BBOA-SNDAE: A Deep Learning Model for HD Prediction in Medical IoT Systems

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Abstract

The recent progress in the Internet of Things (IoT), Artificial Intelligence (AI), and cloud computing has revolutionized the traditional healthcare system, upgrading it into a smart healthcare system. Medical services can be enhanced by integrating essential technology such as IoT and AI. The integration of IoT and AI presents several prospects within the healthcare industry. In this research, a novel hybrid Deep Learning (DL) model called Binary Butterfly Optimization Algorithm with Stacked Non-symmetric Deep Auto-Encoder (BBOA-SNDAE) for HD (HD) prediction based on the Medical IoT technology. The key aim of the work is to categorize and predict HD utilizing clinical data with the BBOA-SDNAE model. Initially, the model is trained using the Cleveland and Statlog datasets. The input data is preprocessed and standardized utilizing the Min-Max normalization. After preprocessing, the selection of features is performed utilizing the BBOA to choose the best optimal features for improved classification. Based on the selected features, the classification is performed using the SNDAE technique. The research model was assessed based on accuracy, sensitivity, precision, specificity, NPV, and F-measure. The model attained 99.62% accuracy, 99.45% precision, 99.32% NPV, 99.56% sensitivity, 99.45% specificity, and 99.38% f-measure using the HD dataset, and the model attained 98.84% accuracy, 98.73% precision, 98.34% NPV, 98.62% sensitivity, 98.21% specificity, and 98.27% f-measure using the sensor data. The results of the research model were compared with the current model for validation, where the research model outperformed all the compared models.

1. Introduction

Chronic diseases such as diabetes, cardiovascular diseases, cancer, asthma, hypertension, stroke, renal disorders, pulmonary ailments, and obesity are characterized by their long-term nature and gradual progression over time. This is the primary factor leading to mortality and impairment, accounting for 63% and 43% of cases, respectively, on a global scale. Cardiovascular disease or HD is the primary cause of death worldwide, making it a major public health concern internationally [1]. HDs are medical conditions that disrupt the normal functioning of the human heart. This medical procedure addresses abnormalities in the structure of the heart, as well as irregularities in heart rate or rhythm, and conditions affecting the arteries. Cardiologists often utilize an electrocardiogram sensor to rapidly and non-invasively assess potential signs of HD and abnormal cardiac rhythm. According to the World Health Organization (WHO), around 18 million people worldwide die of HD annually. Early detection and treatment of HD are essential to prevent sudden deaths resulting from a heart attack or cardiac arrest [2]. Nowadays, healthcare applications employ IoT, Cloud Computing, and AI for efficient operation. Utilizing modern technology in behavioral systems and protective policies can facilitate the early identification of possible health problems and optimize the timing of related interventions, like

developing newer assessments and monitoring treatment [3]. In recent times, Medical IoT is employed in health care systems to collect data from sensor for the assessment and prediction of HDs [4]. IoT is a new technology that has extensive applications across several domains, including healthcare. IoT systems have an intricate framework that integrates many categories of devices to deliver a certain service to the end user [5]. IoT is a system that enables the integration of ordinary things with the ability to detect, measure, networks, and process information. This allows these objects to interact with other devices and deliver services to accomplish a specific objective via the Internet [6]. The Medical-IoT is a healthcare system consisting of smart medical equipment and software applications. The Medical-IoT can offer remote medical diagnostics and quick health services via the Internet. Medical IoT, or healthcare IoT, encompasses a growing array of IoT applications in the field of medicine [7]. The objective of digital healthcare and medical IoT systems is to enable individuals the convenience of accessing high-quality healthcare from their residences. Therefore, Medical-IoT aims to widely implement home-based healthcare systems. Developing intelligent and efficient systems that accurately predict important diseases on time has the potential to save millions of lives and reduce the stress on existing healthcare systems [8]. The progress in IoT has facilitated the ability of both patients and physicians to retrieve real-time data. Efficient sensors and communication technologies have resulted in a reduction in the cost and energy consumption of digital healthcare systems [9].

Figure 1. Common Architecture of Medical IoT

Figure 1 illustrates the essential components of wireless sensors that enable remote monitoring of a patient's health state. These sensors are coupled with communication technologies that transmit the collected information to caregivers. To establish a smart healthcare ecosystem, it is crucial to harness the capabilities of current technology to provide optimal services to consumers and enhance their quality of life [10]. AI is a complementary technology that supports Medical IoT, aiding medical practitioners in several aspects of their expertise, including clinical decision-making. By employing Deep Learning (DL) and Machine Learning (ML) methods, computers can acquire the ability to discern between common and uncommon decisions by analyzing the data provided by healthcare experts and patient input. AI can help with IoMT devices, enabling them to consistently monitor individuals' health [11-12].

