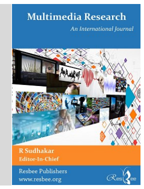
Resbee Publishers

Multimedia Research (MR)

Received 6 May, Revised 22 June, Accepted 3 July



Archimedes Optimization Algorithm: Heart Disease Prediction

Sesham Anand
Professor of CSE, Maturi Venkata Subba Rao Engineering College,
Hyderabad, India
seshamanand282015@gmail.com

Abstract: Heart diseases are the most important reasons behind the high rate of morbidity and mortality among the world's population. In clinical data analysis, heart disease prediction is represented as an important problem. Progressively, the number of data is increasing, to analyze and processing it is very difficult and specially, it turns out to be to maintain the e-healthcare data. In addition, the prediction model in machine learning is considered as a necessary feature in this paper. Thus, this work concentrates to present a novel heart disease prediction technique by means of considering particular processes such as Feature Extraction, Record, minimization of Attribute, and Classification. At first, in feature extraction, both the higher-order and statistical features are extracted. Then, minimization of attribute and record is performed; to solve the curse of dimensionality the Component analysis Principle Component Analysis (PCA) acts an important role. At last, using the Neural Network (NN) model the prediction process is performed which consumes the dimensionally minimized features. Additionally, one of the main contributions of this article is to work on accurate prediction. Therefore, for the weight optimization of NN, the meta-heuristic techniques are exploited in this work. A novel optimization algorithm named Archimedes Optimization Algorithm (AOA) is proposed which resolves the aforesaid optimization issues. At last, the outcomes of the proposed method states that its efficiency over the other conventional methods.

Keywords: Heart Diseases, Machine Learning, Neural Network, Optimization Algorithm, Prediction,

Nomenclature

Abbreviations	Descriptions
CHF	Congestive Heart Failure
CART	Classification and Regression Tree
AOA	Archimedes Optimization Algorithm
DNN	Deep Neural Network
ET	Extra Tree
HF	Heart Failure
DBNKELM	Deep belief Network and Extreme learning machine
ECG	Electrocardiogram
OH	One-Hot
ANN	Artificial Neural Network
SAE	Sparse Autoencoder
SVM	Support Vector Machine
CDSS	Clinical Decision Support System
NLP	Natural Language Processing
RF	Random Forests
FKMAW	Fuzzy K-Medoids Clustering Based Attribute Weighting
CHI-PCA	Chi-Square and Principal Component Analysis
ML	Machine Learning
NN	Neural Network

1.Introduction

One of the most deadly diseases in humans is heart disease; its treatment and diagnosis are somewhat difficult. Here, the most important challenge task is to predict heart disease; in the early stage, the disease is recognized, then the mortality can be significantly minimized, and also the precautionary measures can be taken. Hence, the prediction must be accurate to control the risk of heart disease in humans. In order to attain this, accurate classification is also needed to effectually process the raw heart data [1]. Numerous studies have been done in machine learning techniques to enhance the HD model's performance and also to design several models and they had attained few achievements [2].

The studies on the automated intelligent system have performed an important and stimulating role in medical applications. Generally, by a doctor, the definite diagnostic report, and patient's symptoms, is considered. The diagnostic of the patient precise can be ascertained on the basis of a doctor's experience. Nevertheless, for doctors to maintain up-to-date information regarding clinical practices progression is a somewhat difficult and challenging task because of the research development in treatment remedy and knowledge in medical. Moreover, a huge amount of information can be saved and obtained effortlessly utilizing the advent of advanced computing technologies [10].

Patients with minimum risk from at high risk can be easily separated using an automatic classifier with CHF. Specificity and sensitivity are used to perform the CART correspondingly. A DNN classification was proposed for the ECG signals to learn the optimal set of features and performance enhancement. To analysis the HF a CDSS was performed. The various Machine learning classifiers performances are presented namely SVM, NN [11], a system with fuzzy rules which exploits CART, as well as RF. The optimal performance with a precise is attained by the RF and CART model, which is founded by an NYHA class for HF from unstructured clinical notes by exploiting NLP. In patients, to diagnose heart disease the SVM model was exploited, and also it predicts the features namely blood pressure, age, and blood sugar. In Machine Learning one of the important causes was the high dimensionality of the dataset. The analysis in numerous features needs a large number of memory as well as its lead to overfitting, hence the weighting features are minimized copy data and computing time, hence the enhancement of the algorithm was done [4]. Feature extraction was exploited by dimensionality minimization to transfer and make similar data when features selection minimized the dataset by eradicating ineffective features [5].

