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Novel Internet of Things Based Disease Diagnosis Framework for Smart Healthcare Schemes using Combined Optimized Artificial Intelligence Approach

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Abstract: The Internet of Things (IoT) and Artificial Intelligence (AI) technologies have gotten a lot of attention in recent years as a means to alleviate the load on healthcare systems caused by an aging population and a surge in severe diseases. However, the present diagnosis systems have several flaws, such as a long computational time and reduced prediction accuracy. Due to this reason, this article proposes a new improved IoT-based hybrid AI model for diagnosing heart, diabetes, and kidney diseases. Here, the UCI Repository dataset is used in this research. The implementation of this work is executed in MATLAB software. Also, the exact features from the dataset for accurate classification are obtained by the proposed Hierarchy mapping-based heap optimizer (HM-HO) method. Furthermore, the Shamble Shepherd Optimizer-based Evolving fuzzy neural network (SSO-EuFNN) algorithm is proposed for accurate disease diagnosis classification. Furthermore, 99.91% precision for heart disease, 99.88% accuracy for diabetes, and 99.82% accuracy for kidney disease were attained in the indicated disease diagnostic simulation findings. Thus the simulation results achieved from the proposed model are compared with the conventional methods in terms of various performance measures. As a result, the proposed strategies successfully reduce the death rate by lowering the complexity of disease diagnosis.

Keywords: *Artificial intelligence, Healthcare, performance measure, Internet of Things, Feature extraction, Classification, Sensors and Cloud storage*

1. Introduction

The medical field's expertise is based on the knowledge or information found by medical experts [1]. The human species is like sophisticated machinery with many moving parts that can be influenced by a variety of variables [2]. As a result, modeling its dis-functions or usefulness is a time-consuming operation [3]. By incorporating diverse computing approaches into the medication, smart healthcare has greatly shifted in various disciplines. The major goal of smart healthcare is to provide individuals with ubiquitous and individualized healthcare and treatment programs [4]. Computer-assisted analysis and decision-making for a customized treatment plan are instances of such medical and health care services [5]. Medical data may be utilized to establish diagnoses and forecasts for a variety of ailments. The forecast is typically made based on the doctor's knowledge and expertise, which might be inaccurate at times, resulting in negative consequences [6]. As a result, a computerized diagnostic analysis system must be created to make use of the acquired database and knowledge base [7]. This approach can help diagnose disorders considerably more quickly and with fewer diagnostic tests before the patient notices any obvious complications [8].

Moreover, Artificial intelligence [9], big data analytics, cloud computing, and the Internet of Things (IoT) are some of the enabling computer tools that are helping to advance smart medicine. The IoT is an actual network system propelled by innovation. Because the IoT has connected everything, this related organization offers new opportunities to enhance operations across the board, including manufacturing, agriculture, the industry, and healthcare institutions [10]. Some IoT technologies have been integrated with healthcare, resulting in IoT-enabled healthcare, which is used to generate and gather large amounts of healthcare records, also known as medical big data [11]. It takes sophisticated IoT devices to gather huge data for patients, save it in the clouds, and analyze it to maximize the potential benefits for illness prediction systems [12]. The Internet of Things (IoT) is described as the advent of cyber-physical networks with transmission and sensor technologies in a distributed network manner. Most importantly, the IoT has changed healthcare environments and spawned a new paradigm

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associated with the Internet of Healthcare Technologies [13].

This event opens up several possibilities, as most people utilize sensor modules to improve their health and the well, which is strongly tied to healthcare and e-health [14]. The increased popularity of these sensing devices can be attributed to their minimal price, affordability, and availability [15]. Additionally, this attempts to assist medical systems by collecting electronic health records equipment and apps. To supervise the patient's status in real, it employs a variety of sensors, including a visual sensor, a temperature sensor, a blood oxygen saturation sensor, an accelerometer sensor, a respiration sensor, electrocardiogram (ECG) sensors, and a blood-pressure sensor [16]. These healthcare gadgets track the health of patients, gather patient information, and transmit it to clinicians via a distant cloud computing environment [17]. The biggest difficulty for intelligent healthcare is controlling clinical relevance which creates a vast volume of healthcare records from linked devices [18].

Since healthcare information has become digitized, machine learning has played an essential part in the identification of various diseases such as cancer, kidney problems, cardiovascular disease, diabetes, and others [19]. In the last decade, researchers have investigated several machine learning approaches in the field of health care systems, such as the support vector machine (SVM) [20] and Naive Bayes (NB) algorithms [21], which are employed in cardiovascular disease detection methods. Also forecast diabetes progression by K-Nearest Neighboring (K-NN) [22], SVM [23], fuzzy unordered rule induction algorithm [24], random forest [25], Decision Tree (DT) [26], Multinomial Logistic Regression (MLR) [27], Multi-Layer Perceptron (MLP) [28], and C4.5 [29]. However, when the objective disease classifications intersect, the performance will decrease. The conventional methods are not appropriate for large datasets of disease diagnosis and identification. Also, the existing models are unsatisfied, which influences the accuracy of the disease prediction results. The testing technique takes a long time, and the noise is extremely sensitive. The requirement of training performance is highly affected by the classification methods. Moreover, the fuzzy method gives equal weight to all of the components, which must be united.

To overcome such a problem, this work proposes a new model of IoT-based disease diagnosis framework using novel combined Artificial intelligence methods. The goal of this research is to diagnose different diseases using an improved AI method [30]. The procedure of this framework encloses diverse phases such as data collection, pre-processing, feature extraction, and classification with optimal parameter tuning. The proposed model gathers the data of patients using IoT sensor devices attached to the patient that will save in the cloud storage and the corresponding medical data is considered from the UCI repository. The main features from the pre-processed data are extracted using the proposed Hierarchy mapping-based heap optimizer (HM-HO). Furthermore, a novel Shamble Shepherd Optimizer-based Evolving fuzzy neural network (SSO-EuFNN) method of the classifier is used for disease diagnosis in IoT-based healthcare systems. Then, the significance of the proposed method results is compared with the conventional methods under different instances. The foremost contribution of this work is summarized subsequently:

- Creating a revolutionary AI as well as IoT-based disease detection model for an intelligent healthcare system.
- Collect the corresponding correlated medical data from the data set of the UCI repository and patient medical data from the sensors.
- Preprocessing the gathered data from the exact dataset.
- Extract the suitable features from the data using the HM-HO method.
- Provide a new SSO-EuFNN for accurate disease diagnosis.
- Evaluate the comparative analysis of the proposed system over the conventional techniques in terms of several classification metrics.

The article arrangement of this research is provided as follows: The recent research related to this research is provided in Section 2. The system model along with the problem statement is explained in Section 3. The proposed model of disease diagnosis is detailed in Section 4. The proposed result, discussion, and comparative analysis are elaborated in Section 5. The termination of this research is elaborated in the conclusion of Section 6.

2. Related Work

Some of the research works related to this study are summarized as follows: Even though many researchers have concentrated on heart disease prediction, the accuracy of the outcomes is inadequate. To mitigate this problem, an IoT approach is designed by Khan, Mohammad Ayoub [32] that uses a Modified Deep Convolutional Neural Network (MDCNN) to better precisely diagnose cardiac illness. The MDCNN is used to categorize received sensor information into healthy and pathological categories. These experiments demonstrated that the proposed MDCNN-based heart

disease diagnosis systems have a 98.2 % prediction performance.

In this research, Lakshmanaprabu, S. K., et al [31] presented an IoT integrated cloud storage decision support system for the diagnosis and monitoring of Chronic Kidney Disease (CKD) with its level of severity to produce the highest healthcare benefits to customers via e-health apps. In addition, for the diagnosis of CKD and its seriousness, they used a Deep Neural Network (DNN) classifier. An attribute selection strategy based on Particle Swarm Optimization (PSO) is also employed to increase the effectiveness of the DNN classifier. The suggested DNN classified correctly CKD with an efficiency of 98.25 % on its own, and the PSO-FS approach improves this to 99.25 %.

Kaur, Pavleen, et al [32] used a variety of machine learning algorithms like Random Forest, K-NN, DT, SVM, and MLP as well as accessible health-related information stored in the cloud to create a structure that lets for actual and mobile healthcare tracking using IoT infrastructure and cloud technology. The system will be able to provide suggestions based on cloud-based historical and actual information. Using a variety of illness-specific input features, this article examined prediction algorithms for conditions such as cardiovascular disease, prostate cancer, hyperglycemia, hypothyroidism, dermatological, kidney problems, and postoperative data.

Computer-assisted assessment and therapy, combining deep reinforcement learning with large datasets created and gathered by healthcare IoT. Because many individuals experience lung cancer, Liu, Zhuo, et al [33] examined the implications of deep reinforcement learning for the diagnosis of lung cancer in this work. Furthermore, the open problems and potential prospective areas of research using deep reinforcement learning are discussed to identify lung cancer, which is likely to accelerate the growth of smart healthcare through the healthcare IoT.

In healthcare 4.0, artificial intelligence (AI) is frequently used to produce rapid and reliable outcomes. The work investigated by Kishor, Amit, and Chinmay Chakraborty [34] developed a machine learning-based system of healthcare that can identify proactively and correctly the different illnesses like thyroid, heart disease, breast cancer, diabetics, hepatitis, dermatology, liver disorder, surgery date, and spect heart. Several efficient machine learning methods are utilized to diagnose common diseases in this study including DT, adaptive boosting, SVM, RF, NB, ANN, and K-NN [35]. The greatest efficiency of the RF classifier for various illnesses is 97.62 %.

Optimization algorithms may be used to diagnose cardiac problems, and the findings are accurate and efficient. The primary goal of this study by Basheer, Shakila et al [38] is to present a hybrid fuzzy-based decision tree (HFDT) method for the automatic recognition of heart disease using a constant and distant patient alert system. The suggested HFDT algorithm produces a result with maximum reliability of 98.30 %.

For extremely critical selecting features, Amin UI Haq et al [36] suggested a filter approach based on the DT (Iterative Dichotomiser 3) technique. For extracted features, Ada Boost as well as RF ensemble learning techniques are utilized. The classification of normal and diabetic participants was done using a DT Classifier. The algorithm has been tested using the diabetes statistical model, which is a clinical database depending on the medical data of patients. The authenticity of the suggested system is validated by different validation approaches such as K-fold, hold out, K-fold, drop one sample out, and measuring performance parameters were used. The results of the experiments reveal that the suggested feature extraction was chosen characteristics that improved the forecast model's performance of the classifier and attained maximum accuracy. The summary of the literature review is provided in Table.1.