1.1. Problem Statement

Presently, clinicians predominantly rely on angiography as the primary diagnostic technique for HD due to its unparalleled precision. However, this treatment has significant adverse effects and is accompanied by a substantial expense [13]. Furthermore, the process of examining several elements to diagnose a patient might complicate the physician's task. These issues stimulate the necessity for the advancement of non-invasive techniques for the identification of HD. In addition, traditional approaches to diagnosing HD mostly rely on evaluating a patient's medical records, assessing symptoms reported by a healthcare professional, and analyzing physical examination findings. Hence, these procedures frequently result in inaccurate diagnoses because of human fallibility [14]. Therefore, it is necessary to create an automated diagnostic system using DL to diagnose HD, which can effectively address these issues. Recently, many diagnostic systems that include feature processing and DL have been created to enhance classification accuracy [15]. The implementation of these diagnostic technologies has enhanced the precision of decision-making in the diagnosis of patients by clinicians. Based on these automated diagnostic systems, a novel hybrid diagnostic system that utilizes a DL approach is proposed in this research. This system aims to improve the prediction accuracy of HD.

1.2. Research Contribution

In this research, a novel hybrid DL model is proposed to predict HD based on the IoT and AI technology. The primary purpose of the work was to predict HDs utilizing clinical data through the implementation of the BBOA-SDNAE model. First, the model is trained using the Cleveland and Statlog datasets. The data provided undergoes preprocessing and normalization using the Min-Max normalization technique. Following the preprocessing stage, the feature selection phase utilizes the BBOA algorithm to identify the most ideal features that will enhance the classification performance. The classification is conducted using the SNDAE approach, considering the selected features. During the testing phase, medical data is gathered by utilizing sensors that are equipped on the patient's body. The gathered data is sampled and stored in the cloud database for subsequent analysis. The model utilizes

the existing datasets to make predictions on the input data, based on its previous training. The research model was assessed using metrics such as accuracy, sensitivity, precision, specificity, negative predictive value (NPV), and F-measure.

The remaining sections of the work are arranged in the following. Section 2 discusses a brief analysis of the related works on Medical IoT-based HD prediction, focusing on recent models and summarizing previous research. The proposed model for implementing a predictive model with BBOA for feature selection and SNDAE for classification are described in Section 3. Section 4 comprises the results and discussion, while Section 5 provides the research conclusion with future directions.

2. Related works

This related works section examines various IoT-based prediction models for HD identification. It analyzes different models' approaches, application scenarios, advantages, and disadvantages to highlight advancements and challenges in HD prediction using IoT and DL technologies. Various automatic decision support systems were extensively proposed for the identification of HD. The study [16] presented an automatic diagnostic method that has been created to diagnose HD. The work concentrated on improving the features and resolving the issues caused by the predictive model, namely the difficulties of overfitting and underfitting. Improper network setup and extraneous features can lead to overfitting of the training data. To remove irrelevant features, a chi-squared statistical model was proposed, while the ideally designed deep neural networks (DNN) were discovered by an exhaustive search technique. The technique demonstrated superior detection accuracy for HD, however, the current study did not examine the model's time complexity. The research in [17] collected data on cardiovascular diseases utilizing IoT wearable devices from publicly available benchmark databases. The acquired data was initially subjected to a feature extraction method, where higher-order statistical characteristics were extracted. The method of selecting the most important features was achieved by implementing the hybrid optimization technique known as Particles Swarm-based Grey Wolf optimizer (PS-GWO). Subsequently, the features were classified using a DL method called a modified deep belief network (DBN). The total hidden neurons and activation functions were optimized utilizing the hybrid algorithm, aiming to enhance the accuracy of cardiac diagnosis.

Predicting HD is a complicated process, as it needs expertise with deep knowledge. An IoT-based architecture was proposed in [18] to increase the accuracy of HD evaluation using a Modified Deep Convolutional Neural Network (MDCNN). The heart-monitoring device and smartwatch were used to monitor the patient's blood pressure and ECG. The features were chosen through the utilization of the mapping-based cuttlefish optimizer algorithm (MCFA), while the MDCNN was employed for the diagnosis of both normal and dysfunctional cardiac functioning. The MDCNN was employed to categorize the collected sensor information into typical and pathological categories. The results indicate that the model achieved a better accuracy. The research introduced a novel disease detection model for smart healthcare systems, which was based on the convergence of artificial intelligence (AI) and IoT [19]. The research utilized a model called Crow Search Optimizer-based Cascaded Long Short-Term Memory (CSO-CLSTM) for diagnosing diseases. To enhance the categorization of medical data, the CSO method was utilized to optimize the 'bias' and 'weight' parameters of the CLSTM model. In addition, the research utilized the isolation Forest (iForest) approach to eliminate outliers. Implementing CSO significantly enhanced the diagnostic results of the CLSTM model. The results indicated that the CSO-CLSTM model was successful in its performance.

An automated model for detecting Congestive Heart Failure (CHF) using a hybrid DL approach consisting of a Recursive Neural Network (RNN) and CNN was developed in [20]. The study involved the classification of typical heart rate with sinus signals and CHF signal using ECG and time frequency spectral analysis of the interval. An analysis was conducted to distinguish patients with CHF from healthy individuals using ultrashort-term ECG data. The results showed excellent performance in accurately identifying CHF patients. The hybrid DL system provided unbiased and precise classifications of CHF signals. The model could be used as a valuable tool for the clinical identification of CHF patients. The IoT is supporting the evolution of cardiovascular disease (CVD) prediction. Conventional machine learning (ML) algorithms cannot consider variations in the data and exhibit a poor degree of accuracy in their predictions. The study [21] introduced a compilation of ML models that were employed to tackle this issue. These models consider the data observation methods and training procedures of various algorithms. To assess the effectiveness of the technique, the heart dataset was integrated with additional categorization models. The linear regression approach achieved an accuracy rate of around 96%.

