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Soft Computing-Based Heart Disease Prediction Framework (SC-HDP) Using ANFIS

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Abstract

Wearable technology has become an element of health tracking and occupies a substantial place in growing the Internet of Medical Things (IoMT). IoMT can minimize the mortality rate due to the early diagnosis of the diseases. Although this area is improving, there is still a way to increase the accuracy of prediction. To resolve this, the paper proposes Soft computing enforced Adaptive Neuro-Fuzzy Inference System (ANFIS) model for heart disease prediction, designed to ensure reliable diagnosis. The model integrates fuzzy logic and neural networks, optimized by Particle Swarm Optimization (PSO), to address challenges such as noisy data and local minima in training. Additionally, privacy-preserving mechanisms are incorporated, ensuring optimal data flow and compliance with healthcare regulations: Feature Extraction using Particle Swarm Optimization (PSO) helps in finding the pertinent features of clinical data and also finds the best feature space of clinical data so that the most promising features can be selected to make reliable predictions. Adaptive Neuro-Fuzzy Inference System (ANFIS), which can be used to classify heart disease data (and apply neural network and fuzzy logic), suffers problems with local minima because of the

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gradient nature of this learning. The hybrid ANFIS-PSO model enhances diagnostic accuracy by improving feature extraction and parameter optimization, yielding higher performance than traditional models. The hybridisation of PSO and ANFIS allows attaining higher predictive accuracy and system reliability, highlighting the significance of the optimisation of the feature extraction and parameters setting to gain optimum performance of the health monitoring application.

Keywords: IoMT, Soft Computing, ANFIS, PSO, Heart Disease, Feature Extraction, Accuracy.

1 Introduction

A person with sufficient knowledge and experience can diagnose heart diseases in several levels. Heart disease includes various cardiac diseases, based on different health conditions, having symptoms like, heart attack, arrhythmia, high/low blood pressure, stroke and so on. There is a greater challenge for the medical field to provide better treatment to the patients, which may include the inadequate results caused by improper diagnosis or substandard treatments. Moreover, Decision Support Systems (DSSs) are used in medical institutions for cost effectiveness. The healthcare data comprises of huge number of patient data, resource management and several disease prediction results. The invasive growth of Internet of Things (IoT)and its inhibition in healthcare advancements has enhanced the efficacy and accuracy of remote health monitoring. The IoT serves by connecting diverse devices for monitoring the physical functions seamlessly (Ahmadi et al., 2019). Utilizing the IoT advancement, a model for heart disease diagnosis can observe and transfer the patient data to the remote servers, which is responsible for healthcare monitoring Joyia et al., (2017). Predicting and treating heart disease is very much vital, as it is the most important human organ (Vijayashree & Sultana, 2018).

In the domain of medical or clinical research, diagnosing heart disease is one of the challenging issues, dependent on measuring various symptoms such as, blood pressure variations, breath issues, chest pain, cold sweats and so on Sudeshna et al., (2017). For aiding the diagnosis process, IoT sensors are used for providing inputs. Previously, diseases can only be diagnosed using physical examinations, but now, the process can be accurately done even with the SmartWatch. For instance, the heartbeat rate of an elder can be easily monitored with the device and alarm can be set for sending notification, when a motionless state or abnormality attained.

Several technologies include Bluetooth, RFID and Body Area Networks (BANs) are effectively incorporated in any healthcare applications (Amendola et al., 2014). And, the sensors in clothes can track the person's ECG signals, Blood pressure rate and so on. The sensed data can be transmitted to the cloud servers and can be further provided to the family members, medical practitioners or hospital staffs over any kind of communication devices, for further medical requirements or assistance. With greater sense, wearable devices are enormously developing in monitoring patients and aid in the growth of Internet of Medical Things (IoMT). It may have different types of medical sensors or devices which are linked to a computing device, medical practitioner via Internet. Those devices are responsible for providing, storing, examining and distributing medical data. The IoMT devices comprise of remote patient monitors, wearable devices, health tracking sensors, are used for enhancing the quality of service and patient/user satisfaction.

In the research domain of IoMT, Machine Learning (ML) is progressively used, specifically in disease diagnosis and treatment process (Richens et al., 2020). The inclusion of ML in IoMT can enhance the precision and timing of diagnosis process (Samieinasab et al., 2022). In global medical systems, accurate disease prediction is an essential element. On the other end, inaccurate diagnosis can cause life risks, resource wastages and distrust over the medical management model. Moreover, there is a development of discontent among the medical providers over the time spent and data evaluations using computed, may varied from patients-to-patients (Sinsky et al., 2016). Hence, in recent years, Artificial Intelligence tools are used as powerful technique in diagnosis process. The figure 1 depicts the model of heart disease prediction using IoMT and ML (Khan, 2020).