The main objective of this work is to propose a model for the classification with considerable significance in the process of feature extraction as well as the training phase in the supervised learning step. A higher-order statistical feature is presented besides with well-known features namely, minimum, mean, median, maximum, and standard deviation in the feature extraction. A new optimization algorithm named Archimedes Optimization Algorithm is proposed which trains the neural network to learn the dimension minimized data from PCA.

2. Literature Review

In 2020, Shaker El-Sappagh et al [1], developed a smart healthcare system for the prediction of heart disease by exploiting the collection of feature fusion and deep learning techniques. Initially, the extracted features were combined by the feature fusion technique from both the electronic and sensor data to produce the precious healthcare data. Next, the unrelated and redundant features eradicate the information gain method and choose the significant ones that minimize the computational trouble, as well as the system performance, were enhanced. Moreover, a specific feature weight was computed by the conditional probability model for each class that enhances the system performance.

In 2020, Kartik Budholiya et al [2], worked on Bayesian optimization that was an effective technique for hyper-parameter optimization. An OH encoding technique was also exploited to enhance the prediction precision to encode definite features in the dataset. In the Cleveland heart disease dataset, the effectuality of the developed technique was calculated and evaluated with the ET and RF classifiers.

In 2020, D. Shiny Irene et al [3], developed a hybrid model which was the integration of the FKMAW and DBNKELM based ensemble technique to improve the medical diagnosis procedure. At first, the FKMAW technique was exploited for the input attributes were weighed. Then, the medical data classification performance was enhanced using the weighing technique. A regression model-based heart disease prediction model was developed with the weighted attributes integrating DBNKELM, in that the Extreme learning machine was the top layer of DBN to act as a regression model.

In 2020, Manoj Diwakaret al [4], presented a review of the classification methods for image fusion and ML which was shown to aid the healthcare professionals to recognize heart disease. For diagnosing heart diseases, the machine learning concise and review explanations of the mostly exploited classification methods were performed. Subsequently, a few works on the exploit of classification methods were reviewed and reveal machine learning and image fusion. Additionally, it presents a general idea of the working technique and presents an explanation of the present work.

In 2020, Anna Karen Garate-Escamila et al [5], proposed a dimensionality reduction technique, and heart disease features were discovered by using a feature selection method. For this analysis, the information exploited was attained from UCI, the ML Repository named Heart Disease. Also, they examine six ML classifiers. CHI-PCA with RF had the uppermost accuracy the dataset comprises 74 features and a label.

In 2020, Ibomoiye Domor Mienye et al [6] presented a two phase technique to efficiently predict heart disease. The initial phase includes training an enhanced SAE, an unsupervised NN, to learn the optimal indication of the training data. To predict health status on basis of learned records the next phase includes exploiting an ANN. To train an effectual technique, the SAE was optimized.

3. Heart Disease Prediction Model

Fig 1 illustrates the architectural model of the proposed model. The proposed prediction model comprises such as feature extraction, record and the minimization of attributes and classification.

At first, the extraction of both statistical as well as higher-order statistical features taking place. The feature set may be outsized if the available data are in large numbers as well as handling that in an effective way are a crucial job. Therefore, using a defined process, it is very important to minimize the available feature. Therefore, both records, as well as attribute based minimizing procedures, are focused in this work. Essentially, the pursued process resolves the problems of the curse of dimensionality. For classification, the dimension minimized features are given; hence a renowned classifier called NN is exploited. It is used to classify if the patient possesses heart disease or not. In addition, this paper proposes a novel optimization method to optimizes the NN weights

Moreover, as an important objective, this work tries to optimize the NN weights training by developed optimization; hence a new AOA method is. This creates the prediction outcomes highly precise.