Table 1 Summary of literature review

References	Methodology	Diseases	Metrics	Merits	Limitation
Khan, Mohammad Ayoub [32]	MDCNN	Heart diseases	Accuracy error, precision, F1, Recall, specificity	The accuracy of the prediction performance is high.	The PPV value is low and the error is high. The performance of testing and training is poor.
Lakshmanaprabu, S. K., et al [31]	Machine learning methods	Chronic Kidney Disease	False positive rate (FPR), false negative rate (FNR), sensitivity,	This approach is simple to integrate into real-time applications, allowing for quicker and more accurate remote CKD	For the suggested model to improve CDS security, complexity and encryption standards should be

			specificity, accuracy, area under curve (AUC), F-score, Mathew Correlation Coefficient (MCC) and kappa value	detection.	reduced.
Kaur, Pavleen et al [32]	K-NN, SVM, Random Forest, DT, and MLP	Diabetes, Breast Cancer, Heart Disease, Thyroid, Dermatology Spect-Heart, Surgery, And Liver Disorder	Accuracy and AUC	In this research, more disorders are diagnosed.	On the Dermatology dataset, the Random Forest algorithm for machine learning achieves a maximum accuracy of 97.26% only. It should be improved furthermore.
Liu, Zhuo, et al [33]	Deep reinforcement learning	Lung cancer	-	Accurate tumour localization, a critical component of lung cancer diagnosis, improved the surgical procedure and decreased the recurrence rate.	There is only one disease diagnosis in this paper.
Kishor, Amit, and Chinmay Chakraborty [34]	DT, SVM, Naïve Bayes, adaptive boosting, RF, ANN, and K-NN	Heart Disease, Breast Cancer, Diabetics, Hepatitis, Dermatology, Liver Disorder, Thyroid, Surgery Data, And Spect Heart	Sensitivity, specificity, Accuracy, and AUC.	The created healthcare model will assist doctors in making an early illness diagnosis.	The RF classifier attained maximum accuracy yet for real-time predictions, an algorithm with a high number of trees may be too sluggish.
Basheer, Shakila et al [38]	Hybrid fuzzy DT algorithm	Heart Disease	sensitivity, accuracy, precision, specificity, and recall	The results showed that the suggested strategy was more effective and precise at segmenting the MR images with tumour.	Particular disease is estimated and failed to validate other serious illness.
Amin UI Haq et al [36]	DT-ID3 + LOSO	Diabetics	Accuracy, sensitivity/ recall, specificity, MCC, precision, ROC-AUC, F1-score and execution time	The suggested approach is better appropriate for detecting diabetes in healthcare settings and has excellent accuracy.	It's crucial to develop cures and healing techniques for serious illnesses.

Analysis of previous work with gap identification is provided as follows: After examining recent studies, it was discovered that a lot of effort was already put into predicting diseases in the healthcare system in the past. Nevertheless, there is still more that can be done to enhance the accuracy of healthcare disease forecasts, which will aid doctors in early patient diagnosis and prediction. According to the study of the literature, few researchers are using machine learning approaches but most conventional works have ignored the efficiency of meta-heuristic methods to enhance classification performance.

To solve this problem, an IoT framework is proposed that uses the SSO-EuFNN (Shamble Shepherd Optimizer based Evolving Fuzzy Neural Network) algorithm to more correctly assess heart, kidney, and diabetes conditions. The patient's wearable monitor gadget keeps an eye on things like blood pressure and other vital signs. The received sensor data is classified into normal and pathological states using the SSO-EuFNN. By contrasting the proposed SSO-EuFNN with existing deep learning techniques, the system's performance is examined.

3. System Model

The system model of IoT based smart healthcare scheme is illustrated in fig.1. The main components in the system model are IoT devices implanted in the person, patient medical data, benchmark datasets, cloud storage, data gathering model, disease diagnosis, and prediction section. Various N number of IoT wearable sensors are connected to the patients. The sensors are used to sense the parameters such as blood glucose levels, chronic illness classification, blood pressure information, blood cholesterol levels, smoking utilization artery disease, anxiety levels, respiratory rate, chronic pain location, and workout data. Furthermore, wireless networks are used to transmit and receive information, which is then stored in the cloud. The UCI Repository's benchmark disease dataset is utilized. The patient's historical information is included in the medical dataset, which was collected from the hospitals. Then, the data will be preprocessed and extracted the features using feature extraction.

Moreover, the classification algorithm is used which classify the condition of a person whether he/she is affected by the disease or not. If the person is affected by any diseases, then the responsive alerting system is used by the alerting device, which sends a message to the appropriate physician and provider. When the acquired value exceeds the threshold value, an alarm message is issued, and the threshold values are made depending on the researcher's and administration's previous methods and conclusions. The threshold approach varies by age category and includes maximum and minimum threshold values, therefore the system is always monitoring.

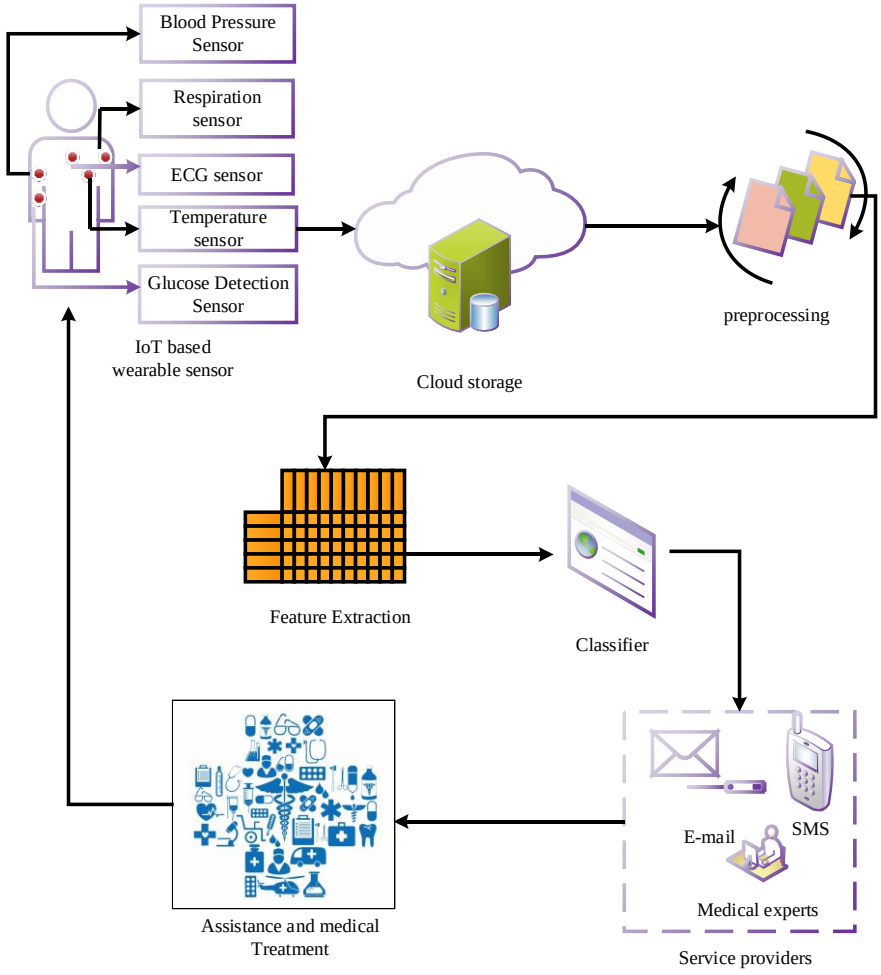


Fig.1 System model of IoT based smart healthcare scheme

3.1 Problem Statement

Let us consider the kidney, diabetic and heart disease dataset that have the test sample as $Y = \{Y_1 \ldots\ldots Y_n\}$ and the optimal target $Z = \{Z_1 \ldots\ldots Z_n\}$ with the selected features $y_i^l(s+1) = \{y_1^l \ldots\ldots y_n^l\}$. Various difficulties in the clinical context are handled to convert healthcare movements into IoT innovation to enhance machine lifespan and interruption to meet people's requirements. A fundamental difficulty in these situations is the quick processing of massive volumes of data to give highly dependable and precise observations and judgments, allowing IoT to realize its promise. Training a classifier takes more time. It is computationally costly because it is extremely tough and takes a long time.

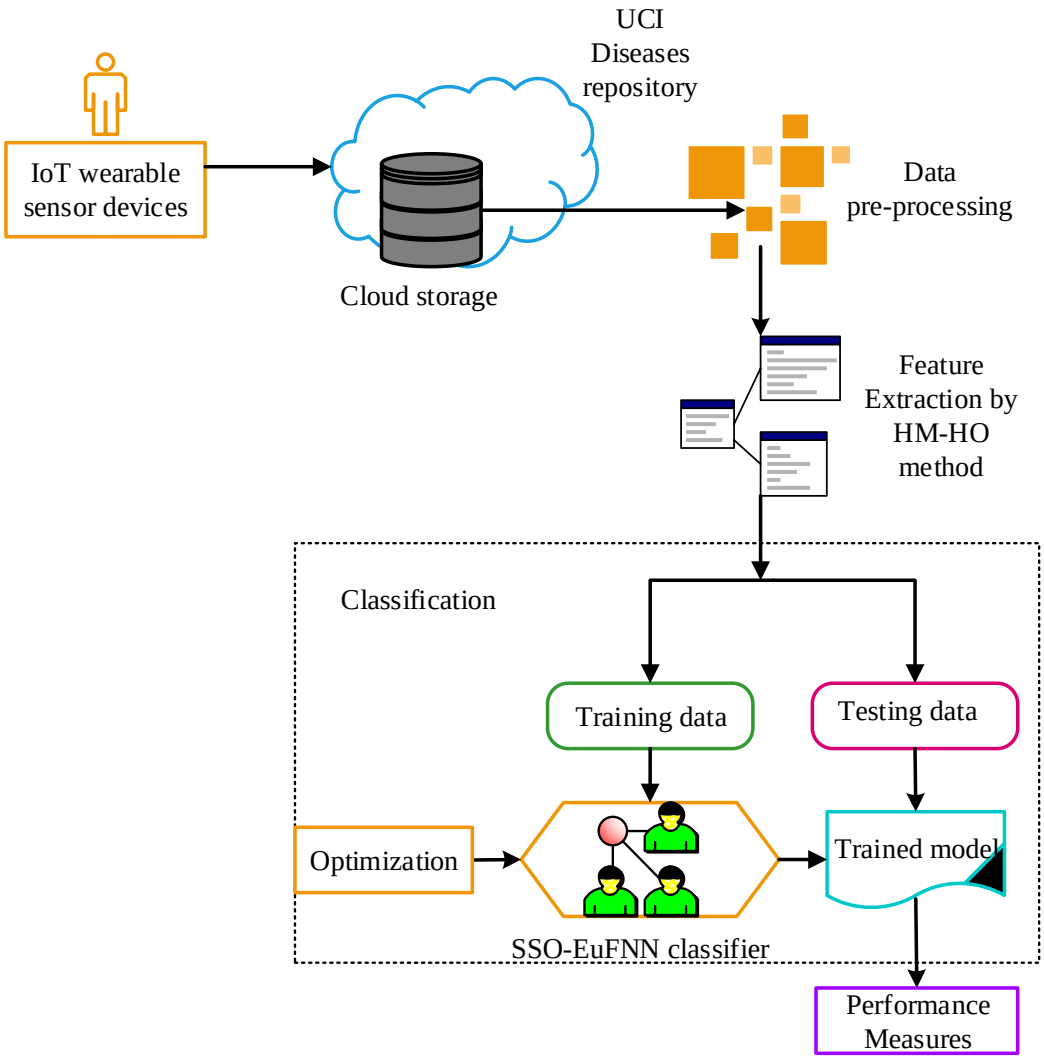


Fig.2 Smart healthcare systems proposed design

4. Proposed Framework

The major goal of this study is to use an IoT dataset and a unique AI technique to diagnose illnesses. Figure 2 depicts the smart health care system's proposed design. Biosensors based on the Internet of Things are implanted in the human body. Here, the IoT data from the UCI dataset is taken for effective validation for various diseases.