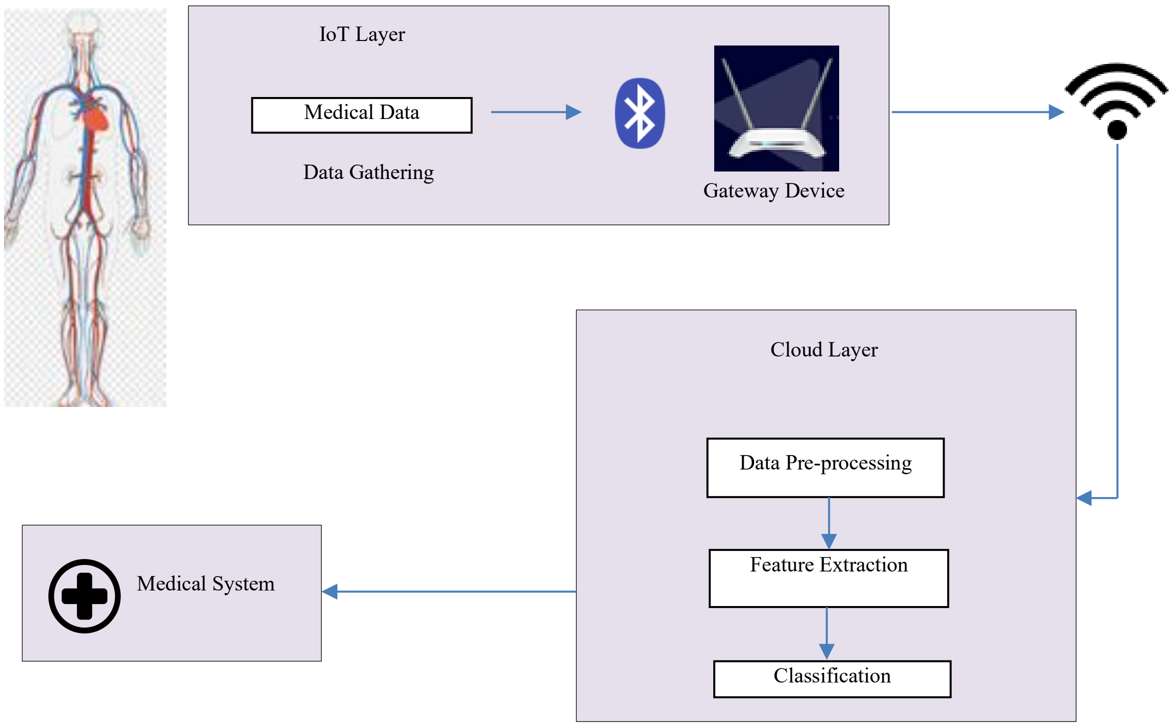

Figure 1: Heart disease prediction model using IoMT and ML

Diagnosing diseases accurately and intercessions to vary the life of patient are the significant motive of ML applications. Still, the heart disease is found to be common among aged people, it is becoming common across people on different age groups. As the remote monitoring is very much effective, the algorithms are becoming more intricate. In recent researches, the machine learning models are employed to the complex procedures for heart disease diagnosis, which makes the prediction process accurate and medical data classification.

For reducing the complications related to heart disease, it needs a complete notice in healthcare management. Hence, the proposed model incorporates the IoMT, ML and AI technique for acquiring improved performance. The observations include age, gender, blood pressure, sugar level, are taken from the medical databases to evaluate the disease risks. The contributions of the proposed Soft Computing-based Heart Disease Prediction Framework (SC-HDP) are listed as follows.

1. A novel ANFIS-based framework for heart disease detection in IoMT systems, with integrated privacy-preserving techniques to secure sensitive health data during transmission and processing.
2. The ANFIS model is augmented with security features to ensure reliable data classification.
3. The PSO optimization technique is utilized to fine-tune ANFIS parameters, overcoming challenges such as local minima in training, improving both the accuracy of heart disease predictions and the security of the model's operation.
4. The proposed model is evaluated under various metrics, demonstrating resilience and higher diagnostic accuracy than existing methods.

The format of the paper is as follows: An overview of similar works on heart disease prediction techniques is included in Section II. The proposed model and algorithms for predicting heart disease are presented in Section III. Section V provides a conclusion and future directions, while Section IV provides an analysis of the simulation's results.

2 Related Works

The growth of medical systems and IoT in automations offers the service to acquire dynamic medical services devoid of visiting hospitals. Hence, the Internet of Medical Things has been considered as the effective solution to solve the confrontations in healthcare domain. There are several works and models are proposed in the field of remote healthcare services, e-health and smart medical management models Majumder et al., 2017; Manogaran et al., 2019). In Islam et al., (2015), extensive research on IoT is processed for deriving solutions for various issues. The automation of smart home is a growing research domain of IoT and has been used in many areas for aiding in everyday life to sustain simple human lives, which may include systems like remote security system, health care assistance for disable people (Yang et al., 2014).

The authors of Agarwal & Lau, (2010) have proposed a healthcare monitoring model for measuring the patient's blood pressure using body sensors. The paper stated that the observed pressure rates are transmitted to the medical practitioners via web interface which can be further analyzed and treat the patients remotely. As mentioned, the model used Body Sensor Network (BSN), is named as BSN-Care for observing the physiological factors such as blood pressure, ECG for stating the heart condition of patients (Gope & Hwang, 2015). Further, the sensed data are provided to the server of proposed model and then used for health measurement of patients. When there is an abnormality in the observed data, the model is designed in such a manner to provide notifications to the related persons for attaining rapid response.

An RFID based healthcare management model is proposed in (Chen et al., 2010), for measuring the patient medical records and communicating that to doctors. The data includes temperature and blood pressure is collected using BSN, also, the data are stored in the server for future references. A classification model for heart signal recognition is presented in (Xiao et al., 2019) using compressed sensing reconstruction. The model used discrete wavelet transform and Support Vector Machine for classifications. A model for evaluating patient's glucose level using near-infrared spectroscopy and machine learning technique has been proposed and discussed in (Jain et al., 2019. The authors Almujally et al., (2023) proposed an approach to track the heart rate of patients using Smart health band. In (Al-Kahtani et al., (2022), a comprehensive survey has been made on the methods that monitor human health using applications on Smart phones. The amalgamation of IoT, mobile applications and cloud paradigm for enhancing the bounds of health monitoring model has been developed.

In Al-Makhadmeh & Tolba, (2019), Deep Belief Neural Networks (DBNN) is used to process the data from IoT for detecting heart diseases. The features from collected data are extracted using high-order Boltzmann machine and DBNN. The authors stated that the model effectively minimizes the prediction errors, which can help in reducing the mortality rate due to heart diseases. For enhancing the accuracy rate of heart disease predictions, Vivekanandan & Iyengar, (2017) combined techniques such as, Modified Differential Evolution (DE) and Fuzzy Analytical Hierarchy Process (AHP). The classifications here are made with the trained Feedforward Neural Networks (FNN), produced the accuracy of 83%.

The model Uyar & İlhan, (2017) adopted the data from UCI dataset and measured for cardiac disease diagnosis with Recurrent Fuzzy Network-based Genetic Algorithm. Fuzzy Analytic Hierarchy model (FAHP) Nazari et al., (2018) discussed for measuring the possibility of heart diseases. The model measures the weights for different factors that affect the cardiac functions. Moreover, tests will be suggested for the patients, when the possibility of cardiac diseases is noticed, can avoid unwanted clinical procedures. Hence, the model can be stated as cost and resource effective.

A combined model with Lineal Model and Random Forest is given in Mohan et al., (2019) for detecting the vital factors using the ML conceits. Similarly, a hybrid model combines SVM and MLP Multi-Layer Perceptron is proposed in Nalluri et al., (2017) for disease prediction. The efficacy of the model has been measured with 11 distinctive datasets and the results stated the model is accurate than compared works and can be applied in telemedicine and e-healthcare applications. The work Haq et al., (2018) used models such as SVM, Decision Tree (DT), Fuzzy Logic (FL), K-Nearest Neighbour (KNN) and Naive Bayes Classification (NB) for heart disease diagnosis. The comparative evaluations are made for measuring the model performances using LASSO with k-fold cross validation. The model shows that the accuracy can be enhanced and processing time can be minimized when reducing the size of feature set. The model attained 89% of classification accuracy in diagnosis heart diseases.