The prediction model in [22] predicted HD using EHRs and IoT data. A soft-margin L1-regularised Support Vector Machine (sSVM) classifier managed high-dimensional input and selected relevant features. The cluster primal-dual splitting technique solved the large-scale sSVM problem, improving computational complexity and scalability. Federated learning allowed cooperative predictive analytics with data protection. The approach enhanced HD prediction and addressed healthcare privacy issues. A healthcare disease diagnostic model called IoTDL-HDD was developed in [23], which combined IoT and DL techniques. The objective of the IoTDL-HDD model was to identify the existence of CVDs by utilizing DL models on biological ECG inputs. The IoTDL-HDD model employed a bidirectional LSTM feature extraction approach to derive valuable feature vectors from the ECG data. The bidirectional LSTM approach utilized the artificial flora optimization (AFO) algorithm as a hyperparameter optimizer to enhance its efficiency. A DNN classifier with fuzzy was used to provide suitable class labels to the ECG data. The results demonstrated that the IoTDL-HDD model performed the best, with an accuracy of 93.452%.

A smart healthcare framework using IoT and cloud technologies was proposed in [24] to predict heart failure patients' survival without manual feature engineering. Heart failure patients receive quick, effective, and best-quality treatment via the smart IoT model, which monitored patients in real-time. The framework used DL models to categorize heart failure patients as alive or dead. The framework processed signals from IoT sensors on the cloud web server. DL models analyzed these signals to assess patient status. Experimental findings showed that the CNN model was more accurate with 92.89%. A smart health care framework was developed in [25] for predicting the risk of HD, which was based on IoT and cloud technology. The prediction was carried out by implementing a Fuzzy Inference System (FIS) and a Bidirectional LSTM recurrent neural network. The system collected data from IoT devices and applied predictive analytics to the electronic clinical data stored on the cloud, which contained information about the patient's medical history. The Bi-LSTM-based smart healthcare system effectively monitored and predicted the risk of HD with improved performance.

A healthcare monitoring framework using a Modified Self Adaptive Bayesian Approach (MSABA) based on IoT was proposed for predicting HD [26]. The framework consistently monitored the essential indicators of patients, like their heart rate and blood pressure, together with relevant environmental data. It also managed the allocation of computing and communication resources to meet the needs of healthcare services. The framework was effective for implementing HD prediction. To strengthen the prediction of HD, it is necessary to improve the categorization technology. A DL method was proposed in [27] to predict arterial events by analyzing a 5-minute ECG recording and extracting time-frequency characteristics from the ECG signals. An LSTM neural network was employed to detect and mitigate these occurrences promptly by leveraging its ability to understand long-term dependencies. In addition, a DBN was employed to encode and choose optimal features from the recorded information. The experimental findings demonstrated that the LSTM-DBN exhibited good performance. A cloud-computing model for the processing of data obtained from remote patient sensors and IoT platforms was proposed in [28]. The study utilized a prioritization strategy to rank sensitive information in IoT. Additionally, in cloud computing, an LSTM-DNN was employed to categorize and remotely monitor patients' status. The Internet facilitates the transmission of sensor data from the IoT platform to the cloud. The prioritization framework was utilized in IoT to prioritize important requests. Through the simulation and evaluation, it has been noted that there has been a substantial improvement in precision, accuracy, and recall.

A prediction method that utilized DL and 5G technology was developed in [29] to monitor the cardiovascular health of COVID-19 patients in real time. A 5G network was utilized to transmit and receive data from wearable medical equipment. In addition, the Flink streaming data processing framework was utilized to get ECG data. The CNN and LSTM models were employed to automatically predict the cardiovascular health of COVID-19 patients. Results demonstrated that the model enhanced the performance of predicting cardiovascular disease. The research [30] presented a medical device based on the IoT that collects cardiac data from individuals both before and after they have a heart illness. The data was processed using the higher-order Boltzmann deep belief neural network (HOBDBNN), which received a continuous transmission from the health care center. The DL technique acquired knowledge of HD features from previous research and enhanced efficiency by effectively handling intricate data. The HOBDBNN and analysis based on IoT accurately identified HD with high precision and efficiency, resulting in reduced mortality rates by simplifying the diagnostic process.

Table 1: provides a comparative analysis of the above-reviewed current works

Ref	Approach Used	Application Scenario	Advantages	Disadvantages
[16]	Chi-squared statistical model and DNN	Automatic diagnostic method for HD	Superior detection accuracy, and addresses overfitting and underfitting.	Did not examine the model's time complexity.
[17]	IoT wearable devices, PS-GWO, and modified DBN	Cardiac diagnosis using IoT data and deep learning	Enhanced accuracy by optimizing activation function and number of hidden neurons; effective feature selection.	Complexity of hybrid optimization technique.
[18]	IoT-based architecture MDCNN and MCFA	HD evaluation using a smartwatch and heart monitoring device	High accuracy in diagnosing normal and dysfunctional cardiac functioning.	Implementation complexity due to multiple IoT devices and sensors.
[19]	CSO-CLSTM with iForest	Disease detection in smart healthcare systems	Enhanced diagnostic results and effective outlier removal.	Potential computational overhead due to complex optimization techniques.
[20]	Hybrid DL approach using CNN and RNN	Classification of CHF using ECG and time-frequency spectra analysis	Excellent performance in identifying CHF, and unbiased and precise classification.	Limited to CHF detection and requires significant computational resources.