Data preparation, feature extraction of the data using the Hierarchy mapping-based heap optimizer (HM-HO) approach, and classification using a Shamble Shepherd Optimizer-based Evolving fuzzy neural network (SSO-EuFNN) were the three processes in this work. The parameters of the proposed EuFFN method are optimized using the SSO algorithm. If people are affected by any diseases, they will be notified by SMS, emails, and other means, and they will be able to seek treatment and advice from physicians based on the effective diagnosis.

4.1 Data pre-processing

Data preprocessing is the process of eliminating noisy and inconsistent features from a dataset, as well as inaccurate and duplicate records from the initial health datasets acquired. Furthermore, inconsistent data is

rectified and missing data is replaced as needed, and an abnormality of data is found.

4.2 HM-HO for Feature extraction

After preprocessing, the raw data the function of feature extraction is carried out for accurate disease classification. The dataset has numerous numbers of attributes but in this work, a certain 14 number attributes are required. For this reason, the novel HM-HO method is proposed for the accurate extraction of features. The proposed HM-HO method is the combined mapping form of heap optimization. The fitness of optimization is used to extract the appropriate features from the database. Some of the instance of features for the extraction such as age, gender, blood glucose levels, heartbeat rate, Chronic pain category, Respiratory rate, blood pressure, Anemia, 2 h Serum Insulin, Body Mass Index (BMI), Total cholesterol, Exercise data, Pus Cell clumps and output.

4.2.1 Initialization

Set essential parameters like population size (N), maximum number of iterations (S), number of input variables (F), and design variable limits (B_i, A_i). The significant fitness parameter for the computation is evaluated using eqn. (1),

$$D = \frac{S}{s} \tag{1}$$

Here, s is the present iteration. Then, initialize the population by creating an arbitrary sample of (M) of (N) feature solutions, each with v attributes. The group (M) is represented by eqn. (2)

$$M = \begin{bmatrix} y_1^1 & y_1^2 & y_1^3 & \cdots & y_1^v \\ y_2^1 & y_2^2 & y_2^3 & \cdots & y_2^v \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ y_N^1 & y_N^2 & y_N^3 & \cdots & y_N^v \end{bmatrix} \tag{2}$$

Despite the fact that this approach is a tree-shaped data model, it can be easily done using an array due to its correctness. Where y_i represented as i^{th} feature of the dataset.

4.2.2 Hierarchical feature interaction

In a hierarchical organization, the topmost procedures and regulation are enforced, and subordinates follow their immediate supervisor. This behavior may be simulated by changing the location of each feature extraction, assuming that each source data is a proximal feature to its extraction $\vec{y}_i$ reference to its source data is updating by eqn. (3),

$$y_i^l(s+1) = C^l + \chi\delta^l \left| C^l - y_i^l(s) \right| \tag{3}$$

Where l is the superscript of the vector element, s is the present iteration, χ and δ are the significant parameters. Also, χ decreases linearly from 2 to 0 over the duration of iterations, and then begins to rise again to 2 with iterations after achieving 0. Nevertheless, the parameter D controls how often cycles c completes in S iterations. Ackley measures are used to determine how the value of D impacts the performance of HM-HO.

4.2.3 Interaction of consequent feature points

The precise features are defined as feature points with the same score. They communicate with one another to complete formal responsibilities. The variables at the same rank are featured in this work, and each search agent changes its location according to the expression concerning its randomly drawn features.

$$y_i^l(s+1) = \begin{cases} W_i^l + \chi\delta^l \left| W_i^l - y_i^l(s) \right| & , h(\vec{W}_l) < h(y_i(s)) \\ y_i^l + \chi\delta^l \left| W_i^l - y_i^l(s) \right| & h(\vec{W}_l) \geq h(y_i(s)) \end{cases} \tag{4}$$

Where the objective function of the system is denoted as h the search agent explore the feature point area W_i^l if $h(\vec{W}_l) < h(y_i(s))$ and provides the certain feature value otherwise it explore the another feature value y_i^l in the source data.

4.2.4 Updating features

The purpose of a roulette wheel is to equalize these probabilities, which are divided into three portions such as f_1, f_2 and f_3. The extracted features are updating by eqn. (5),

$$y_i^l(s+1)=\begin{cases} y_i^l & f \le f_1 \\ C^l+\chi\delta^l\left|C^l-y_i^l(s)\right| & f>f_1 and f\le f_2 \\ W_i^l+\chi\delta^l\left|W_i^l-y_i^l(s)\right| & f>f_2 and f\le f_3 and h(\vec{W}_l)<h(y_i(s)) \\ y_i^l+\chi\delta^l\left|W_i^l-y_i^l(s)\right| & f>f_2 and f\le f_3 and h(\vec{W}_l)\ge h(y_i(s)) \end{cases} \quad (5)$$

Where f is an integer between 0 and 1 that was produced at random. Thus, feature points change their scores in based on the previously described equations on a regular basis in order to converge on the best global solution.

4.3 SSO-EuFNN based classification algorithm

The SSO-EuFNN algorithm is the combination of shuffled Shepard and an improved intelligence method. The parameters of the EuFNN algorithm are enhanced and optimized by the fitness function of the SSO algorithm.

4.3.1 EuFNN for disease diagnosis

EFuNN is a five-layer structure that creates units and links based on data. The Input layer, fuzzy quantization, rule layer, membership function, and defuzzification are all included in this model's five-layer scheme. The constituents of an input feature vectors make up its input layer. Assume that Y_i is an input vector. The second layer's output Y_{if} for Y_i, and provides fuzzified data (a vector of membership functions) derived from symmetrical triangular fuzzy numbers set in field or subject Y_i. Furthermore, the fourth layer output is represented as Z_{if}. The input and output weight indices fit the fuzzification inputs and outputs when a rule neuron n_r is generated, which is expressed using eqn. (6)

$$K_1(n_r)=Y_{if} \text{ and } K_2(n_r)=Z_{if} \quad (6)$$

In the second layer, fuzzification is accomplished by determining the membership functions of an input to a collection of triangular MFs. The normalized fuzzy proximity between a fresh fuzzy sample Y_{1f} as well as the k^{th} recorded characteristic $K_1(k)$ may be calculated by eqn. (7),

$$N_k=\frac{\left\|Y_{1f}-K_1(k)\right\|_b}{\sum_{k=1}^{n_r}\left\|Y_{1f}-K_1(k)\right\|_b} \quad (7)$$

Here, $\|.\|_b$ is denoted as p-norm. For p-norms, $\|c\|_{b+x}\le\|c\|_b$ for any $c\in\Re^n, k\ge 1, b\ge 0.$ Each specified vector v's p-norm $\|c\|_b$ does not expand with b; every other norm is lower-bounded through the 1-norm. As a result, the Euclidean standard was used $b=2.$ Also, rule neuron activation thresholds can be estimated using radial basis equations. This article makes use of eqn. (8)

$$G1_i=1-N_k \quad (8)$$

Where, $G1_i, N_k\in[0,1]$. The model's sensitivity to the development or adjustment of rule neurons is controlled by this threshold $T\in[0,1]$. A higher number of hidden neurons and parameters are possible with greater scores of T. Moreover, EFuNNbegan learning with a null fuzzy rule and also no experience of the dataset in some of the most general case. In this situation, it is acceptable to place the threshold midway between neuron generation and adjustment. Let assume, the initial value of threshold value is default as 0.3.The following is a quick and easy way to modify T. Consider w be the target value generated in each of the t number of iterations. If the neuron number w grows rapidly than a specified rate β that is $w>\beta$, thus T is reduced,

If $w>\beta$, T is reduced;

$$T(n+t)=\left(1+\frac{w-\beta}{t}\right)T(n) \quad (9)$$

Otherwise, if the neuron numbers w grows smaller than a specified rate β that is $w<\beta$, thus T is increased,

If $w > \beta$, T is increased;

$$T(n+t) = \left(1 + \frac{\beta}{t}\right) T(n) \quad (10)$$

Enormous developmental processes are to be avoided since they enhance the complexity of the model but may not improve generalization. This approach uses this process to keep a data-dependent dynamic threshold. The neurons whose activity value exceeds a specific threshold communicate their results forward by the Many-to-Many technique. According to the earlier, all the most active neuron sends their signal to another layer. A saturated scaling factor of the form is employed to propagate the activation of the winning neuron by Eqn. (11),

$$G_{\max} = \begin{cases} 0 & \text{if } G(w_{\max})K_2 < 0 \\ 1 & \text{if } G(w_{\max})K_2 > 1 \\ G(w_{\max})K_2 & \text{otherwise} \end{cases} \quad (11)$$

Triangular MFs are also found in fourth-layer. The most active fuzzy neuron is identified after computing the fuzzy output vector. Moreover, $G_{\max}$ is the neuron with the highest value of membership and $G_{a\max}$ is the activation. The error E_r among the actual fuzzy outcome vector Y_{1f} and evaluated $G_{a\max}$ contrasted to a threshold T . If the mistake exceeds the threshold, a rule neuron is formed. Meanwhile, the leading neuron m weight parameters K_1 as well as K_2 are generated from eqn. (12),

$$K_{1m}(n+1) = K_{1m}(t') + \mu_1(Y_i - K_{1m}) \quad (12)$$

$$K_{2m}(n+1) = K_{1m}(n) + \mu_2 G_{\max} E_r \quad (13)$$

Where μ_1 and μ_2 are the constant learning values, Y_i is the i^{th} input vector. Finally, the fifth layer is referred to as the output layer. The output layer defuzzification the data and calculates the quantitative score for the output. The rule function maximum activation is extended to the next level. As a result, the optimal disease diagnoses are categorized. However, the parameters of the EuFNN method are optimized by the fitness function of the SSO algorithm.

4.3.2 SSO for EuFNN Performance

Shepherds group horses or any other animals together in a herd, relying on the animals' instincts to choose the best route to the pasture. The shepherd directs sheep near horses for this function. The SSO was created as a result of this behavior. The learning parameter of the EuFNN method is optimized and improved by the meta-heuristic algorithm of SSO. The fitness function of the SSO algorithm is used.