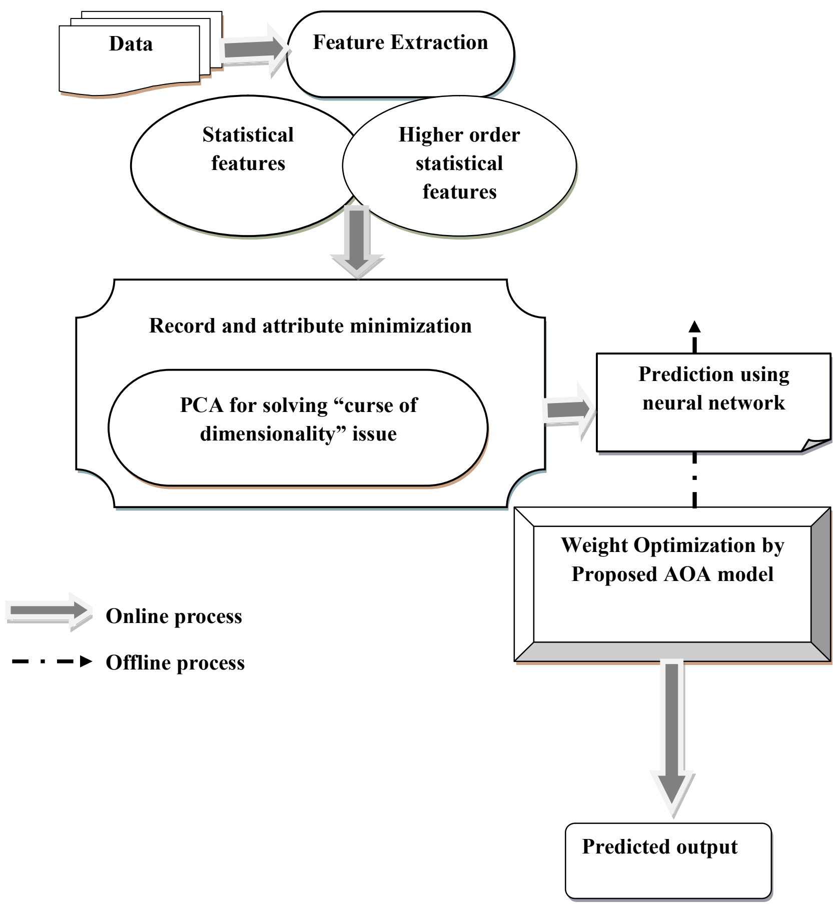


Fig. 1_Architecture diagram of the proposed model_

3.1 Feature Extraction

In the proposed model, for each record, the statistical, and higher-order features in this feature extraction process, are ascertained. Moreover, the considered dataset such as 13 features (conventional features), for that the statistical metrics namely maximum median, mean, minimum, and standard deviation is ascertained. As per eq. (1), the least measure is obtained, when the utmost measure is obtained as per Eq. (2), whereas *NF* indicates a number of features that is 13 features.

$$\text{Normalized index} = \frac{\text{Features at minimum position}}{\text{NF}} \tag{1}$$

$$\text{Normalized index} = \frac{\text{Features at maximum position}}{\text{NF}} \tag{2}$$

Furthermore, on the basis of the probability of the feature's incidence, higher-order statistical features are ascertained. Let the conventional features as $Fe = fe_1, fe_2, fe_3 \ldots\ldots fe_{NF}$, as per Eq. (3) if fe_l happens for n_l times in Fe, it can be calculated, whereas Pr_l indicates the probability of fe_l in Fe.

$$Pr_l = \frac{n_l}{NF} \tag{3}$$

Similarly, $Pr_2, Pr_3 \ldots\ldots Pr_{NF}$ is calculated, and hence, as per Eq. (4), the entropy function for each probability is ascertained.

$$\text{Entropy} = -Pr_i \log Pr_i \tag{4}$$

Subsequently, by means of the aforesaid- estimations the statistical measures namely minimum, median, mean, maximum, and standard deviation are ascertained to attain entropy features. Finally, as per Eq. (5), the total number of features extracted is ascertained, whereas 5 indicates from statistical measures, the number of features obtained. Hence, from the feature extraction process, a total of 36 features are obtained. Fig. 2 illustrates the proposed feature extraction process.

$$\begin{aligned} &\text{NF (No. of existing features)} + 5\text{(statistical measures} \\ &\text{from existing features)} + \text{NF(No. of entropy features)} + \\ &5\text{(statistical measures from entropy features)} \\ &= 2NF + 10 = 36 \end{aligned} \tag{5}$$