3 Working Procedure of Soft Computing-Based Heart Disease Prediction Framework (SC-HDP)

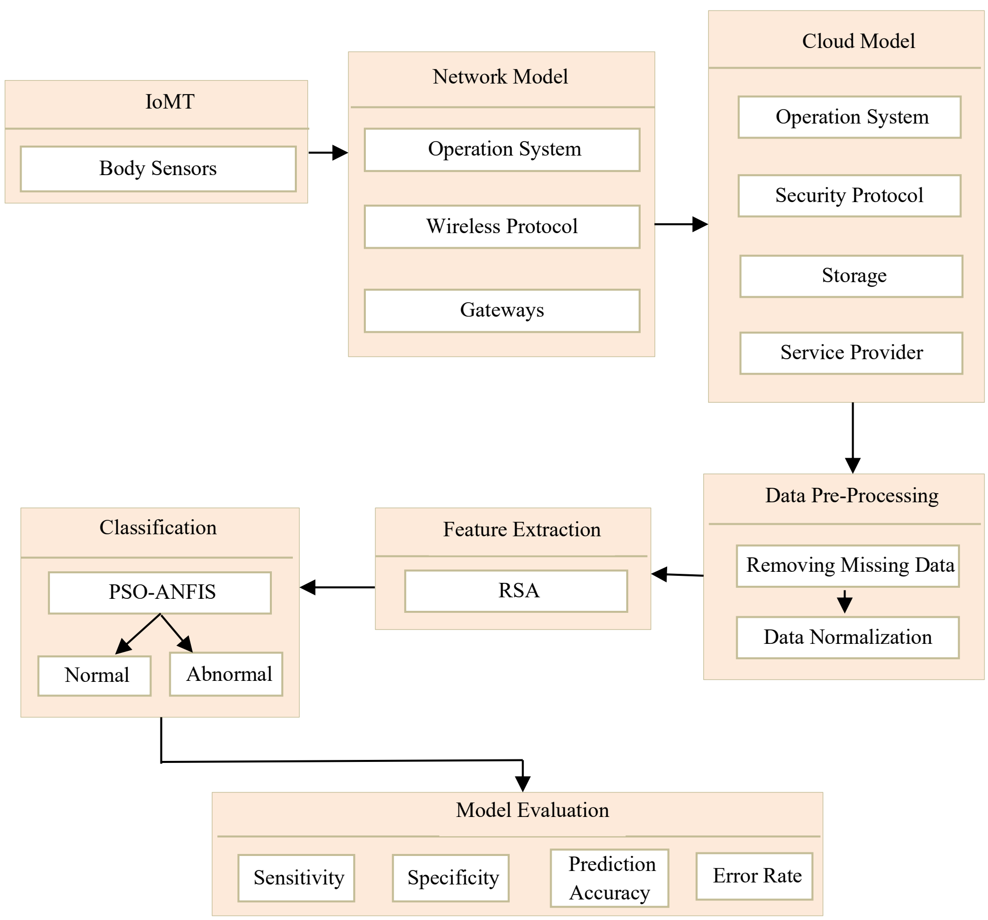

Figure 2: Framework of SC-HDP

Earlier diagnosis of heart disease can reduce the life risks of people. Hence, in this proposed model, a soft computing based heart disease prediction model is proposed. Here, the IoMT devices are used to sense the patient data, according to the heart parameters. The patient data are tracked in real-time, persistently, remotely, and further stored and forwarded to the servers, can enhance the model efficacy, accessibility and also provides cost-effectiveness.

For detection the heart conditions, the medical data are acquired and provided to the practitioners. Further, the training and testing phases of operations are carried out for determining the patient's health state. The data from UCI data repository (www.kaggle.com) is obtained to train the network, followed by pre-processing, feature extraction and classification. The results after classification shows that the heart condition is Normal or Abnormal, and according to that, the treatment guidance will be provided to that patient. The framework of proposed SC-HDP is presented in figure 2. The figure comprises of devices for sensing, network tier, cloud tier, Data Collection Tier and HDP Tier. Each tier describes many functions to be performed by significant elements of the model.

Model Description

After acquiring the inputs, the health condition of patient's heart is observed and abnormalities are obtained if any. The proposed SC-HDP framework for heart disease diagnosis performs ANFIS based training and testing. For training the network, the patient data are acquired from UCI data repository. The data are further pre-processed, and the features are extracted before classification. The results of classification process are compared with the classification outcomes of other existing ML based disease diagnosis models. The operations carried out in each phase of the proposed model are presented in the following sections.

Pre-processing Medical Data

Initially, the values are obtained from the benchmark dataset, following, the noise removal and data replacement operations are carried out. It is significant to process with noiseless data, for obtaining accurate results from the detected patterns related to heart abnormalities. Here, median studentized residual technique is used for eliminating noisy data. The technique works on determining the correlating among values in the dataset. The technique is computed by dividing the residual values based on the derivation of its standard deviation (SD) value. The SD of each element is calculated based on examinations eliminated.

A. Missing Data Replacement

The initial process is to derive the data provided in the benchmark dataset and compute the median for missing data, which is calculated by organizing the values in rising order. The undesirable and missing values are replaced based on the calculated median value.

B. Data Normalization

For minimizing the difficulty of determining the heart disease patterns, followed by missing data replacement, the processed data should be normalized between (0,1). Here, data normalization process is carried out via several data distributions and regression analysis for HDP. The equation (1) derives the regression for data normalization.

$$R = \rho_0 + \rho_i D + \gamma_i \qquad for\ i = 1,2,..,m \qquad (1)$$

Each pair of obtained data (R) complies with the process of HDP. Here, 'ρ_0' and 'ρ_i'are denoted as, the least square rates, 'D' is the input data and, 'γ_i' denotes the error value, respectively. Further, the regression model can be reframed as,

$$R = \rho_0 + \rho_i D + \gamma_i^* \quad (2)$$

The equation (1) and (2) are used to derive the residual value, which can be given as, 'γ_i^*'. Using SD, the data and its average are determined, and equation 3 is given as,

$$\mu = \frac{\sum_{i=1}^{m} D_i}{G} \quad (3)$$

Data frequency is represented as, 'G' and the data normalization is derived as equation 4,

$$N_r = \frac{D_i - \mu_i}{\sigma_i} \quad (4)$$

Here, 'σ_i' is the variance. The pre-processed data are further given for feature extraction, in which, the significant medical data features are extracted for HDP.

Mathematical Formulation for Secure IoMT Data Flow

A. IoMT Data Acquisition and Encryption

The patient data are collected from IoMT devices, $D(t) = [d_1(t), d_2(t), \dots, d_n(t)]$, where, $d_i(t)$ denotes the body signals. Here, the data is encrypted using advanced homomorphic encryption in equation 5,

$$E\big(D(t)\big) = \varepsilon(D(t), k) \quad (5)$$

Here, k is the encryption key, and 'ε'denotes the encryption function.