Initialization: The mathematical model starts SSO with a randomly chosen starting population parameter in the solution space:

$$L_{a,b}^{0} = L_{\min} + r \times (L_{\max} - L_{\min}); \quad \text{a} = 1,2,....\text{xandb} = 1,2,....\text{y} \quad (14)$$

Where $L_{\min}$ and $L_{\max}$ are the minimum and maximum boundaries of model parameters, respectively; r is a random variable for each constituent created between 0 and 1; y is the number of individuals in each group, and x is the number of groups. In this technique, the overall number of community members may be calculated using eqn. (15),

$$yL_p = x \times y \quad (15)$$

Parameter tuning: In this procedure, the first x individuals of each population are randomly put in the first column of the multi-community conditions Eqn. (16) as other members of each population depending on their objective functions. The following x members are picked similarly to the previous stage and are randomly arranged in the section to construct the second column of multi-community parameter. This technique is repeated y times till the multi-community matrix are created as follows:

$$L_p = \begin{bmatrix} L_{1,1} & L_{1,2} & \cdots & L_{1,y} & \cdots & L_{1,y} \\ L_{2,1} & L_{2,2} & \cdots & L_{2,y} & \cdots & L_{2,y} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ L_{a,1} & L_{a,2} & & L_{a,b} & & L_{a,y} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ L_{x,1} & L_{x,2} & \cdots & L_{x,b} & \cdots & L_{x,y} \end{bmatrix} \quad (16)$$

It's important to note that each row of the multi-community parameter represents the individuals of each group, with the top column of the multi-community parameter representing the best individuals of each group. Moreover, the people in the last section are the group's weakest variable.

Optimal Parameter optimization: Two parameters are used to create a customized step size for each member of that group. The first variable $S_{a,b}^{w}$ depicts the capacity to explore additional areas of the solution space. The second variable $S_{a,b}^{f}$ denotes the ability to explore the vicinity of previously visited potential solution space sections (intensification strategy). The following is the mathematical expression for the step size:

$$S_{a,b} = S_{a,b}^{w} + S_{a,b}^{f} \quad \text{a} = 1,2,....\text{xandb} = 1,2,....\text{y} \tag{17}$$

The worst and finest function of stepsize for tuning the parameter is estimated using eqn. (18)

$$S_{a,b}^{w} = \gamma \times r_1 \times (L_{a,w} - L_{a,b}) \tag{18}$$

$$S_{a,b}^{f} = \varphi \times r_2 \times (L_{a,f} - L_{a,b}) \tag{19}$$

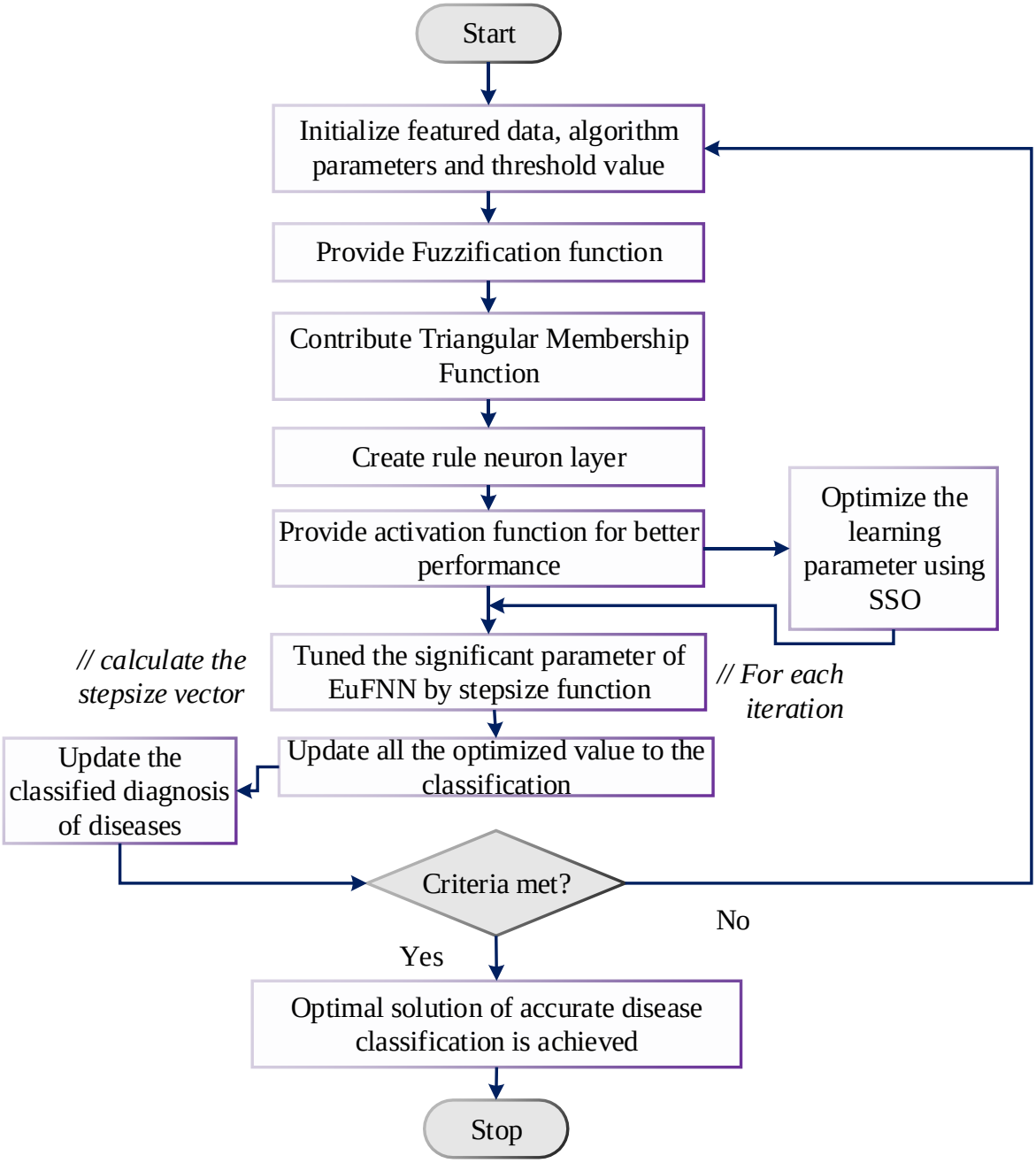


Fig.3 flow diagram of proposed SSO-EuFNN algorithm in disease diagnosis

In comparison to $L_{a,b}$, r_1 and r_2 are random parameters with each component created between 0 and 1; $L_{a,f}$ and $L_{a,w}$ are the better and worse parameters in terms of objective function value. It's valueobserving that the x^{th} community's initial parameter $L_{a,1}$ doesn't have an affiliate who is better than it. As a result, $S_{a,1}^{f}$ is an equivalent to 0. Consequently, $L_{a,y}$ does not have a worse parameter than itself due to the x^{th} group final parameters. Hence $S_{a,y}^{w}$ is likewise zero. Furthermore, γ and φ are the variables that influence exploration as well as exploitation, respectively.The following are the definitions for these variables:

$$\varphi = \varphi_0 + (\varphi_{\text{maximum}} - \varphi_0) \times s \quad (20)$$

$$\gamma = \gamma_0 - \gamma_0 \times s; \qquad s = \frac{\text{Valueofiteration}}{\text{Totalvalueofiteration}} \quad (21)$$

It is obvious that as the number of iterations s grows, γ increases and φ decreases. Therefore, exploration slows down while exploitation accelerates.

Parameter updating: The new parameter of the $L_{x,y}$ is computed using Eqn. (22) according to the previous step. Afterwards, if the $L_{x,y}$ parameter is not inferior to its previous objective function rate, it will be updated:

$$NewL_{x,y} = L_{x,y} + S_{x,y} \quad (22)$$

Termination: The optimization process will be ended after a specified Maximum iteration. If not, it returns to back to step for another set of iterations. The flow diagram of proposed SSO-EuFNN algorithm performance is provided in fig.3.

5. Result and Discussion

The efficiency of the proposed SSO-EuFNN algorithm and the results are reviewed in this part. The proposed SSO-EuFNN approach for IoT-based illness detection is performed in the MATLAB 2018Rb tool, which runs on a Windows 7 64-bit platform with an Intel 5 CPU and 4 GB RAM. Math Works designed this numerical and restricting programming language. Various ailments, such as heart disease, diabetes, high cholesterol, kidney disease, and high blood pressure, are considered in this study based on risk factors. Heart disease, kidney disease, and diabetes are all caused by excessive blood pressure and cholesterol. As a result, the assessment of heart disease, kidney disease, and diabetes disorders is dependent on the forecast of high blood pressure and high cholesterol. Furthermore, standard statistical calculation criteria such as specificity, accuracy sensitivity, precision, recall, and others are used to assess prediction performance.

5.1 Case study

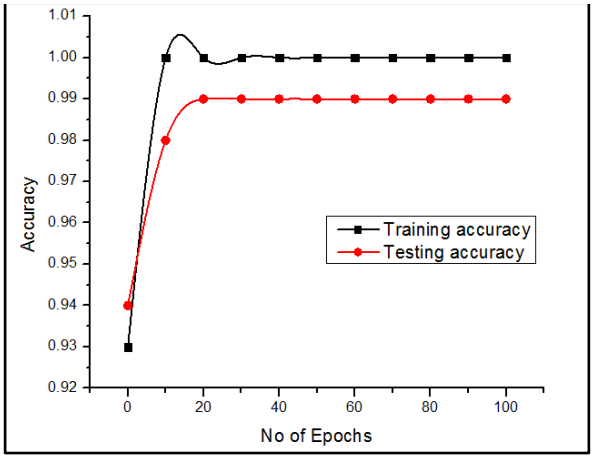
The performance efficiency of IoT-based SSO-EuFNN method classification models in a remote distant location is investigated in this study. Assume that X is the remote area. The IoT-based wearable sensors are linked to each patient as Y1 to Yn, and data is gathered from individuals. The IoT implantable devices sensors capture about 25 gigabytes of data, and the set of data and health records are used for training. The IoT wearable sensor devices are estimated the details of patients, diseases, blood glucose level, blood pressure level, heartbeat rate and so on. In this research, the performance validation is carried out using UCI datasets, which contains the details of patients, health details, and disease categorizes like heart, diabetics and kidney problem. The acquired information is examined, and missing or inconsistent information is substituted with noise data using typical feature score parameters. In this database, there are 74 characteristics and 253 occurrences. 120 patient data points were collected, including age, gender (G), blood glucose levels (BGL), heartbeat rate (HR), Chronic pain category (CPC), Respiratory rate (RR), blood pressure (BP), Anemia (A), 2 h Serum Insulin (2-h SI), Body Mass Index (BMI), Total cholesterol (TC), Exercise data (ED), Pus Cell clumps (PCC), and output (Ot). The diagnosis features and codes are provided in Table.2.