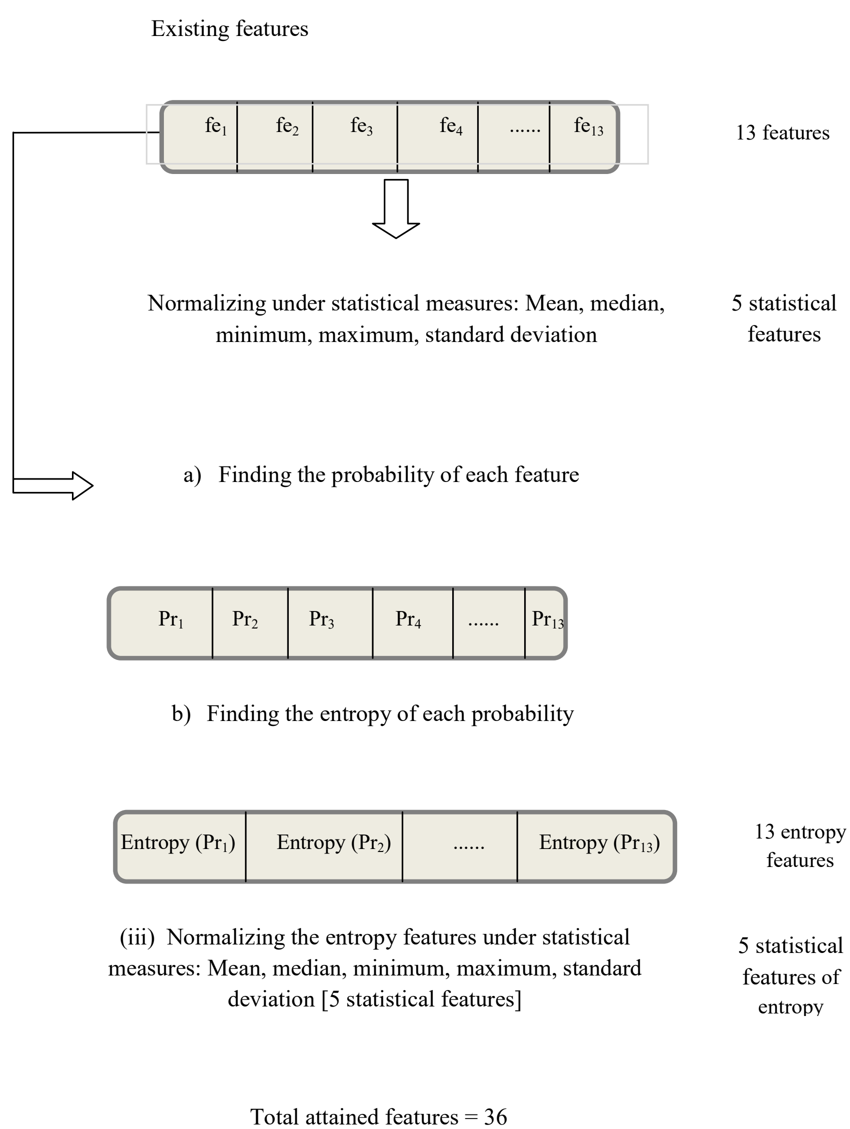


Fig. 2 *Architecture model of the proposed feature extraction*

3.2 Proposed Dimensionality Reduction

It is very important to create the extracted features in a suitable manner, definite processes are necessary. Here, under two cases, the dimensionality procedure is handled such as record as well as minimization of the attribute.

3.2.1 Minimization of Record

In this phase, intraclass records that are the same records in both the class labels such as a) disease absence, as well as (b) disease present, are extracted. The correlation coefficients are ascertained from the extracted intraclass records. Moreover, 0.98 is the threshold value, which is fixed as well as the obtained correlations coefficients are evaluated with the value of the threshold. The related records will be concatenated if the correlation coefficients is equal or above the threshold value. Hence, the number of attributes residuals constant, the number of records can be reduced. Moreover, the PCA model is used in order to reduce the number of the attribute that resolves the dimensionality curse.