[21]	Compilation of ML models including linear regression	Prediction of CVD using ML models	High accuracy of around 96% and considers data observation methods and training procedures.	Conventional ML algorithms lack robustness against data variations.
[22]	L1-regularised SVM and federated learning	Predicting HD using EHRs and IoT data	Improved computational complexity and scalability, and enhances prediction while protecting data privacy.	Complexity in implementing federated learning and handling high-dimensional data.
[23]	IoTDL-HDD model with bidirectional LSTM and AFO algorithm and fuzzy DNN	Identification of CVDs using ECG inputs and DL models	High accuracy of 93.452% and effective hyperparameter optimization.	Implementation complexity and requires high-quality ECG data.
[24]	Smart healthcare using IoT and DL models	Predicting heart failure patients' survival without manual feature engineering	Quick, effective, and high-quality treatment; accurate classification using CNN.	Dependency on cloud infrastructure and IoT devices.
[25]	Fuzzy Inference System (FIS) and Bidirectional LSTM.	Predicting the risk of HD using IoT and cloud technology	Effective monitoring and prediction, and improved performance.	Complexity in integrating IoT, cloud, and DL models.
[26]	IoT-based framework with MSABA	Predicting HD with real-time monitoring	Effective prediction and resource management.	Requires continuous monitoring and data collection.
[27]	LSTM neural network and DBN	Prediction of arterial events using ECG recordings and time-frequency characteristics	Good performance; prompt detection and mitigation of arterial events.	Requires precise ECG recordings and extensive data preprocessing.
[28]	Cloud computing model with LSTM-DNN	Remote monitoring and categorization of patients' status using IoT and cloud	Improved precision, accuracy, and recall; effective remote monitoring.	Dependency on cloud infrastructure and prioritization strategy.
[29]	DL and 5G technology with CNN-LSTM	Monitoring cardiovascular health using wearable medical equipment and a 5G network	Enhanced performance in predicting CVD and real-time data transmission.	Dependency on 5G infrastructure and wearable medical equipment.
[30]	IoT-based medical device with HOBDBNN	Continuous monitoring and diagnosis of HD using IoT	High precision and efficiency in detecting HD and reducing mortality rates.	Requires continuous data transmission and handling from IoT devices.

3. Proposed SNDAE-BBOA Modelling

This work introduces a new hybrid deep learning model for accurately classifying and predicting HD based on clinical data. This research implements the binary butterfly optimizer with the stacked NDAE approach for the purpose of clinical data classification. The data is obtained from the sensors positioned on the human body, as seen in Figure 2. The ECG data was taken at a rate of 100Hz. The data was transmitted to the model over Bluetooth and saved in .csv and binary format. IoT systems encompass both IoMT devices and intelligent devices. Their purpose is to collect medical data from distant locations. The data is gathered as patient information and acquired by IoT devices that are linked to the human body. This approach based on IoT was executed in three distinct steps. During the initial step, the IoT device gathers data pertaining to the individual's physiological state, information from the data gathering process, and the patient's medical history. During the second phase, the entirety of the acquired knowledge is analyzed and computed in the cloud. Data classification is the final step that concludes the process of HD classification. Afterwards, the approach proceeds to the testing step, where it employs the data set to train the classification model for heart diagnosis.

Therefore, the model that has been trained is prepared to analyze the input data of the patient in order to identify the presence of a disease.
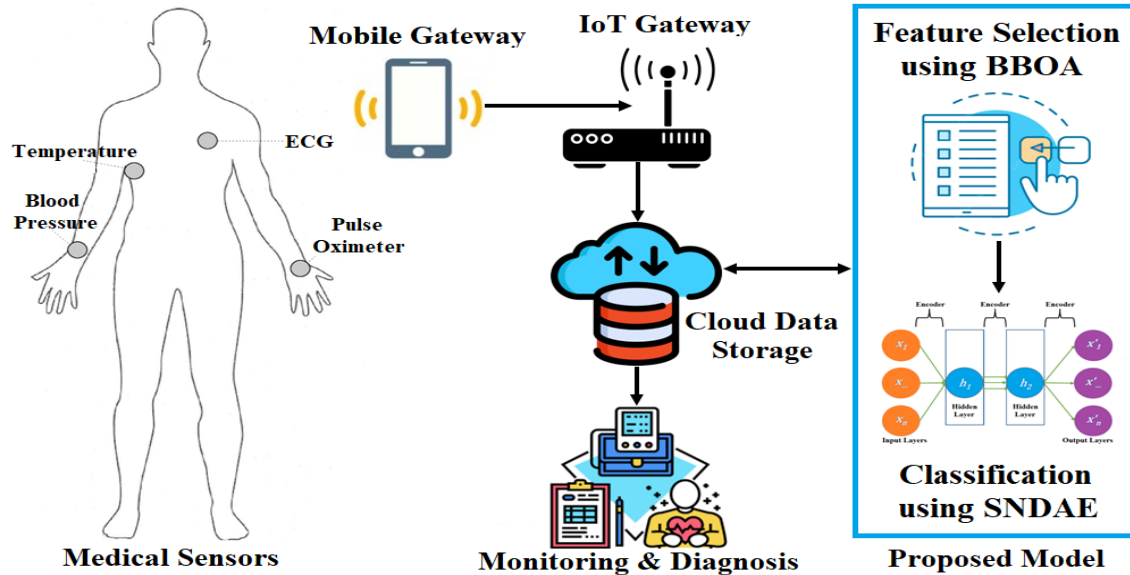