B. Data Integrity Validation

The Trust Rate (TR) here is calculated for each input $D(t)$, corresponding to its integrity, ensuring that the efficient data is provided for diagnosis. For measuring the input data consistency, the TR is computed as equation 6,

$$TR\big(D(t)\big) = \frac{1}{1 + \left(\frac{\sum_{i=1}^{n} |D_i(t) - \widehat{D_i}(t)|}{n}\right)} \quad (6)$$

C. Fuzzy Member Function for Secure Classification

This function $\mu_{Ai}(D_t)$, directs the securely protected data to its fuzzy state, which works on normalized data for privacy preservation equation 7.

$$\mu_{Ai}(D_t) = \exp\left(-\frac{(d - C_i)^2}{2\sigma^2}\right) \quad (7)$$

Here, C_i is the cluster center and 'σ' is the standard deviation of fuzzy set, which ensures that the given data are private while the heart data classification is performed.

Feature Extraction

The process of feature extraction is to reduce the number of inputs for training and aid to attain precise classification results. Moreover, the performance efficacy and modelling of the proposed model can be enhanced. Here, Reptile Search Algorithm is used for feature extraction, in which the prediction methodology works on the basis of social behavioral nature of crocodiles. There are two phases called, exploration phase and exploitation phase. The random strategy is given as equation 8,

$$A = \begin{bmatrix} a_{1,1} & \cdots & a_{1,d} \\ \vdots & a_{N-1,j} & \vdots \\ a_{N,1} & \cdots & a_{N,d} \end{bmatrix} \tag{8}$$

Where, 'N' denotes the number of crocodiles, 'd' is its dimension, and 'A'is 'N' candidate solution is given in the following equation 9.

$$A_{i,j} = rand \times (L_{max} - L_{min})L_{min} \tag{9}$$

Here, 'rand' is given as stochastic number, $\boldsymbol{L_{max}}$denotes the maximal and $\boldsymbol{L_{min}}$denotes the minimal limits of optimization problem. The enhanced moving patter of global RSA model states that the behaviours are divided as two, aerial and abdominal walk. This may not get the food for the candidates. Hence, the crocodile needs to locate the common place for getting its target food after many attempts of searching, global search of whole explained spatial range. For the moment, it is ensured that the stage is seamlessly acquired to the preceding stage. The following equation provides the encircling pattern of crocodile.

$$\boldsymbol{A_{i,j}}(m+1) = \begin{cases} best_j(m) \times \left(-\alpha_{i,j}(m)\right) \times \gamma - R_{i,j}(m) \times r, m \le \frac{I_{max}}{4} \\ best_j(m) \times A_{r\,i,j} \times PS(m) \times r, \frac{I_{max}}{4} \le m < \frac{2 \times I_{max}}{4} \end{cases} \tag{10}$$

Here, '$best_j(m)$' denotes the crocodile in best position at 'm' iterations and 'r' ranges between 0 and 1. 'I_{max}' is the maximal iteration, 'γ' is the sensitive factor can be taken as, 0.1, and '$R_{i,j}(m)$' is the reduce operator in equation 11.

$$R_{i,j}(m) = \frac{best_j(m) - s_{r_3,j}}{best_j(m) + \varepsilon} \tag{11}$$

Where, 'r_3' be the random number lies between $(1, N)$ and '$R_{i,j}$' denotes the fraction of difference between the current and the best position of the crocodiles. Further, the average position of the crocodile can be determined with the following equation 12.

$$M(A_{i,j}) = \frac{1}{m} \sum_{j=1}^{m} A_{i,j} \tag{12}$$

Following the RSA searching process hunting process is functioned based on two procedures, as, cooperation and coordination. Because of the impact of clinching method, the crocodiles fix the target prey location and their hunting mechanism makes the process easier to reach the target. The computational representation of the simulated hunting behaviour of crocodiles is given in the following equation 13.

$$\boldsymbol{A_{i,j}(m+1)} = \begin{cases} best_j(m) \times R_{i,j}(m) \times r, \frac{2 \times I_{max}}{4} \le m < \frac{3 \times I_{max}}{4} \\ best_j(m) - \alpha_{i,j}(m) \times \gamma - R_{i,j}(m) \times r, \frac{3 \times I_{max}}{4} \le m < \frac{4 \times I_{max}}{4} \end{cases} \tag{13}$$

Here, '$best_j$' denotes the crocodile's optimal position. Based on the above computations, the crocodiles having minimal predation skills are removed and the optimal individuals are rehabilitated. When the iteration limit is reached, the optimal rate is taken for processing feature extraction. The figure 3 describes the work process of RSA.

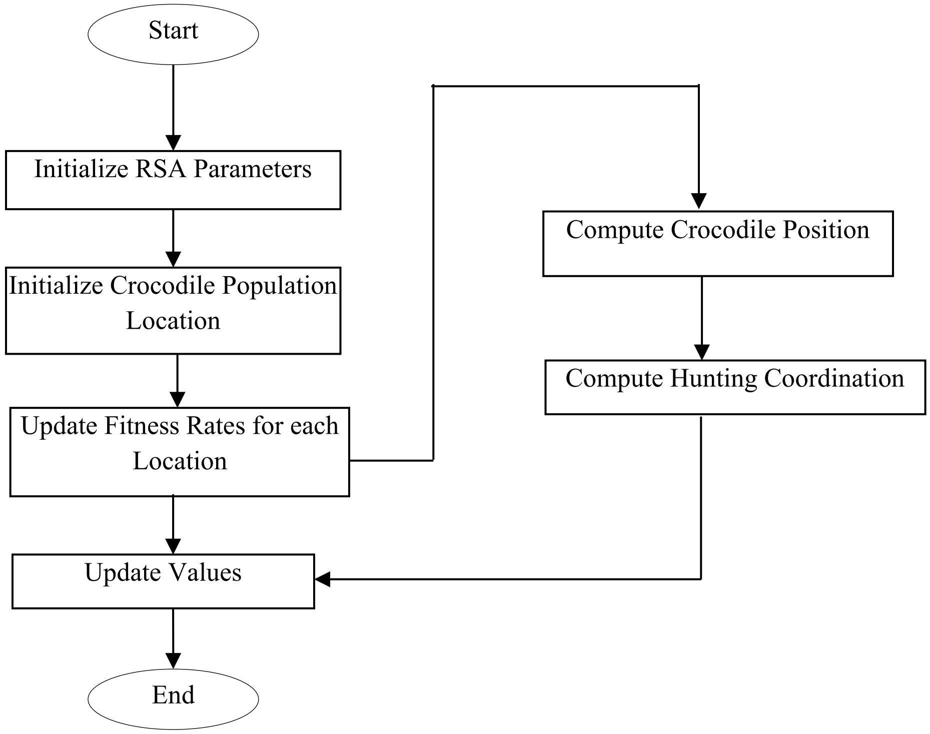

Figure 3: Work process of RSA

ANFIS Based Training in HDP

In this model, HDP is done using a non-linear and dynamic computational ANFIS model, which is the integration of Fuzzy logic and Artificial Neural Networks (ANN). The results show that ANFIS can detect most of the functions by employing the logical rules. Still, the fuzzy models are efficient for clinical diagnosis, the analytical process control eventually becomes inapt for complicated functions. This may because the interference similarity measure cyclically ran without energy. Hence, there is a requirement of optimization technique, hence, in order to account for the constraints of the interpretation engine, the computation is lowered while the machine learning algorithm continuously learns.

