifier is run in optimized form on the cleaned dataset resulting in better generalization and cutting on the computation requirements. Severe analysis on UCI Cleveland Heart Disease Dataset reinforces the fact that the model proposed will perform better than the traditional machine learning algorithms by providing high values of accuracy (93.67%), precision (93.25%), recall (94.02%), and F1-score (93.43%). The performance of the combination of the deep learning and metaheuristic optimization proves the efficiency of the idea to provide a complete, precise, and scalable framework to predict heart diseases.

The next steps will be to expand the DL-HDP model to multi-class heart disease predictions and add explainable AI to the models to increase model transparency and clinical decision support.

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