Figure 2. Architecture of the Proposed Model

For training the research model, medical datasets from the UCI repository are utilized as input. The data is then generally preprocessed, and the preprocessed data is then used to choose features using BBOA. The SNDAE classifier is used to categorize the data using the features selected. The predicted and validated classification findings are based on the classification of disease. The predicted outcome is based on a binary class classification, where the results will be either predicted as disease present or not.

3.1. Data Collection

The Cleveland dataset is publicly available via the UCI Repository to predict HD. This dataset is a mixed-attribute data collection containing HD data acquired from the Cleveland Clinic. This data collection contains 303 instances, each with 6 numeric and 8 category features. This database has 76 features and some important features of the dataset are represented in Table 2 [25]. Another dataset called Statlog is also used in this work. The Statlog dataset was obtained from the University of California, Irvine's machine learning repository. It is freely available on the internet for medical researchers to use. This HD dataset consists of 270 instances. These features are important in the identification of heart disorders. A fasting blood sugar test must show less than 120mg/dl for a patient with no disease and a test result of greater than 120mg/dl for a patient with HD. The patient with serum cholesterols of more than 180mg/dl was also known to have HD. The Statlog dataset is similar to the Cleveland dataset but in a slightly different form and a description of these, datasets is shown in Table 2 [25].

Table 2: Details of the Datasets

Features	Descriptions
Age	Age in year
Sex	0- Women and 1- Men
Cp	Types of Pain 1: typical angina 2: atypical angina 3: non-anginal pain 4: asymptomatic
Chol	Serum cholesterols in mg/dl

Trestbps	Resting blood sugar in mm Hg
Thalach	Max heart rate obtained
Restecg	Resting ECG results
Oldpeak	ST depression caused by exercises related to rest
Fbd	Fasting blood sugar > 120 mg/dl; (0 = false; 1 = true;)
Exang	Exercise caused angina
Ca	Total major vessels coloured by fluoroscopy
Slope	Peak or Slope exercises ST segments
Thal	Defect type
Num	The feature predicted

3.2. Data Preprocessing

Preprocessing involves a sequence of procedures performed on data to modify its original form. This is the initial phase of the diagnostic process. The processing comprises three steps: substitution of missing data, elimination of unnecessary elements, and division. The missing value of a particular characteristic is substituted after examining the complete age groups, level of cholesterol, and BP of the patient. If several patients feature values correspond, then the value was changed in the exact place. Elimination of unnecessary elements is to decrease the count of data by removing attributes that are duplicated or not useful. Subsequently, the patients were classified according to the particular kind of chest pains they experience: (1) normal angina, (2) abnormal angina, (3) non-anginal, and (4) asymptomatic [18]. Min-max normalization is a commonly employed method for normalizing data. Min-max normalization is a technique employed to convert data. Using the lowest and maximum values, this process converts the outcome of each quantitative characteristic into a specific goal value. Min-max normalization is a helpful tool in the process of data normalization. The data will be normalized to a range of 0 to 1. Data transformation is identified through the utilization of Equation (1).

$$Data_t = \frac{(X - X_{min})}{(X_{max} - X_{min})} \qquad (1)$$

Here, X represents a set of forecasted values that are indicated in the dataset. The lower and upper bounds of X are represented by X_{min} and X_{max} [26].

3.3. Binary BOA for Feature Selection

The BOA is a resilient metaheuristic that emulates the foraging behavior of butterflies in search of food. The inspiration and movement behavior of butterflies may be described as an optimization algorithm, where butterflies act as search agents and the smells, they generate represent the fitness values. Within the context of BOA, the butterflies or search agents possess the ability to produce a fragrance or fitness value that possesses a certain level of potency, allowing it to be differentiated from other perfumes. This behavior can assist other search agents in updating their location inside the search space. When a butterfly in the search space discovers the most optimal source of food, it emits a smell that attracts all nearby butterflies to its position. The process used for updating is referred to as global search in BOA. Alternatively, if the scent of other butterflies is detected, the butterflies will travel randomly inside the search area. This is referred to as local search in the context of BOA [31].