An ANFIS is created using two SC techniques: neural networks and fuzzy reasoning systems. The integrated model is framed by combining the efficient features of both. The ANFIS is suitable for data processing, pattern identification, data classification, and decision-making, among other information disciplines. The five ANFIS levels are shown in figure 4. It also has a higher success rate in treating human illness in the medical field than fuzzy expert systems, fuzzy inference systems, and neural networks. This is an explanation of the five levels of the adaptive neuro-fuzzy inference system.

Layer 1: Fuzzification Layer

Layer 1 is acquiring the input values. Appropriate values are taken as the inputs for processing membership operations. In other words, each node in fuzzification layer involves in membership function in equation 14 and 15.

$$F_{1,iy} = \mu_S(B), i = 1,2, \tag{14}$$

$$F_{1,ix} = \mu_T(A), i = 3,4 \tag{15}$$

Here, the mean rates are given as, '$\mu_S(B)$' and '$\mu_T(A)$', which can be computed by the following operations equation 16 and 17.

$$\mu_S(B) = \frac{1}{1+|(a-p)/y|^{2x}} \tag{16}$$

$$\mu_T(A) = \frac{1}{1+|(b-p)/y|^{2x}} \tag{17}$$

Where, x,y, and p are the intrinsic factors.

Layer 2: Rule Layer

Based on the rules, this layer is responsible for strengthen the inputs into the system equation 18.

$$F_{2,i} = \mu_A \mu_S(B) * \mu_T(A) = R_i \tag{18}$$

Layer 3: Nomalization Layer

In this layer, the nodes are considered as fixed, denotes the normalization of firing strength. This can also be stated that the layer calculate the weight that are effectively normalized in equation 19.

$$F_{3,i} = \frac{n_i}{n_1+n_2}; i = 1,2. = N_i \tag{19}$$

Layer 4: Defuzzification Layer

Based on every input signal of Layer 1, there are corresponding linear functions in Layer 4, which has adaptive nodes in equation 20.

$$F_{4,i} = N_i * f_i \tag{20}$$

Layer 5: Summation Layer

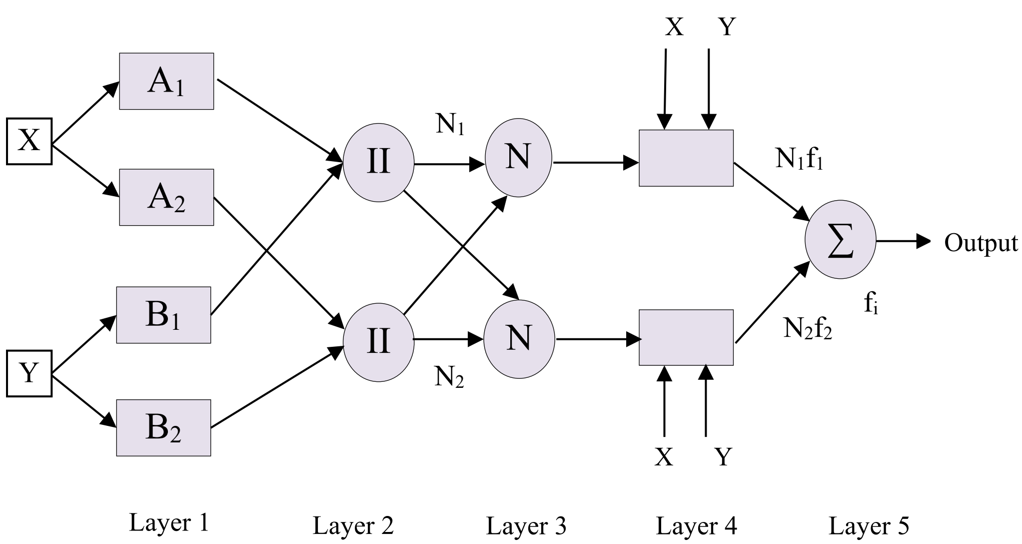

Figure 4: ANFIS based training in disease detection

The term "∑" designates the summation layer, which is the last layer of the ANFIS. The main job of this layer is to calculate the total or final output by summing together all of the signals from the layer that came before it.

$$F_{5,i} = \sum N_i * f_i \tag{21}$$

The set of rules establishes the link between the model parameters and the resulting categorization. These guidelines are designed with different degrees of expertise. The rules of the inference engine function in an IF-THEN fashion to carry out their jobs. The Mamdani inference rule-based paradigm is used in this approach, with the guiding principles being articulated as follows.

The functionality of the fuzzy inference system is contingent upon the input-output rules. The number of input/output rules generated and accumulated in the knowledge concentration of a professional approach is directly correlated with the effectiveness or efficiency of a certain technique.

The defuzzification technique use MATLAB to construct the result using the centroid approach, which calculates the center of gravity of a picture. This outcome is generated after the linguistic variable of each input has been analyzed and evaluated. In addition, it presented a visual representation of the surface areas of the results. The centroid technique determines that the midpoint of the base of a rectangle is its centroid. In relation to this, the designated location for measuring the output of triangular areas is located at one-third of the triangle's base and corresponds to the angle created between the base and the hypotenuse of the triangle. The parameters are optimized using PSO algorithm.

The output's value was then determined using the centroid technique. The value of the variable is obtained by dividing the product of the centroid and the entire surface by the sum of the surface product. figure 5 illustrates the procedure for constructing a SC-HDP model. The creation of an adaptive neuro-fuzzy inference system involves many distinct processes.

Step 1: The dataset of diverse patients from the dataset are collected.

Step 2: Pre-processing the dataset, such as normalization, is done after the dataset has been acquired.

Step 3: Feature extraction is done using RSA.

Step 3: Execute the partitioning procedure now. Divide the training set from the dataset in this. Let's take 80% of the dataset's data samples for the suggested model's training phase.

Step 4: Train the medical diagnostic system to recognize heart disease (HD) using the training data.

Step 5: Similarly, the remaining data samples from the dataset will be used as testing data, allocating 20% of the dataset to assess the performance of the medical diagnostic system.

Step 6: Employ several metrics, including as sensitivity, specificity, and accuracy, to assess the effectiveness of a recently produced clinical diagnostic for heart disease in the healthcare field.