3.2.2. Principle Component Analysis

The PCA approach is used in this paper to solve the dimensionality curse by minimizing the dimensions of the features.PCA [7] exploits the revealed mathematical principles to transfer an amount of probably correlated variables into a lesser amount of variables named principal components. The PCA comes under factor analysis and it is a statistical method. To minimize the higher dimension of data space the PCA is exploited which is required to show the data in an efficient way. This happens when an improved relation subsists amid the experimental parameters. PCA is an existing system that can perform definite things in the linear domain, as well as the appliances with linear models, are appropriate.
The complete record of PCA is shown below.

a): Mean: For n size of sample presume to $N_1, N_2 \cdots N_n$ be the arbitrary parameters. The average of the data set is stated in eq. (6), which is a random variable.

$$\overline{N} = \frac{1}{n}\sum_{i=1}^{n} N_i \tag{6}$$

b): Standard deviation (SD): It represents a number that measures how distant data values are from their mean. In order to estimate the SD, from the mean of the data set the average distance must be calculated to a particular point. That is from every point of data the square of the distance is calculated to the average of the set as stated in Eq. (7).

$$SD = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(N_i - \overline{N}\right)^2} \tag{7}$$

c): Covariance: The covariance is calculated between 2 dimensions and the variance can be obtained if the covariance is calculated amid 1 dimension. For covariance, the formulation is equivalent to the variance equation. If the properties of O_i and N_i for $i = 1,2,...n$ are computed, for N and O the sample variances can be formulated as in Eq. (8).

$$Cov(N,O) = \frac{\sum_{i=1}^{n}\left(N_i - \overline{N}\right)\left(O_i - \overline{O}\right)}{n} \tag{8}$$

d): Eigenvectors and Eigenvalues of a matrix*:* It is essential to identify the Eigenvalues and Eigenvectors. If Q is a $n \times n$ matrix, subsequently $N \neq \bar{0}$ is an eigenvector of Q , in that λ indicates a scalar and $N \neq \bar{0}$. Eq. (10) indicates for a $|Q \; n \times n$ matrix, the Q polynomial for the degree n.

$$[Q][N] = \lambda X \tag{9}$$

$$\det([Q| - \lambda I = 0]) \tag{10}$$

Hence, in both records and minimization of the attribute, F_D indicates dimension minimized features that are further subjected to the NN model in order to predict the disease.

4. Neural Network-Based Model

To predict the disease the F_D represents the extracted features are subjected to the NN model. Eq. (11) states the NN [8], which represents the features as input, whereas the total number of features are indicated as nu .

$$F_D = \{F_{D1}, F_{D2}, ...F_{Dnu}\} \tag{11}$$

The NN comprises an input layer, hidden layer, and an output layer; it is a condition to identify the hidden layer output ahead of calculating the entire network output. On the basis of eq. (12), the hidden layer output $e^{(H)}$ is ascertained, $\hat{i}$ simplifies the hidden neuron, nf simplifies the activation function, j simplifies the input neurons, $n_{\hat{i}}$ simplifies a number of input neurons, $W^{(H)}_{(B\hat{i})}$ simplifies bias weight to $\hat{i}^{th}$ hidden neuron, $W^{(H)}_{(j\hat{i})}$ simplifies the weight from j^{th} input neuron to $\hat{i}^{th}$ hidden neuron, and F_{PCA} simplifies the input features. In addition, eq. (13) simplifies the common network output $\hat{G}_o$ which is ascertained from the output layer, n_h simplifies the number of hidden neurons $\hat{o}$ simplifies the output neurons, $W^{(G)}_{(B\hat{o})}$ simplifies bias weight to the output of $\hat{o}^{th}$ neuron, and $W^{(G)}_{(\hat{i}\hat{o})}$ simplifies weight from $\hat{i}^{th}$ hidden neuron to output of $\hat{o}^{th}$ neuron. Moreover, eq. (14) is used to calculate the error amid the predicted and actual values which needs to be minimized. In Eq. (14), $\hat{G}_{\hat{o}}$ simplifies the predicted output, n_G simplifies the number of output neurons, $G_{\hat{o}}$ simplifies the actual output.