The intensity of fragrance is theoretically expressed by Equation (2):

$$pf_i = cI^a \qquad (2)$$

In this context, pf_i represents the fragrance strength of the ith butterfly, I represents the stimulus intensity, 'c' represents the sensor modality, and 'a' was the power exponent that varies depending on the modality and represents the level of absorption. The position of each butterfly was represented as a vector of numerical numbers. The expression in Equation (3) can be used to update the location to discover a more optimal one.

$$x_i^{t+1} = x_i^t + F_i^{t+1} \qquad (3)$$

Here, x_i^t represents the current location of a butterfly labeled 'i' in iterations 't', the subsequent location of butterfly 'i' was denoted by x_i^{t+1}, and F_i^{t+1} represents the smell used by x_i to update its location during iterations. As previously stated, the updating technique was divided into two phases: local and global searches. During the global search, the butterfly labeled 'i' glides towards the fittest butterfly denoted as g^*, which may be mathematically represented by Equation (4):

$$F_i^{t+1} = (r^2 \times g^* - x_i^t) \times pf_i \qquad (4)$$

Here, *r* was a randomly generated value between 0 and 1. Equation (5) was used to express the updating movement in local search.

$$F_i^{t+1} = (r^2 \times x_j^t - x_k^t) \times pf_i \qquad (5)$$

In this equation, x_j^t and x_k^t in the search space represent the coordinates of the jth and kth butterflies. In BOA, a new parameter called switch probability p was used to alternate the algorithm's behavior among global and local search. This allows for finding the optimal balance among exploitation and exploration.

BOA has strong performance in terms of convergence, exploitation, exploration, and avoiding local optima. The primary advantage of BOA lies in its effective utilization of random walk and elitism, resulting in a high convergence rate. However, BOA benefits from enhanced exploration due to smell attenuation, enabling it to efficiently seek the solution area. The promising features of BOA serve as a driving force for researchers to employ it in several additional applications, including wrapper-based feature selection. The binary versions of BOA are developed using two transfer functions: V-shaped and Sigmoid transfer functions. This research introduces a V-shaped transfer function, which is achieved by utilizing Equations (6) and (8).

$$V\left(F_i^k(t)\right) = \left|\mathrm{erf}\left(\frac{\sqrt{\pi}}{2}F_i^k(t)\right)\right| \qquad (6)$$

Equation (6) could be restated as Equation (7):

$$V\left(F_i^k(t)\right) = \left|\frac{\sqrt{\pi}}{2}\int_0^{(\sqrt{\pi}/2)F_i^k(t)} e^{-t^2} dt\right| \qquad (7)$$

The rules of threshold can be expressed numerically using Equation (8):

$$x_i^k(t+1) = \begin{cases} \left(x_i^k(t)\right)^{-1} & if\ \ rand < V\left(F_i^k(t)\right) \\ x_i^k(t) & if\ \ rand \geq V\left(F_i^k(t)\right) \end{cases} \qquad (8)$$

The variables $x_i^k(t)$ and $F_i^k(t)$ represent the location and smell, respectively, of the *i*th butterfly at step *t* in the *k*th dimension. The term $x_i^k(t)^{-1}$ refers to the counterpart of $x_i^k(t)$. The transfer function, Eq. (6), is employed in this binary technique to convert the scents of butterflies into probabilities that determine the changes in the elements of their position vectors. Thus, the position vectors of butterflies are updated using the principles specified in Eq. (8). The advantage of the transfer function V-shaped was it makes butterflies to have values other than 0 or 1. It stimulates butterflies to transition to their complements exclusively when their scent values are higher; else, the butterflies will remain in their present places, considering their minimal values of fragrance.

The selection of feature is a problem in binary optimization, where the search agents were limited to binary values of either 0 or 1. In this study, all the solutions are represented as 1D vector, with the size of the vectors determined by the total attributes/features in the data set. Each element of the vector could hold one of two values: 1 or 0. A value of 1 indicates that the relevant feature or attribute has been chosen, whereas a value of 0 indicates that the feature or attribute has not been chosen. The feature selection problem may be viewed as a multi-objective optimization issue, where the aim is to achieve two conflicting objectives: minimizing the number of selected features and maximizing the classification accuracy. The optimal solution in feature selection issues is one that has the fewest number of features while achieving the maximum classification accuracy. The fitness function (FF) evaluates each solution based on the KNN classifier's classification accuracy and the number of chosen features. The FF in Equation (9) is used in all the optimization techniques to assess the solutions, with the aim of achieving a balance between the number of characteristics and classification accuracy.