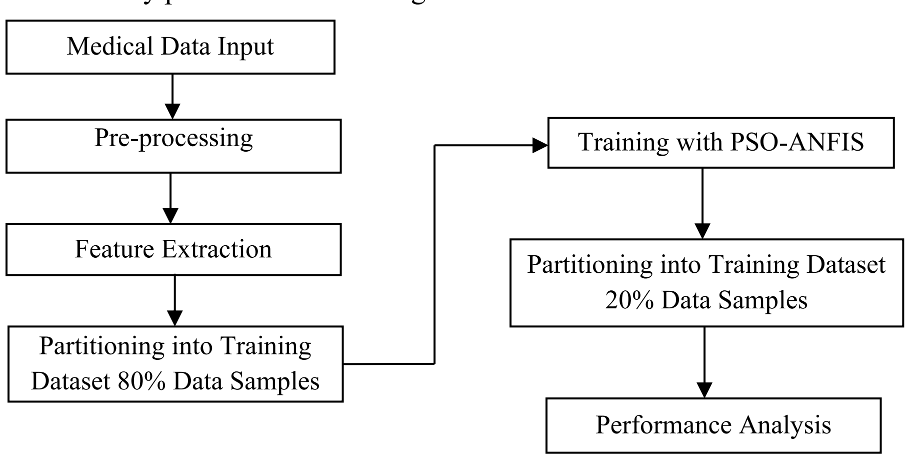

Figure 5: ANFIS model for SC-HDP

4 Results and Discussions

This section shows how the efficacy validation of the suggested SC-HDP is based on sensitivity, specificity, and accuracy rate. For the assessments, the benchmark datasets are acquired from the UCI data repository, consisting of features such, age, gender, cholesterol rates, blood pressure and so on. The dataset is further pre-processed by handling missing values**,** removing noise, and normalizing data. The two classifications of Normal and Abnormal are used in the HDP, which is conducted using the classification model. The simulation tool MATLAB is used to do the experimental assessments.

ANFIS-based Evaluations

The model assessment results for the input variables of the suggested fuzzy inference system are shown in this section. The evaluation formula is shown in table 1.

Table 1: Formula for ANFIS based evaluation

S. No	Description	Formula
1.	Mean	$\mu\overline{(x,y)} = \frac{\sum(x,y)}{N}$
2.	Entropy	-sum (r. *$\log_2$ (r))
3.	Correlation	$\frac{\sum(x,y)_{r_{x,y}} - \mu^2}{\sigma^2}$
4.	Area	D = $\sum R_{x,y}$
5.	Sharpness Estimation	$\sqrt{H_x^2 - H}$, H_x- Ratio between sharp pixels and edge pixels

Where, N - the pixels' number, r - the histogram counts, μ - the mean of the co-occurrence matrix, σ - standard deviation. And, the evaluation parameters are presented in table 2.

Table 2: Evaluation parameters

S. No	Domains	Values
1	Number of samples	800
2	Number of inputs (Features)	9
3	Number of outputs	2
4	ANFIS layout	[3, 3, 3, 3, 3, 3, 3, 3, 3]
5	Number of premise functions	27
6	Number of consequent functions	19683
7	Number of variables	393741
8	Used Membership Function	Gaussian membership function

While the false positive and false negative are the inappropriate positive and negative class predictions, the true positive and true negative are the proper classification predictions on the normal and abnormal heart conditions that are consistent with the reality.

The evaluation findings for sensitivity rate are shown in figure 6 shows the comparison graph with the current model. The findings show that, when compared to prior works, the suggested model provides better sensitivity. The result comparisons are made with the existing models such as, Fuzzy Analytic Hierarchy model (FAHP) (Uyar & Ilhan, 2017) Deep Belief Neural Networks (DBNN) and (Al-Makhadmeh & Tolba, 2019) Feedforward Neural Networks (FNN) (Vivekanandan & Sriman Narayana Iyengar, 2017).

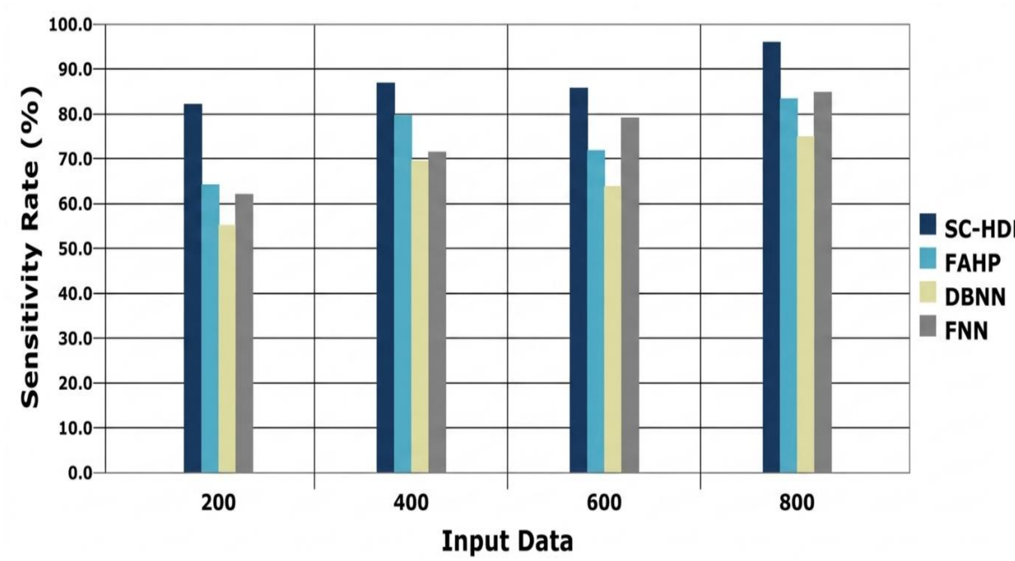

Figure 6: Model comparison-SR analysis

Specificity rate analysis is another crucial assessment component in a classification model that works similarly to sensitivity. This is computed, and the result is shown in a graph for comparison in figure 7. The results show that the suggested model has a higher specificity rate than other models that were also taken into consideration, with an average of 94.53%.