$$e^{(H)} = nf\left(W^{(H)}_{(B\hat{i})} + \sum_{j=1}^{n_{\hat{i}}} W^{(H)}_{(j\hat{i})} F_D\right) \tag{12}$$

$$\hat{G}_{\hat{o}} = nf\left(W^{(G)}_{(B\hat{o})} + \sum_{\hat{i}=1}^{n_h} W^{(G)}_{(\hat{i}\hat{o})} e^{(H)}\right) \tag{13}$$

$$E^* = \underset{\left\{W^{(H)}_{(B\hat{i})}, W^{(H)}_{(j\hat{i})}, W^{(G)}_{(B\hat{o})}, W^{(G)}_{(\hat{i}\hat{o})}\right\}}{\arg\min} \sum_{=1}^{n_G} \left|G_{\hat{o}} - \hat{G}_{\hat{o}}\right| \tag{14}$$

5. Proposed Archimedes Optimization Algorithm

5.1 Objective Function

In this paper, the proposed AOA model is used to train the NN model for the enhanced achievement of heart disease prediction, through optimal weights selection (W) of NN (training).

Moreover, the objective model of the proposed method tries to maximize the prediction accuracy as exhibited in Eq. (15), whereas Acc denotes the accuracy.

$$\text{Objective function} = \text{Max(Acc)} \tag{15}$$

5.2 AOA

In this paper, the AOA technique is used to resolve the developed optimization technique with NR mathematical technique [9]. The proposed model is a metaheuristic model which exploits to resolve several mathematical optimization issues and it have shown its capability to obtain the near-global solution in a short period. The proposed model is the important criterion turning point on Archimedes' principle of optimism. Via multiple stages towards The AOA passes to find a near-global solution, and these phases are stated as below:

Step 1: Initialization: Here, the population, such as the immersed objects (solutions) characterized by their densities, accelerations, and volumes. Each object is initialized with an arbitrary position in the fluid as stated in Eq. (16), subsequently the fitness value for each object is calculated.

$$O_i = lb_i + rn(0,1) \times (ub_i - lb_i), \forall i \in \{1,2,3,...., N\} \tag{16}$$

$$Den_i = rn(0,1) \tag{17}$$

$$Vol_i = rn(0,1) \tag{18}$$

$$Acc_i = lb_i + rn(0,1) \times (ub_i - lb_i), \forall i \in \{1,2,3,...., N\} \tag{19}$$

Whereas, O_i indicates the i^{th} object in population, and $rn(0,1)$ indicates an arbitrary scalar having a value among 0 and 1, ub_i and lb_i indicates the upper as well as lower bounds of the i^{th} object, correspondingly, N indicates the population size, Den_i, Vol_i, and Acc_i indicates the density, volume, and the acceleration of the i^{th} object.

Step 2 'Update densities and volumes': Here, the volumes and the densities of each object are updated by exploiting the subsequent equations:

$$Den_i^{(t+1)} = Den_i^{(t)} + rn(0,1) \times \left(Den_{best} - Den_i^{(t)} \right) \quad (20)$$

$$Vol_i^{(t+1)} = Vol_i^{(t)} + rn(0,1) \times \left(Vol_{best} - Vol_i^{(t)} \right) \quad (21)$$

whereas $Vol_i^{(t)}$ and $Den_i^{(t)}$, are the volume and density of i^{th} object at the t^{th} iteration., Vol_{best} and Den_{best} are the best volume and density of the best object possessing the optimal fitness value.

Step 3 'Transfer density as well as operator factor':

Here, the collision among objects till their equilibrium state. The mathematical formulation of collision is stated as below:

$$TF = \exp\left\{ \frac{t - t_{max}}{t_{max}} \right\} \quad (22)$$

where TF indicates the transfer operator transferring ability of the search process from the exploration to the exploitation phase. t_{max} indicates the utmost number of iterations.

$$d^{t+1} = \exp\left\{ \frac{t - t_{max}}{t_{max}} \right\} - \left(\frac{t}{t_{max}} \right) \quad (23)$$

Step 4 'Exploration': Here, the collision among objects occurred. Hence, if $TF \leq 0.5$, an arbitrary material mr indicates chosen whereas the object acceleration is updated as below:

$$ACC_i^{(t+1)} = \frac{Den_{mr} + Vol_{mr} + Acc_{mr}}{Den_i^{(t+1)} \times Vol_i^{(t+1)}} \quad (24)$$

Den_{mr} Vol_{mr} Acc_{mr} indicates the density, volume, and acceleration of the random material.