Table 2 Diagnosis features and codes

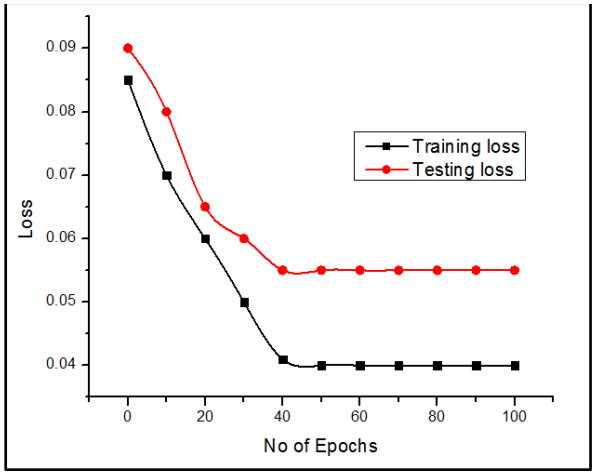
S. No	Features	Codes and Values
1	Gender	Female (1), Male (0)
2	Age	Age in years

3	Blood glucose levels	High (0) and low (1)
4	Heartbeat rate	60-100 beats/min, Normal (0); >60-100 beats/min high(-1); <60-100 beats/min, low (1)
5	Chronic pain category	Normal angina(0); atypical angina(1); non-angina pain(2); asymptomatic(3)
6	Respiratory rate	12-18 breaths/min, Normal(0); <12-18 breaths/min High(1); >12-18 breaths/min Low(-1)
7	blood pressure	between 90/60mmHg (0) and 120/80mmHg (1)
8	Anemia	Yes (0), No (1)
9	2 h Serum Insulin	Yes(0) ; No (1)
10	Body Mass Index (BMI)	Normal (0); Overweight (1) ; Obesity (2)
11	Total cholesterol	Normal(0), 200mg/dL; High(1), >200mg/dL
12	Exercise data	Flat (0), upsloping (1) and downsloping(2)
13	Pus Cell clumps	Yes (0); No(1)
14	Output	Heart disease(0); Diabetic(1); Kidney failure(2)

Afterward, noise-free data is analyzed, and the HM-HO approach is used to extract features. From that, 14 attributes are significantly used to diagnose the different diseases without failure. Patient information is acquired via constant monitoring and data has been gathered with the use of the mentioned 14 features. The extracted features from the HM-HO method values are 17, 11, 18, 10, 13, 5, 12, 7, 9, 10, 6, 5, 16, and 14. The patients' selected data is then fed into the proposed SSO-EuFNN classifier. The presented approach effectively processes the generated input, and the outcome is acquired through an efficient training procedure. To evaluate the efficiency of the disease diagnosis, 70 percent of information is obtained for training and 35 percent of data is used for testing.



(a)



(b)

Fig. 4 a) Training and Testing accuracy, b) Training and testing loss

The training and testing accuracy is shown in fig.4 a). From that when the number of epochs increases the training and the testing accuracy is reduced. Moreover, the training and testing loss is illustrated in fig. 4 b), the results show that when the number of epochs increases, the losses of testing and training are reduced. This method is repeated until the most effective illness prediction technique is found, which requires the most feature analysis iterations. The accuracy, precision, FPR,

recall, positive and NPV, F-measure, and other metrics are then used to evaluate the system's effectiveness.

5.2 Performance Measures

The proposed SSO-EuFNN's performance in illness diagnosis is compared to that of other traditional classifier algorithms such as, PSO-DNN [31], HDFT [35], CSO-CLSTM [37], Deep Trained Neocognitron Neural Network (DTNNN) [38] and Adaptive hybridized Deep Convolutional Neural Network (AHDCNN) [39]. In this study, a variety of metrics to evaluate the classification performance including accuracy, sensitivity, recall, specificity, precision, MCC, F1-score, Positive Predictive Value (PPV), Negative Predictive Value (NPV), False Positive Rate (FPR), False Negative Rate (FNR), and processing time. These matrices were computed using the binary confusion matrix. When the diseases subject is categorized as illnesses, the anticipated outcome is True Positive $(\vec{TP})$, and if the healthy person is classified as healthy, the forecasted outcome is True Negative $(\vec{TN})$. False Positive $(\vec{FP})$ is defined as if a healthy person is mistaken for a diseased person, and False Negative $(\vec{FN})$ is evaluated as if a diseased person is mistaken for a healthy one.

5.2.1 Sensitivity/Recall

This demonstrates the capacity to locate a patient with a variety of illness risks. Sensitivity is defined as the ratio of true positives to the combination of true positives and false negatives, which is evaluated using eqn. (23)

$$\text{Sensitivity} = \frac{\vec{\text{TP}}}{\vec{\text{TP}} + \vec{\text{FN}}} \quad (23)$$

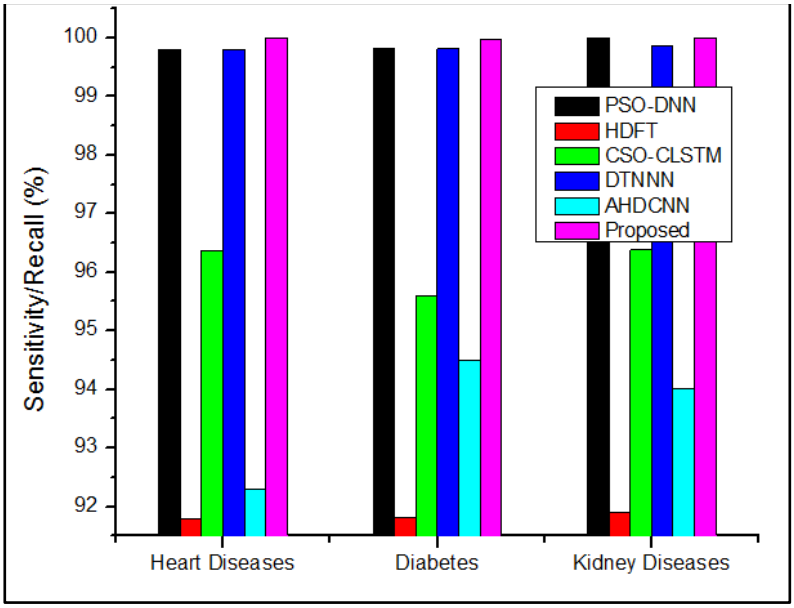


Fig. 5 Comparative analysis of the proposed sensitivity/Recall over existing methods

The proposed SSO-EuFNN classifier recognizes disease problems with greater accuracy due to its higher sensitivity assessment. The comparative analysis of the proposed sensitivity/Recall over existing methods is illustrated in figure 5.

The proposed method achieved sensitivity/recall has been diagnosed with different diseases like heart disease, diabetes, and kidney diseases, which is compared with the conventional methods like PSO-DNN, HDFT, Filter based DT-(ID3), DTNNN, and AHDCNN methods. The heart diseases diagnosis of the proposed approach has obtained a higher sensitivity/recall of 100% over the existing PSO-DNN (99.8%), HDFT (91.8%), Filter based DT-(ID3) (96.37%), DTNNN (99.8%) and AHDCNN (92.3%) methods. Also, the proposed approach to diagnosed diabetes disease has obtained a higher sensitivity/recall of 99.98% over the existing PSO-DNN (99.81%), HDFT (91.82%), Filter based DT-(ID3) (95.6%), DTNNN (99.81%) and AHDCNN (94.5%) methods. Consequently, the proposed approach to diagnosed kidney disease has obtained a higher sensitivity/recall of 100% over the existing PSO-DNN (100%), HDFT (91.9%), Filter based DT-(ID3) (96.38%), DTNNN (99.87%) and AHDCNN (94.01%) methods. This shows the effective performance of the proposed approach in different diseases with higher sensitivity values.

5.2.2 Specificity

The ratio of a number of true negatives to the combination of true negatives and false positives is

known as specificity. The highest specificity is 1.0, while the lowest is 0.0.

$$\text{Specificity} = \frac{\vec{\text{TN}}}{\vec{\text{TN}} + \vec{\text{FP}}} \tag{24}$$

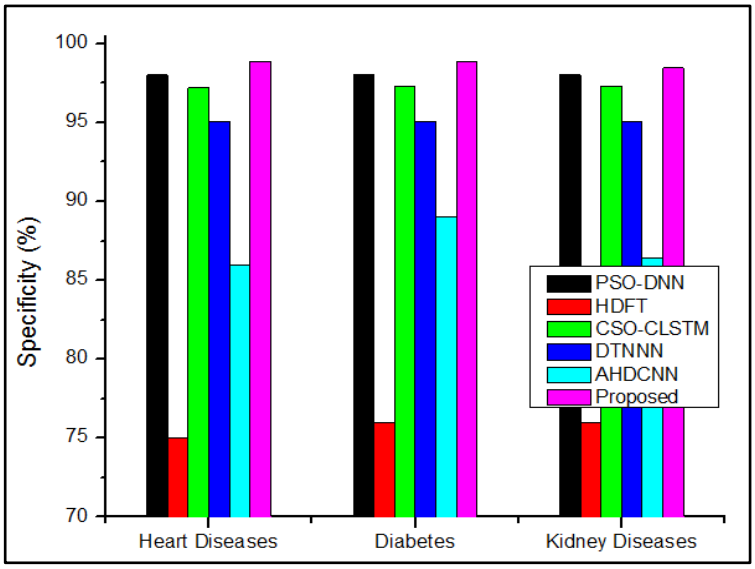


Fig. 6 Comparative analysis of the proposed specificity over existing methods

The comparative analysis of the proposed specificity over existing methods is illustrated in figure 6. The proposed method achieved specificity has been diagnosed with different diseases like heart disease, diabetes, and kidney diseases, which is compared with the conventional methods like PSO-DNN, HDFT, Filter based DT-(ID3), DTNNN, and AHDCNN methods. The heart diseases diagnosis of the proposed approach has obtained higher specificity of 98.9% over the existing PSO-DNN (98.02%), HDFT (75%), Filter based DT-(ID3) (97.20%), DTNNN (95.05%) and AHDCNN (86%) methods. Also, the proposed approach to diagnosed diabetes disease has obtained higher specificity of 98.85% over the existing PSO-DNN (99.81%), HDFT (76%), Filter based DT-(ID3) (97.31%), DTNNN (95.06%) and AHDCNN (89.05%) methods. Consequently, the proposed approach to diagnosed kidney disease has obtained higher specificity of 98.46% over the existing PSO-DNN (98.03%), HDFT (76%), Filter based DT-(ID3) (97.30%), DTNNN (95.07%) and AHDCNN (86.4%) methods. This shows the effective performance of the proposed approach in different diseases with a higher specificity value.