$$FF = \alpha\gamma_R(D) + \beta\frac{|R|}{|N|} \qquad (9)$$

Here, $\gamma_R(D)$ represents the error rate of KNN's classification. |R| denotes the size of the chosen subset of features, where |N| indicates the overall quantity of features in the data set. α and β were two parameters that reflect the significance of classification accuracy and subset length, respectively. α belongs to the range [0,1], while β is equal to (1-α).
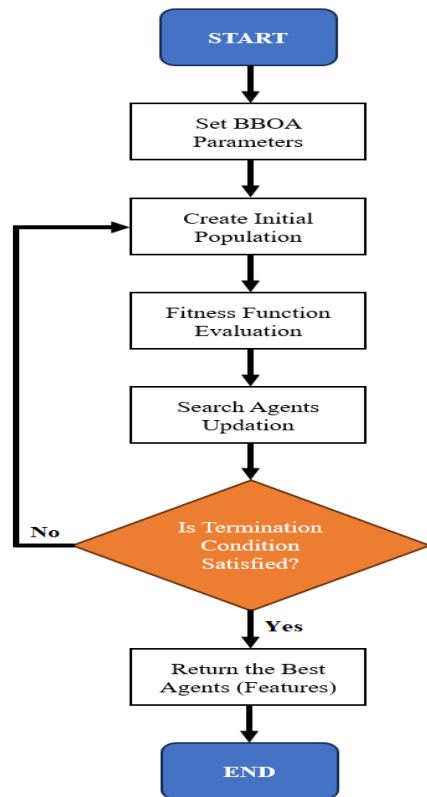
Figure 3. Flowchart of the BBOA

Seven optimal features are chosen and employed to predict the presence of HD, with the final feature serving as outcome or predicted feature for the presence of HD in an individual. The "num" element encompasses numbers ranging from 0 to 4, representing the diagnosis of HDs. The numerical value corresponds to the severity of the problem, with 4 indicating the most severe level [32]. Table 3 presents the selected features that were utilized for this research.

Table 3: Selected Features for the Experiment

Attributes	Description
cp	Types of Chest pain 1: typical angina 2: atypical angina 3: non-anginal pain 4: asymptomatic
trestbps	Resting blood sugar in mm Hg
restecg	Resting ECG result 1. Normal 2. Having abnormal ST-T wave (inversion of T wave and/or elevated ST or depressions of >0.05 mV). 3. Showing definite left ventricular hypertrophy by Estes' criteria or probable.
oldpeak	ST depressions caused by exercises related to rest
thalach	Max heart rate obtained
slope	Peak or Slope exercises ST segments

	1. Upsloping;
	2. Flat;
	3. Down-sloping
num	Diagnosis of the HD (Angiographic disease)
	0 represents the absence of HD; 1-4 represents the presence of HD.

3.4. SNDAE for Disease Prediction

DL is an advanced form of ML that brings ML closer to AI. It simplifies the depiction of intricate relationships and concepts by employing many layers of modeling. Supervised and unsupervised learning algorithms are employed to systematically build increasingly complex conceptual representations, which are specified based on the output characteristics obtained from lower-level stages. The proposed SNDAE model utilizes auto-encoders, which are a common approach in current DL research. An auto-encoder is an algorithm based on unsupervised neural networks that aims to learn the optimal parameters needed for reconstructing its output as accurately as possible to its input. An advantageous feature of this method is its capacity to offer a more potent and nonlinear generalization compared to Principal Component Analysis (PCA).
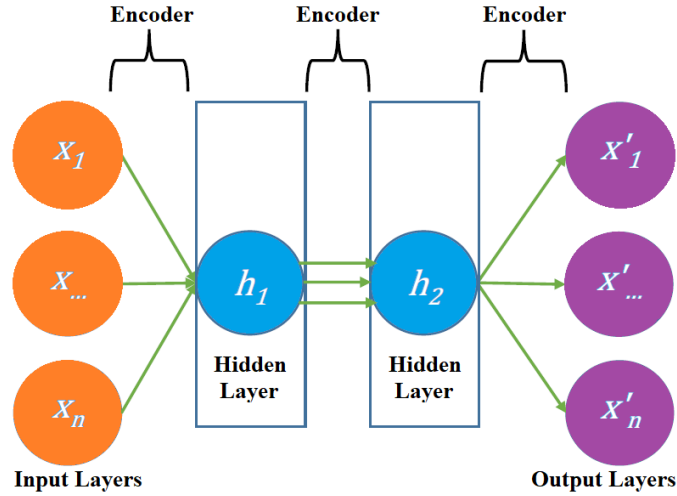

Figure 4. Architecture of NDAE

This work employed a non-symmetrical multiple hidden layer autoencoder called NDAE. Essentially, this entails transitioning from the symmetric encoder-decoder model to just employing the encoder phase in a non-symmetric manner. The reason for this is that by implementing an appropriate learning framework, it is feasible to minimize both computational and time complexities, while providing a high level of efficiency and accuracy. NDAE serves as a hierarchical unsupervised feature extractor that efficiently handles high-dimensional inputs. The model acquires complex characteristics by employing a training approach similar to that of a conventional auto-encoder. Figure 4 illustrates the architecture of the NDAE [33].

The NDAE receives an input vector $x \in R^d$ and gradually transforms it into the hidden representations $h_i \in R^{d_i}$. The size of the vector is denoted by d and is determined using the function described in equation (10) as follows:

$$h_i = \sigma(W_i.h_{i-1} + b_i); i = \overline{1,n} \qquad (10)$$

In this context, $h_0 = x$, an activation function σ (specifically, the sigmoid functionality $\sigma(t) = (1/(1 + e^{-t}))$), and n denotes the total hidden layers. In contrast to a traditional AE and DAE, the NDAE does not include a decoder layer. Instead, its output vector was calculated utilizing an equation similar to equation (11) as the hidden representation.

$$y = \sigma(W_{n+1}.h_n + b_{n+1}) \qquad (11)$$

The estimator of model $\theta = (W_i, b_i)$ could be acquired by reducing the square reconstruction error over m samples used for training $\left(x^{(i)}, y^{(i)}\right)_{i=1}^m$, as seen in equation (12).