Step 5 'Exploitation': Here, no collision amid objects happens. Hence, if $TF \geq 0.5$, the acceleration of the object is updated as below:

$$ACC_i^{(t+1)} = \frac{Den_{best} + Vol_{best} + Acc_{best}}{Den_i^{(t+1)} \times Vol_i^{(t+1)}} \quad (25)$$

whereas Acc_{best} indicates the acceleration of the object possessing the optimal fitness.

Step 6 'Normalize acceleration': The acceleration is normalized to estimate the change percentage as below:

$$ACC_i^{(t+1)} = \frac{Den_{best} + Vol_{best} + Acc_{best}}{Den_i^{(t+1)} \times Vol_i^{(t+1)}} \quad (26)$$

whereas g, and z indicates the normalization range. $ACC_{i-norm}^{(t+1)}$ indicates exploited to step on the percentage that each agent will step.

Step 7 'Evaluation': The fitness value of each object is evaluated at this phase, and the optimal solution is registered, that is update the optimal solution (x_{best}), Den_{best}, Vol_{best}, and Acc_{best}

6. Result and Discussion

For heart disease prediction the experimentation analysis of the adopted technique was implemented and the equivalent outcomes were attained and described in this section. Here, the performance of the presented technique was compared against existing schemes such as Levenberg-Marquardt-NN (LM-NN), Particle Swarm Optimization – NN (PSO-NN), Whale Optimization Algorithm- NN (WOA-NN), Firefly-NN FF-NN, and Lion Algorithm - NN (LA-NN) regarding the performance metrics like accuracy, specificity, sensitivity, and Matthews correlation coefficient (MCC) , precision, False Negative Rate (FNR), False Positive Rate (FPR), False Discovery Rate (FDR), and F1Score.

Fig 3 illustrates the overall analysis of the adopted model as well as existing techniques for the heart disease prediction model. Here, the proposed method is 16% better than the LM-NN, the proposed method is 23% better than the WOA-NN, the proposed method is 23% better than the FF-NN, the proposed method is 20% better than the PSO-NN, the proposed method is 16% better than the LA-NN in terms of accuracy. Fig 4 illustrates the feature analysis of the conventional features after dimensionality reduction is summarized. The superior outcomes are attained by the proposed model with the conventional features from the analysis. Here, the proposed feature and dimensionality reduction is 25% better than the conventional feature and dimensionality reduction.

Fig 5 illustrates the features of the proposed technique with dimension reduction and without dimension reduction is presented. The superior performance is obtained using the proposed method. Here, the proposed feature and dimensionality reduction is 32% better than the conventional feature and dimensionality reduction.