5.2.3 Accuracy

The most often used categorization performance parameter is accuracy. It is measured in percentages and indicates the proportion of accurately categorized instances. The classification performance should be reaching 100 % for improved classification results.

$$\text{Accuracy} = \frac{\vec{\text{TP}} + \vec{\text{TN}}}{\vec{\text{TP}} + \vec{\text{TN}} + \vec{\text{FP}} + \vec{\text{FN}}} \tag{25}$$

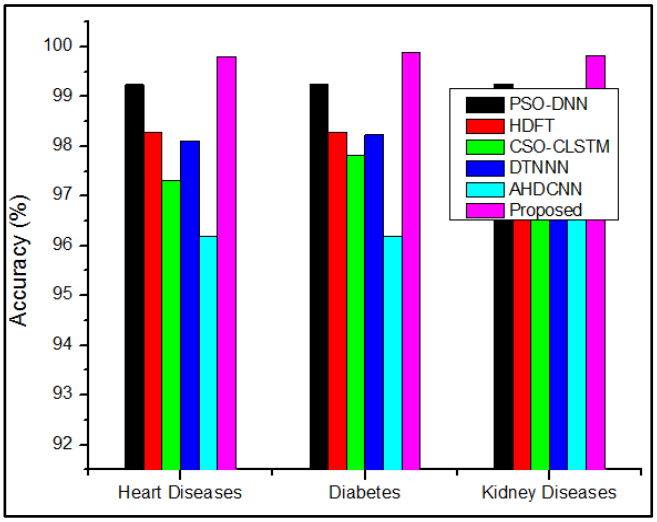


Fig. 7 Comparative analysis of the proposed accuracy over existing methods

The comparative analysis of the proposed accuracy over existing methods is illustrated in figure 7. The proposed method achieved accuracy has been diagnosed with different diseases like heart disease, diabetes, and kidney diseases, which is compared with the conventional methods like PSO-DNN, HDFT, Filter based DT-(ID3), DTNNN, and AHDCNN methods. The heart diseases diagnosis of the proposed approach has obtained higher accuracy of 99.8% over the existing PSO-DNN (99.24%), HDFT (98.29%), Filter based DT-(ID3) (97.31%), DTNNN (98.1%) and AHDCNN (96.2%) methods. Also, the proposed approach to diagnosed diabetes disease has obtained higher accuracy of 99.88% over the existing PSO-DNN (99.246%), HDFT (98.28%), Filter based DT-(ID3) (97.81%), DTNNN (98.23%) and AHDCNN (96.2%) methods. Consequently, the proposed approach diagnosed kidney disease has obtained higher accuracy of 99.82% over the existing PSO-DNN (99.25%), HDFT (98.30%), Filter based DT-(ID3) (97.80%), DTNNN (98.2%) and AHDCNN (97.3%) methods. This shows the effective performance of the proposed approach in different diseases with a higher accuracy value.

5.2.4 Precision/ PPV

This is the possibility that a patient who has a positive diagnostic test has the diseases.

$$\text{Precision/PPV} = \frac{\vec{\text{TP}}}{\vec{\text{TP}} + \vec{\text{FP}}} \tag{26}$$

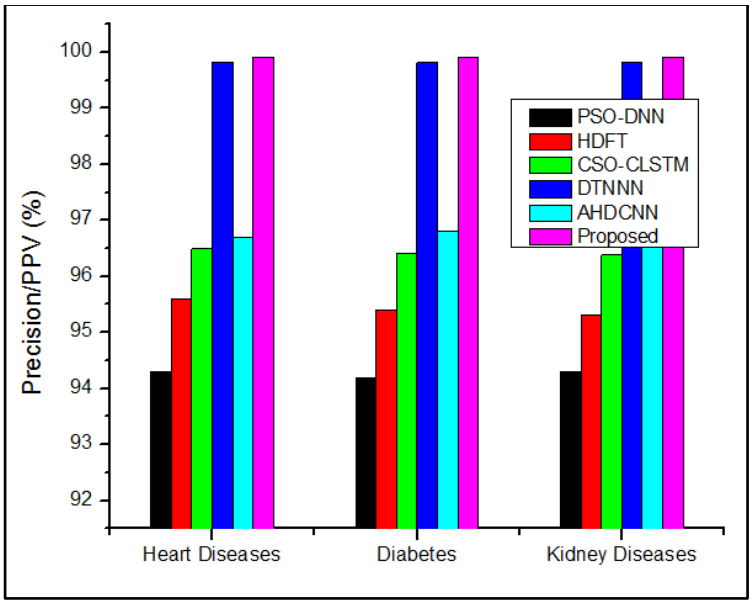


Fig. 8 Comparative analysis of the proposed precision/PPV over existing methods

The comparative analysis of the proposed precision over existing methods is illustrated in figure 8. The proposed method achieved precision/PPV has been diagnosed with different diseases like heart disease, diabetes, and kidney diseases, which is compared with the conventional methods like PSO-DNN, HDFT, Filter based DT-(ID3), DTNNN, and AHDCNN methods. The heart diseases diagnosis of the proposed approach has obtained a higher precision/PPV of 99.91% over the existing PSO-DNN (94.302%), HDFT (95.6%), Filter based DT-(ID3) (96.5%), DTNNN (99.82%) and AHDCNN (96.7%) methods. Also, the proposed approach to diagnosed diabetes disease has obtained a higher precision/PPV of 99.915% over the existing PSO-DNN (94.2%), HDFT (95.4%), Filter based DT-(ID3) (96.4%), DTNNN (99.81%) and AHDCNN (96.8%) methods. Consequently, the proposed approach to diagnosed kidney disease has obtained a higher precision/PPV of 99.91% over the existing PSO-DNN (94.3%), HDFT (95.3%), Filter based DT-(ID3) (96.38%), DTNNN (99.83%) and AHDCNN (96.82%) methods. This shows the effective performance of the proposed approach in different diseases with higher precision/PPV value.

5.2.5 Negative predictive value (NPV):

The Negative Predictive Value is the percentage of negative test outcomes that are examined. This represents the possibility of identifying a patient who is not at risk for any diseases.

$$NPV = \frac{\vec{T}\vec{N}}{\vec{T}\vec{N} + \vec{F}\vec{N}} \tag{27}$$

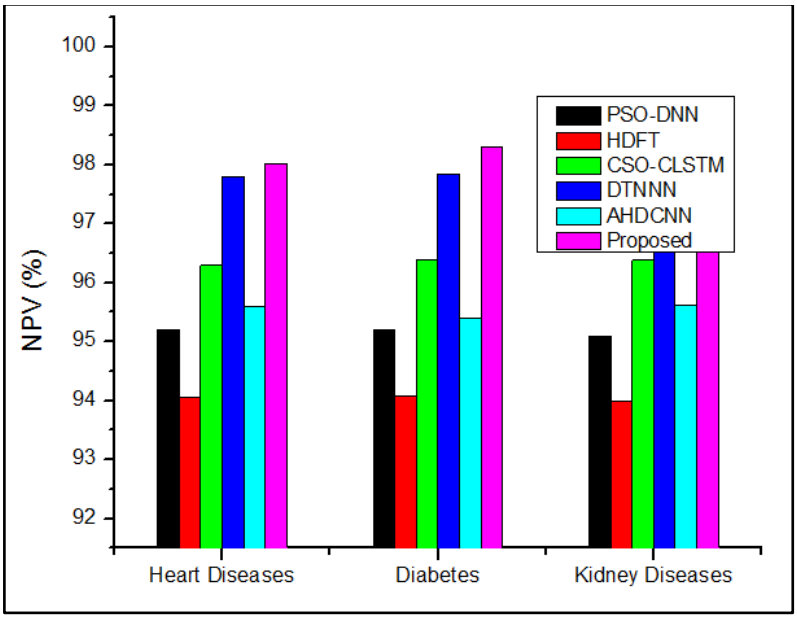


Fig. 9 Comparative analysis of the proposed NPV over existing methods

The comparative analysis of the proposed NPV over existing methods is illustrated in figure 9. The proposed method achieved NPV has been diagnosed with different diseases like heart disease, diabetes, and kidney diseases, which is compared with the conventional methods like PSO-DNN, HDFT, Filter based DT-(ID3), DTNNN, and AHDCNN methods. The heart diseases diagnosis of the proposed approach has obtained a higher NPV of 98.02% over the existing PSO-DNN (95.2%), HDFT (94.06%), Filter based DT-(ID3) (96.3%), DTNNN (97.8%) and AHDCNN (95.6%) methods. Also, the proposed approach to diagnosed diabetes disease has obtained a higher NPV of 98.3% over the existing PSO-DNN (95.21%), HDFT (94.08%), Filter based DT-(ID3) (96.382%), DTNNN (97.85%) and AHDCNN (95.4%) methods. Consequently, the proposed approach to diagnosed kidney disease has obtained a higher NPV of 98.012% over the existing PSO-DNN (95.1%), HDFT (94%), Filter based DT-(ID3) (96.38%), DTNNN (97.2%) and AHDCNN (95.62%) methods. This shows the effective performance of the proposed approach in different diseases with higher NPV value.

5.2.6 F-measure

The effectiveness of the validation process is determined by the F-measure. It's a weighted average that takes into account both high precision as well as recall.

$$F-measure = \frac{2\vec{T}\vec{P}}{2\vec{T}\vec{P} + \vec{F}\vec{P} + \vec{T}\vec{N}} \tag{28}$$

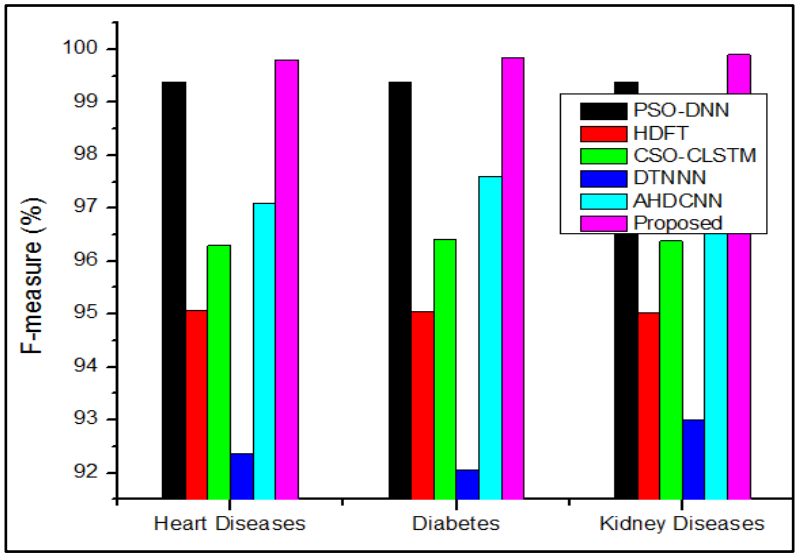


Fig. 10 Comparative analysis of the proposed F-measure over existing methods

The comparative analysis of the proposed F-measure over existing methods is illustrated in figure 10. The proposed method achieved F-measure has been diagnosed with different diseases like heart disease, diabetes, and kidney diseases, which is compared with the conventional methods like PSO-DNN, HDFT, Filter based DT-(ID3), DTNNN, and AHDCNN methods. The heart diseases diagnosis of the proposed approach has obtained a higher F-measure of 99.8% over the existing PSO-DNN (99.38%), HDFT (95.06%), Filter based DT-(ID3) (96.3%), DTNNN (92.36%) and AHDCNN (97.1%) methods. Also, the proposed approach to diagnosed diabetes disease has obtained a higher F-measure of 99.85% over the existing PSO-DNN (99.38%), HDFT (95.036%), Filter based DT-(ID3) (96.4%), DTNNN (92.06%) and AHDCNN (97.6%) methods. Consequently, the proposed approach to diagnosed kidney disease has obtained a higher F-measure of 99.9% over the existing PSO-DNN (99.39%), HDFT (95.03%), Filter based DT-(ID3) (96.38%), DTNNN (93%) and AHDCNN (97.3%) methods. This shows the effective performance of the proposed approach in different diseases with higher F-measure value.