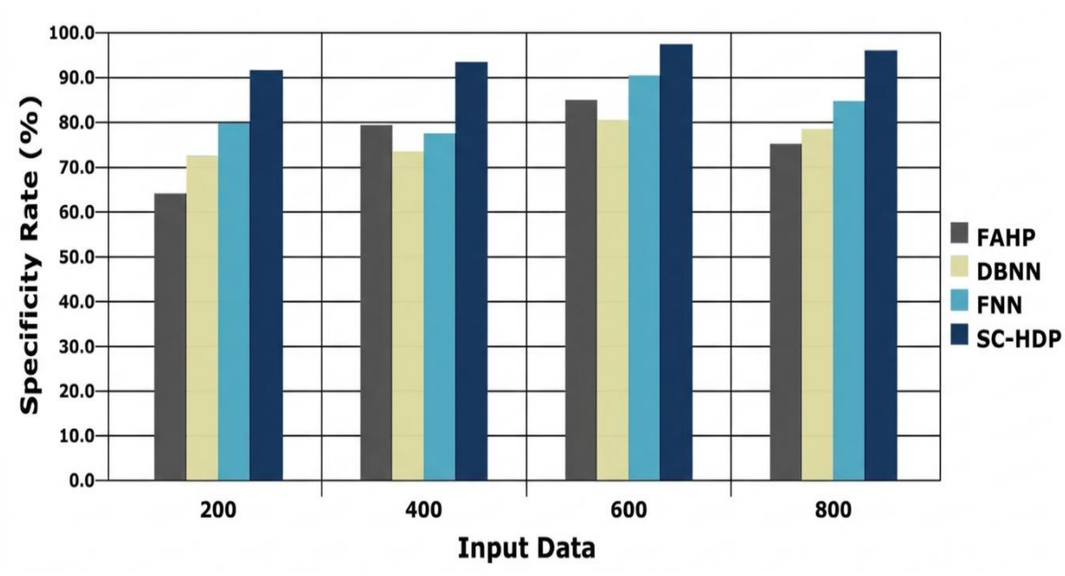

Figure 7: Model comparison-SP analysis

The results for classification accuracy are shown in figure 8. The results for the precision rate in predicting illness are also shown in figure 9. The effective fusion of fuzzy logic with machine learning models allows the model to operate at a greater pace. This is shown by the model's 96.11% classification accuracy, which is greater than that of other similar models in the diagnosis of illness. As shown in the accompanying figure and data, the model also employs ANFIS for classification, which considerably raises the accuracy rate.

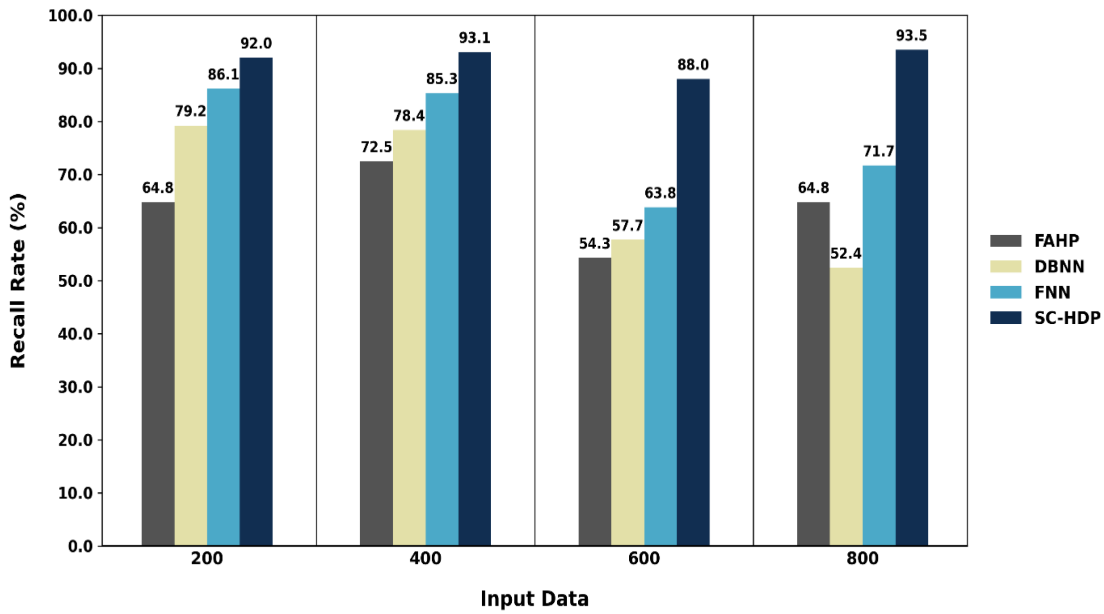

Figure 8: Model comparison-RA analysis

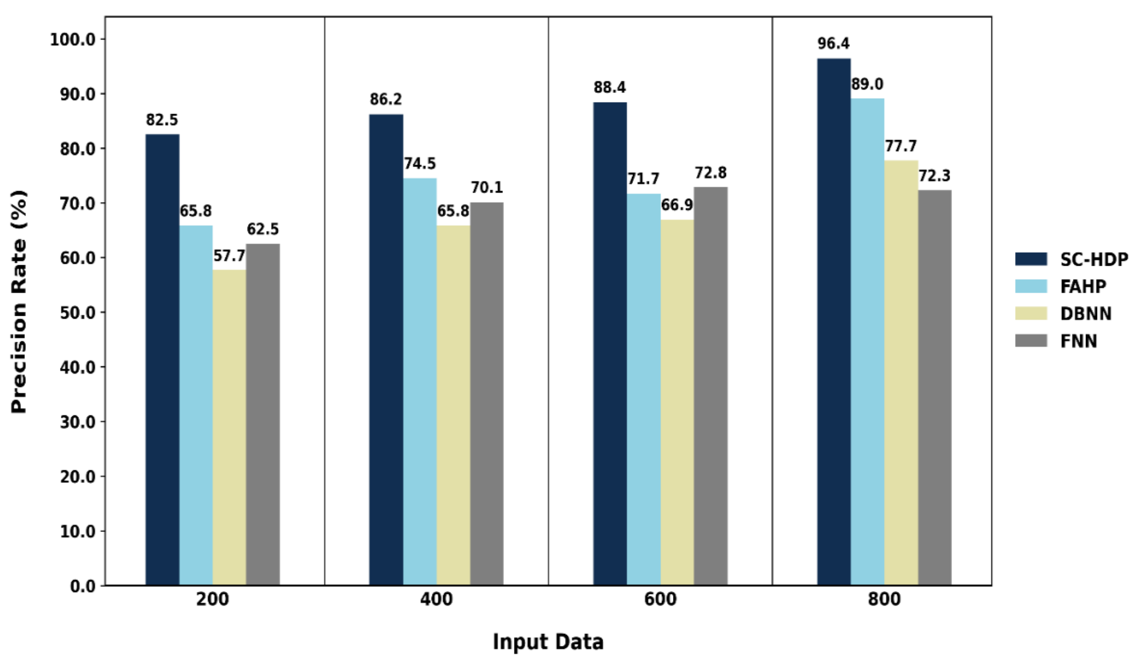

Figure 9: Model comparison- precision rate analysis

A disease diagnosis model should have a low mistake rate because the results have a higher impact on patient life. The model achieves a greater rate of result correctness and produces minimal error by employing fuzzy logics and appropriate feature extraction using RSA. Based on the outcomes, the evaluations are processed with that in mind, and the outcomes are presented in figure 10. According to the graph, the results show that the suggested model achieves a lower rate of error in disease prediction than previous methods, which is negligible. Processing time is another important parameter; in this case, good outlier detection and feature selection maximize the findings and significantly lower the time complexity. Additionally, the comparison graph is shown in figure 11. The suggested model's performance is clearly demonstrated by the aforementioned figures and tables. During the analysis process, it acquired the highest rates of classification accuracy and precision, 96.23% and 97.34%, respectively, in the normal and abnormal classes.