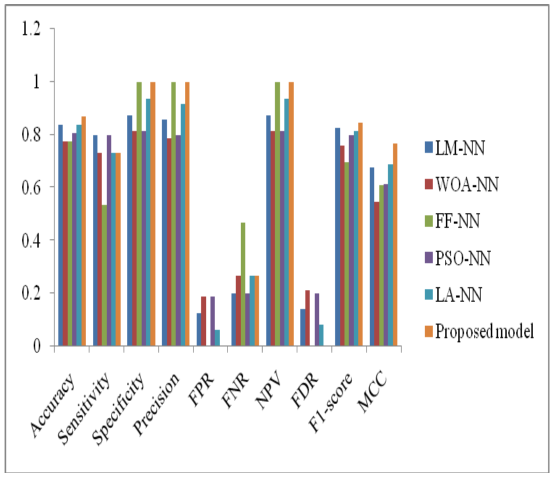


Fig 3: Performance analysis of proposed model

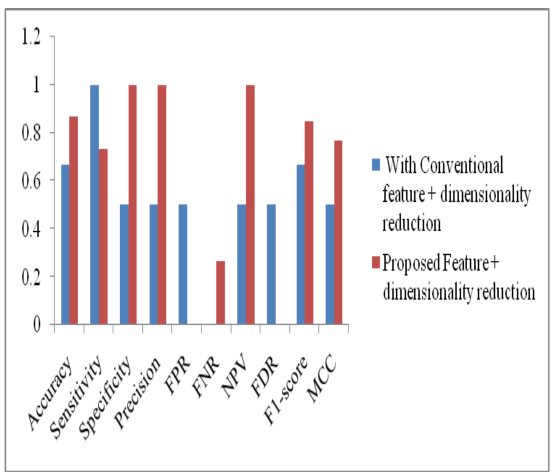


Fig 4: Prediction model analysis of proposed model

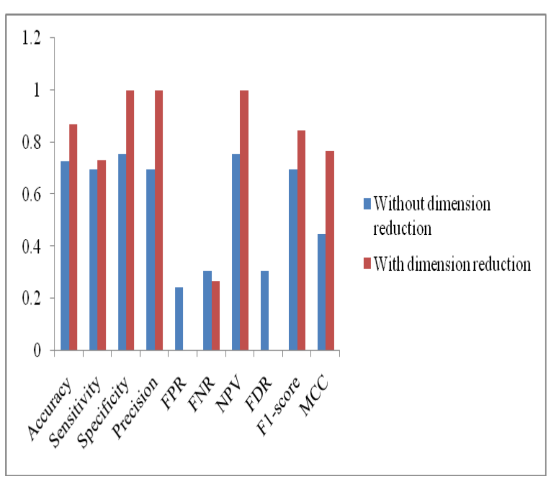


Fig 5: Proposed model analysis without dimensions and with dimension reduction

7. Conclusion

A heart disease prediction model was demonstrated in this paper which consists of phases namely feature extraction, record as well as minimization of attributes and classification. At first, extraction of both statistical and higher-order statistical features took place as well as subsequently, the minimization of attribute and record was carried out. Moreover, PCA was used to solve the dimensionality curse. Consequently, to the NN, the dimensional minimized features were subjected, hence the prediction process occurs. The proposed model mainly tackles precise prediction and hence, it was attempts to optimize the NN weights. Hence, the AOA model was proposed to train the NN. Finally, the proposed model performance was calculated with the conventional models and the results were attained by varying the performance measures such as positive and negative metrics.

References

[1] Farman AliShaker El-SappaghKyung-Sup Kwak,"A smart healthcare monitoring system for heart disease prediction based on ensemble deep learning and feature fusion", Information Fusion26 June 2020.

[2] Kartik BudholiyaShailendra Kumar ShrivastavaVivek Sharma," An optimized XGBoost based diagnostic system for effective prediction of heart disease", Journal of King Saud University - Computer and Information SciencesAvailable online 23 October 2020.

[3] D. Shiny IreneT. SethukarasiN. Vadivelan,"Heart disease prediction using hybrid fuzzy K-medoids attribute weighting method with DBN-KELM based regression model," Medical Hypotheses5 July 2020.

[4] Manoj DiwakarAmrendra TripathiNeeraj kumar,"Latest trends on heart disease prediction using machine learning and image fusion", Materials Today: Proceedings15 October 2020.

[5] Anna Karen Gárate-EscamilaAmir Hajjam El HassaniEmmanuel Andrès,"Classification models for heart disease prediction using feature selection and PCA", Informatics in Medicine Unlocked27 April 2020.

[6] Ibomoiye Domor MienyeYanxia SunZenghui Wang,"Improved sparse autoencoder based artificial neural network approach for prediction of heart disease", Informatics in Medicine Unlocked5 March 2020.

[7] Y. Jin, C. Qiu, L. Sun, X. Peng, J. Zhou, Anomaly detection in time series via robust PCA, in: 2017 2nd IEEE International Conference on Intelligent Transportation Engineering (ICITE), Singapore, Singapore, 2017, pp. 352–355.

[8] Yogeswaran Mohan, Sia Seng Chee, Donica Kan Pei Xin and Lee Poh Foong, Artifcial Neural Network for Classifcation of Depressive and Normal in EEG, in: 2016 IEEE EMBS Conference on Biomedical Engineering and Sciences (IECBES), 2016.

[9] Hashim FA, Hussain K, Houssein EH, Mabrouk MS, Al-Atabany W. Archimedes optimization algorithm: a new metaheuristic algorithm for solving optimization problems. Appl Intell 2020:1–21.

[10] K.Srinivas,"Prediction of E-Learning Efficiency by Deep Learning in EKhool Online Portal Networks",Multimedia Research, vol. 3, no. 4, October 2020

[11] Arvind Madhukar Jagtap,"Developing Deep Neural Network for Learner Performance Prediction in EKhool Online Learning Platform",Multimedia Research, vol. 3, no. 4, October 2020