5.2.7 MCC

MCC is a symmetrical measure that is used in circumstances when classes are of varying sizes. Furthermore, the MCC stands for Matthews's correlation coefficient, which is defined as the predicting power of the proposed SSO-EuFNN classifier and has a value ranging from -1 to +1. If the classification properly diagnoses the disease at the level of MCC, the result is positive; otherwise, the result is negative, indicating that the classifier identified the disease wrong. When the MCC is near 0, the classifier makes an erroneous prediction. Eqn. (30) is used to assess the MCC calculation.

$$MCC = \frac{\vec{TP} \times \vec{TN} - \vec{FP} \times \vec{FN}}{\sqrt{\left(\vec{TP} + \vec{FP}\right)\left(\vec{TP} + \vec{FN}\right)\left(\vec{TN} + \vec{FP}\right)\left(\vec{FN} + \vec{TN}\right)}} \tag{29}$$

The comparative analysis of the proposed MCC over existing methods is illustrated in figure 11. The proposed method achieved MCC has been diagnosed with different diseases like heart disease, diabetes, and kidney diseases, which is compared with the conventional methods like PSO-DNN, HDFT, Filter based DT-(ID3), DTNNN, and AHDCNN methods. The heart diseases diagnosis of the proposed approach has obtained higher MCC as 0.998% over the existing PSO-DNN (0.981%), HDFT (0.91%), Filter based DT-(ID3) (0.962%), DTNNN (0.99%) and AHDCNN (0.95%) methods. Also, the proposed approach diagnosed diabetes disease has obtained higher MCC as 0.999% over the existing PSO-DNN (0.98%), HDFT (0.92%), Filter based DT-(ID3) (0.961%), DTNNN (0.992%) and AHDCNN (0.93%) methods.

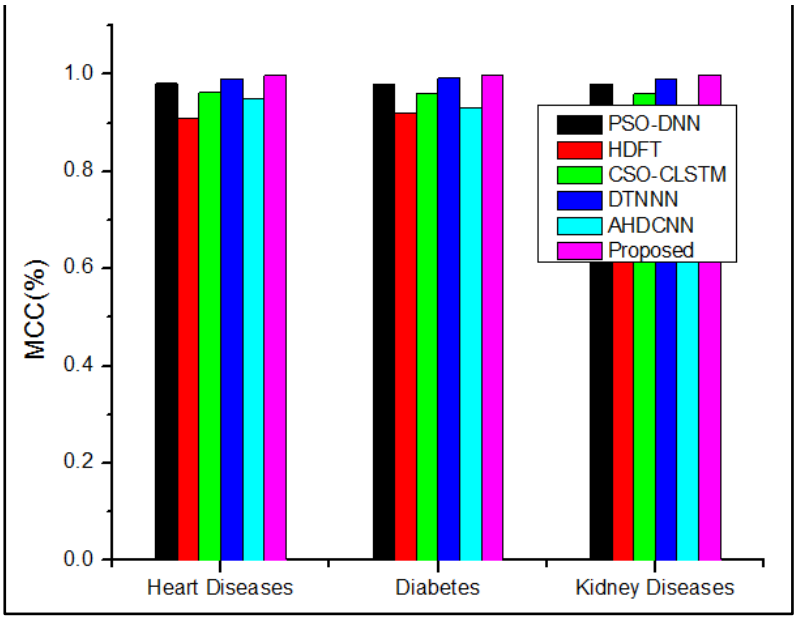


Fig. 11 Comparative analysis of the proposed MCC over existing methods

Consequently, the proposed approach diagnosed kidney disease has obtained higher MCC as 0.998% over the existing PSO-DNN (0.98%), HDFT (0.912%), Filter based DT-(ID3) (0.96%), DTNNN (0.99%) and AHDCNN (0.92%) methods. This shows the effective performance of the proposed approach in different diseases with higher MCC value.

5.2.8 False Positive Rate (FPR)

The FPR is used to calculate the chance of testing the null hypothesis incorrectly for certain analysis. The proportion of inaccurate true positives divided by the total number of negativity yields the FPR.

$$FPR = \frac{\vec{FP}}{\vec{FP} + \vec{TN}} \tag{30}$$

The comparative analysis of the proposed FPR over existing methods is illustrated in figure 12. The proposed method achieved FPR has been diagnosed with different diseases like heart disease, diabetes, and kidney diseases, which is compared with the conventional methods like PSO-DNN, HDFT, Filter based DT-(ID3), DTNNN, and AHDCNN methods. The heart diseases diagnosis of the proposed approach has obtained a lesser FPR of 0.24% over the existing PSO-DNN (1.95%), HDFT (2.44%), Filter based DT-(ID3) (0.95%), DTNNN (0.97%) and AHDCNN (1.05%) methods. Also, the proposed approach diagnosed diabetes disease has obtained lesser FPR as 0.21% over the existing PSO-DNN (1.98%), HDFT (2.09%), Filter based DT-(ID3) (0.968%), DTNNN (0.95%) and AHDCNN (1.055%) methods. Consequently, the proposed approach diagnosed kidney disease has obtained lesser FPR as 0.23% over the existing PSO-DNN (1.96%), HDFT (2.3%), Filter based DT-(ID3) (0.96%), DTNNN (0.94%) and AHDCNN (1.026%) methods. This shows the effective performance of the proposed approach in different diseases with lesser FPR value.

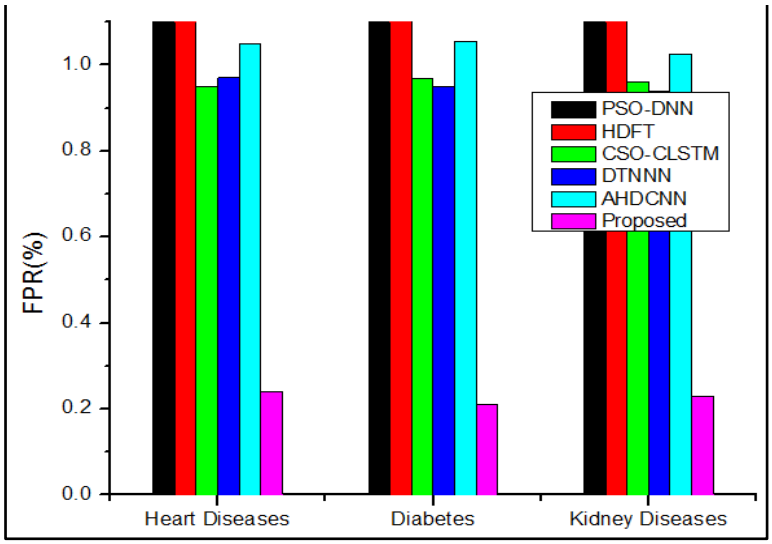


Fig. 12 Comparative analysis of the proposed FPR over existing methods

5.2.9 False Negative Rate (FNR)

The number of inaccurate negative diagnosis divided by the overall amount of negativity yields the FNR.

$$FNR = \frac{\vec{FN}}{\vec{FN} + \vec{TP}} \tag{31}$$

The comparative analysis of the proposed FNR over existing methods is illustrated in figure 13. The proposed method achieved FNR has been diagnosed with different diseases like heart disease, diabetes, and kidney diseases, which is compared with the conventional methods like PSO-DNN, HDFT, Filter based DT-(ID3), DTNNN, and AHDCNN methods. The heart diseases diagnosis of the proposed approach has obtained lesser FNR as 0.001% over the existing PSO-DNN (0.01%), HDFT (0.2%), Filter based DT-(ID3) (0.93%), DTNNN (0.92%) and AHDCNN (0.5%) methods. Also, the proposed approach diagnosed diabetes disease has obtained lesser FNR as 0% over the existing PSO-DNN (0.011%), HDFT (0.21%), Filter based DT-(ID3) (0.96%), DTNNN (0.92%) and AHDCNN (0.56%) methods.

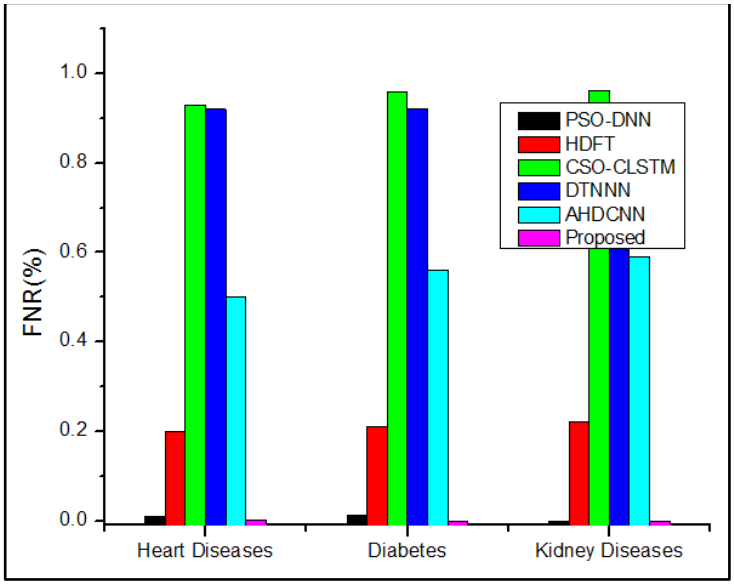


Fig. 13 Comparative analysis of the proposed FNR over existing methods

Consequently, the proposed approach diagnosed kidney disease has obtained lesser FNR as 0% over the existing PSO-DNN (0%), HDFT (0.22%), Filter based DT-(ID3) (0.963%), DTNNN (0.921%) and AHDCNN (0.59%) methods. This shows the effective performance of the proposed approach in different diseases with lesser FNR value.

5.2.10 Error rate

The percentage of error is calculated by dividing an accurate disease diagnosis by the one excluding an accurate disease diagnosis. As a result, it's known as the misclassification illness prediction rate. Eqn. (32) is used to calculate the amount of error.

$$e = 1 - \text{Accuracy} \tag{32}$$

The comparative analysis of the proposed error rate over existing methods is illustrated in figure 14. The proposed method achieved error rate has been diagnosed with different diseases like heart disease, diabetes, and kidney diseases, which is compared with the conventional methods like PSO-DNN, HDFT, Filter based DT-(ID3), DTNNN, and AHDCNN methods. The heart diseases diagnosis of the proposed approach has obtained a lesser error rate of 0.2% over the existing PSO-DNN (0.76%), HDFT (1.71%), Filter based DT-(ID3) (2.69%), DTNNN (1.9%) and AHDCNN (3.8%) methods. Also, the proposed approach to diagnosed diabetes disease has obtained a lesser error rate of 0.12% over the existing PSO-DNN (0.754%), HDFT (1.72%), Filter based DT-(ID3) (2.19%), DTNNN (1.77%) and AHDCNN (3.8%) methods.