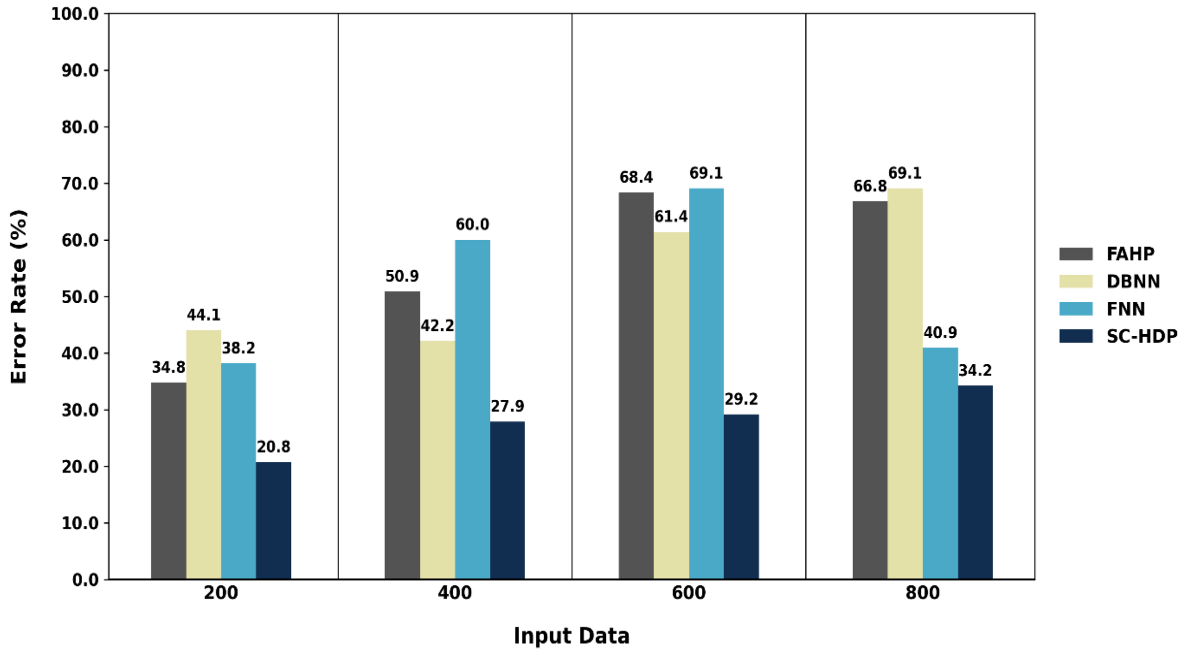

Figure 10: Model comparison- error rate analysis

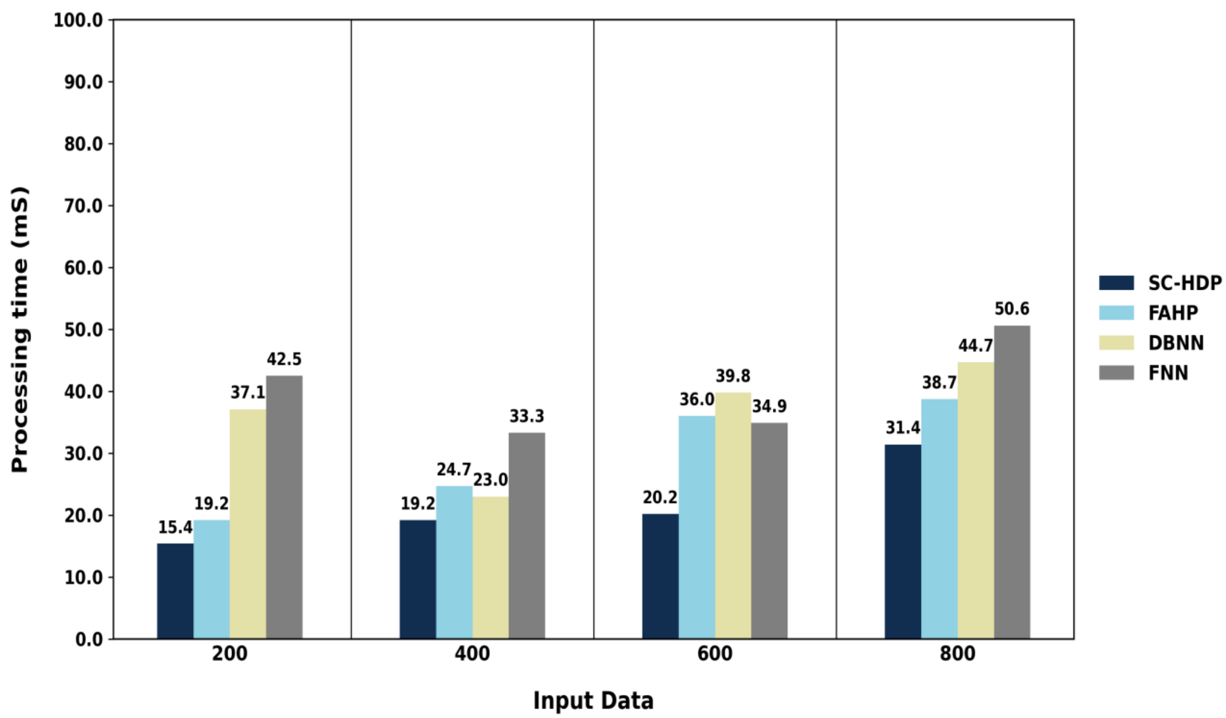

Figure 11: Model comparison- processing time analysis

5 Conclusion and Future Work

In present scenario, healthcare monitoring and disease detection model is significant in saving people life, when they are unable to reach hospitals physically. In the proposed model, an IoMT based heart disease prediction model is proposed using ANFIS framework. Feature extraction has been carried out using RSA, attained highest fitness values. The results are compared based on factors such as, sensitivity, specificity, accuracy, precision and error rates. The results show that the proposed model attains better results than the compared classification models. Based on the classification results, the normal and abnormal states, the concern person can be notified, following the treatment can be processed.

In future, the study can be enhanced with other optimization models for enhancing the accuracy of the detection results in HDP. Moreover, the advancements of wearable technologies can be used for enhancement.

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