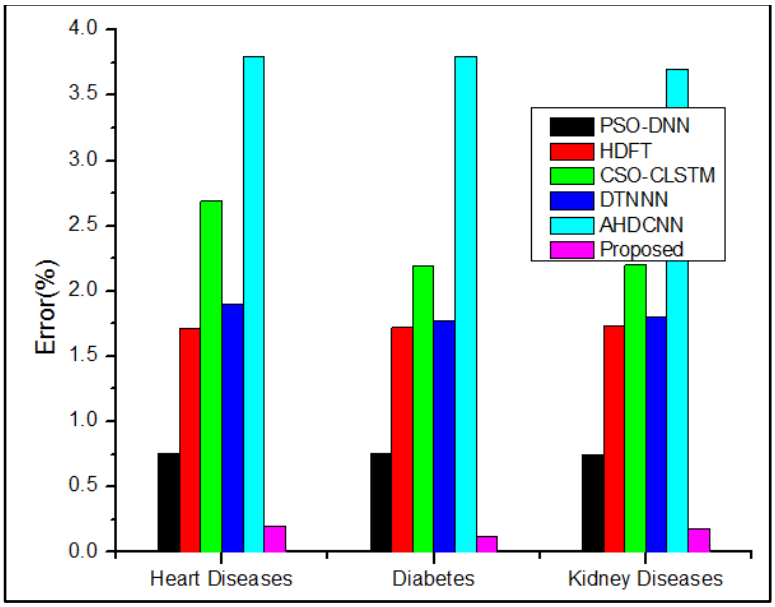


Fig. 14 Comparative analysis of the proposed error rate over existing methods

Consequently, the proposed approach to diagnosed kidney disease has obtained a lesser error rate of 0.18% over the existing PSO-DNN (0.75%), HDFT (1.73%), Filter based DT-(ID3) (2.20%), DTNNN (1.8%) and AHDCNN (3.7%) methods. This shows the effective performance of the proposed approach in different diseases with a lesser error rate value.

5.2.11 Processing time

The comparative analysis of the proposed processing time over existing methods is illustrated in figure 15. The proposed method achieved processing time has been diagnosed with different diseases like heart disease, diabetes, and kidney diseases, which is compared with the conventional methods like PSO-DNN, HDFT, Filter based DT-(ID3), DTNNN, and AHDCNN methods. The heart diseases diagnosis of the proposed approach has obtained a lesser processing time of 10% over the existing PSO-DNN (21%), HDFT (15%), Filter based DT-(ID3) (20%), DTNNN (31%), and AHDCNN (19%) methods. Also, the proposed approach to diagnosed diabetes disease has obtained a lesser processing time of 10.2% over the existing PSO-DNN (21.2%), HDFT (15.3%), Filter based DT-(ID3) (20.6%), DTNNN (30%) and AHDCNN (18%) methods. Consequently, the proposed approach to diagnosed kidney disease has obtained a lesser processing time of 10.13% over the existing PSO-DNN (21.5%), HDFT (15.5%), Filter based DT-(ID3) (20.8%), DTNNN (31.02%) and AHDCNN (18.6%) methods. This shows the effective performance of the proposed approach in different diseases with lesser processing time value.

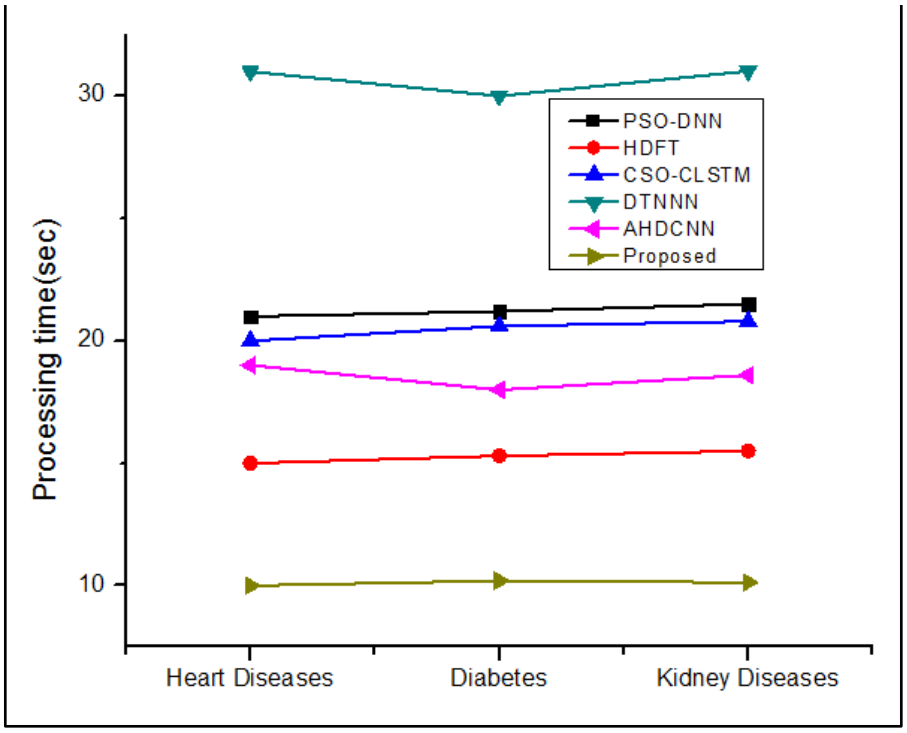


Fig. 15 Comparative analysis of the proposed error rate over existing methods

5.3 Discussion

The comparative analyses of proposed and existing methods for heart disease, diabetes and kidney disease are demonstrated in Table 3, Table 4 and Table.5. The observations show that the comparison of the selected SSO-EuFNN algorithm is conducted over traditional schemes for a variety of conditions including heart disease, diabetes, and kidney disease. When comparing the results of the analysis, the proposed SSO-EuFNN algorithm achieved greater positive values for all metrics than the existing techniques. In particular, the selected scheme has greater accuracy (99.8%) than typical PSO-DNN [31], HDFT [35], CSO-CLSTM [37], DTNNN [38], and AHDCNN [39] models, with 99.24 %, 98.29 %, 97.31 %, 98.1 %, and 96.2 %, respectively. Furthermore, when compared to the current PSO-DNN (99.246 %), HDFT (98.28 %), Filter based DT-(ID3) (97.81 %), DTNNN (98.23 %), and AHDCNN (96.2 %) approaches, the new methodology has a greater accuracy of 99.88 %.

Table.3 Comparative analysis of proposed and existing methods for heart disease

Number of instances	**PSO-DNN [31]**	**HDFT [35]**	**CSO-CLSTM [37]**	**DTNNN[38]**	**AHDCNN [39]**	**Proposed**
Sensitivity	99.8	91.8	96.37	99.8	92.3	100
Specificity	98.02	75	97.20	95.05	86	98.9
Accuracy	99.24	98.29	97.31	98.1	96.2	99.8
Precision/PPV	94.302	95.6	96.5	99.82	96.7	99.91
NPV	95.2	94.06	96.3	97.8	95.6	98.02
F-measure	99.38	95.06	96.3	92.36	97.1	99.8
MCC	0.981	0.91	0.962	0.99	0.95	0.998
FPR	1.95	2.44	0.95	0.97	1.05	0.24
FNR	0.01	0.2	0.93	0.92	0.5	0.001
Error rate	0.76	1.71	2.69	1.9	3.8	0.2

Processing time	21	15	20	31	19	10

Table.4 Comparative analysis of proposed and existing methods for Diabetes

Number of instances	**PSO-DNN [31]**	**HDFT [35]**	**CSO-CLSTM [37]**	**DTNNN[38]**	**AHDCNN [39]**	**Proposed**
Sensitivity	99.81	91.82	95.6	99.81	94.5	99.98
Specificity	98.012	76	97.31	95.06	89.05	98.85
Accuracy	99.246	98.28	97.81	98.23	96.2	99.88
Precision/PPV	94.2	95.4	96.4	99.81	96.8	99.915
NPV	95.21	94.08	96.382	97.85	95.4	98.3
F-measure	99.38	95.036	96.4	92.06	97.6	99.85
MCC	0.98	0.92	0.961	0.992	0.93	0.999
FPR	1.98	2.09	0.968	0.95	1.055	0.21
FNR	0.011	0.21	0.96	0.92	0.56	0
Error rate	0.754	1.72	2.19	1.77	3.8	0.12
Processing time	21.2	15.3	20.6	30	18	10.2

Table.5 Comparative analysis of proposed and existing methods for Kidney disease

Number of instances	**PSO-DNN [31]**	**HDFT [35]**	**CSO-CLSTM [37]**	**DTNNN[38]**	**AHDCNN [39]**	**Proposed**
Sensitivity	100	91.9	96.38	99.87	94.01	100
Specificity	98.03	76	97.30	95.07	86.4	98.46
Accuracy	99.25	98.30	97.80	98.2	97.3	99.82
Precision/PPV	94.3	95.3	96.38	99.83	96.82	99.91
NPV	95.1	94	96.38	97.2	95.62	98.012
F-measure	99.39	95.03	96.38	93	97.3	99.9
MCC	0.98	0.912	0.96	0.99	0.92	0.998
FPR	1.96	2.3	0.96	0.94	1.026	0.23
FNR	0	0.22	0.963	0.921	0.59	0
Error rate	0.75	1.73	2.20	1.8	3.7	0.18
Processing time	21.5	15.5	20.8	31.02	18.6	10.13

As a result, the proposed methodology has a greater accuracy of 99.82% when compared to the current PSO-DNN (99.25 %), HDFT (98.30 %), Filter based DT-(ID3) (97.80 %), DTNNN (98.2 %), and AHDCNN (97.3 %) approaches for diagnosing kidney illness.

Furthermore, the generated model's sensitivity, specificity, MCC, F-measure, precision, and NPV is determined to be greater than the current model for all diagnoses. As a result, the total evaluation demonstrates that the built model is improving in illness diagnosis utilizing IoT and AI techniques.

6 Conclusion

A medical emergency is becoming the main cause of mortality all across the world. Disease diagnosis is a

difficult endeavor that demands both experience and sophisticated understanding. IoT technology has recently been implemented in healthcare systems to collect sensed data for illness prediction and diagnosis. Furthermore, the IoT is assisting in the advancement of AI applications in healthcare. However, standard AI systems have challenges with parameter adjustment and accuracy. Therefore, a novel SSO-EuFNN classification algorithm is proposed for diagnosing various diseases. Also, the accurate classification performance is improved by the suitable feature extraction using the HM-HO method. Furthermore, the proposed diseases diagnosis simulation results were achieved 100% of sensitivity, 98.9% of specificity, 99.8% of accuracy, and 99.91% of precision for heart diseases, 99.98% of sensitivity, 98.85% of specificity, 99.88% of accuracy, and 99.915% of precision for diabetes and 100% of sensitivity, 98.46% of specificity, 99.82% of accuracy, and 99.91% of precision for kidney diseases. When compared to traditional disease diagnosis methodologies, the proposed IoT-based AI solution effectively diagnosed the disease. The dimension of data will be raised in the future to examine the effectiveness of the particular disease prediction system, and improved methodologies will be used to improve the prediction performance.

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