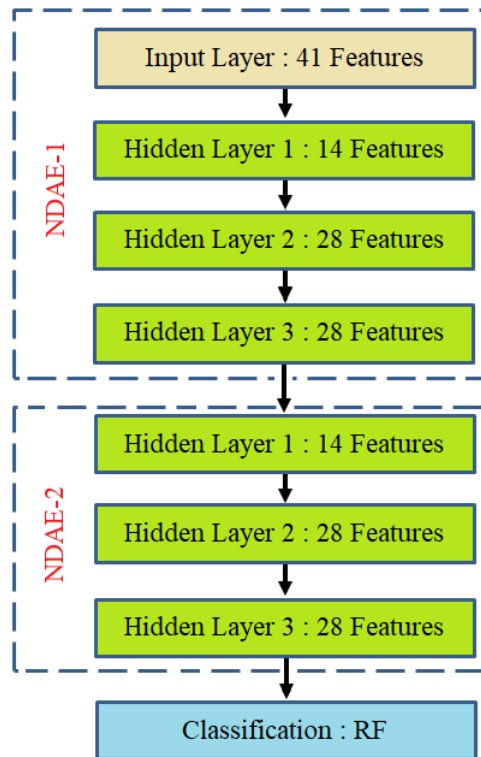$$E(\theta) = \sum_{i=1}^m \left(x^{(i)} - y^{(i)}\right)^2 \qquad (12)$$

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Figure 5. SNDAE Model Architecture

The SNDAE model utilizes the NDAE approach for DL. This is accomplished by arranging the NDAEs in a stacked manner to form a deep learning hierarchy. The process of stacking the NDAEs provides a technique for learning representations in a layer-by-layer manner without supervision. This enables the model to acquire knowledge about the intricate connections among various characteristics. Additionally, it possesses the ability to extract features, allowing it to enhance the model by giving priority to the most informative characteristics. Nevertheless, when it comes to classification, stacked AE with a standard soft-max layer have a slightly lower ability comparing with other discriminative models such as random forest (RF), KNN, and SVM. Therefore, this research integrated the deep learning capabilities of SNDAEs with a shallow learning classifier. The RF algorithm is employed as a classifier for shallow learning. The RF classifier in this model is trained utilizing the encoded representations acquired by the SNDAEs. These representations are then used to classify HD data as either normal or abnormal. According to Figure 5, the model utilizes a stack of two NDAEs and is integrated with the RF method. The NDAE consists of three hidden layers, each containing the exact quantity of neurons as the number of features. The precise parameters were established using cross-validation of the neuron counts and hidden layer configurations, resulting in the identification of the most optimal combination. This enables the assessment of performance without the potential problem of overfitting [34].

Initialization
Generate a population of n butterflies $x_i = (i = 1,2,...,n)$
Initialize parameters for SNDAE
when stopping criterion not met do
  for each butterfly in the population do
    Compute the fragrance for butterfly with Equation (2)
  end for
  Find the best butterfly
  for each butterfly in the population do
    Generate a random integer rand from [0, 1]
    if rand < p then
      Move towards the best butterfly with Equations (3) and (4)
    else
      Move randomly with Equations (3) and (5)
    end if
    Calculate the value of the transfer function using Eq. (6) or (8)
    Evaluate the new butterfly
    If the new butterfly is better, update it in the population

end for
Update the value of c
Find the current global best butterfly
if a significant improvement in the global best butterfly is observed then
    Train NDAE with the current selected features
    Fine-tune NDAE using backpropagation and update weights
  end if
end while
Use the final NDAE model to classify the data
Output the best solution found and the classification results

4. Results and discussion

4.1. Experimental Setup

This section presents the results of the experiments carried out utilizing the BBOA-SNDAE research model. The model was developed using Keras and Python 3.7.9, with TensorFlow being used as the backend engine. The computer environment consisted of a Core i7-620M central processor unit, 16 gigabytes of RAM, and a 64-bit version of the Windows 10 operating system. For the evaluation of the proposed model, Cleveland and Statlog datasets from the UCI database and obtained sensor data were utilized in the work.

4.2. Performance Metrics

The proposed model's performance is assessed using performance measures such as accuracy, sensitivity, specificity, precision, or PPV, NPV, and f-measure. True positives (TPs), false positives (FPs), true negatives (TNs), and false negatives (FNs) measures are used to calculate these metrics.

Generally, accuracy is defined by how the data was collected. Accuracy is computed by comparing several measures from similar or variable sources.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \qquad (13)$$

Precision was the likelihood that a subject with a positive screening test has the HD. As indicated in the equation, the precision could be calculated.

$$Precision = \frac{TP}{TP+FP} \qquad (14)$$

The negative predictive values (NPV) reflect the likelihood of discovering the subject who is not at risk for HD and was calculated by the following equation.

$$NPV = \frac{TN}{TN+FN} \qquad (15)$$

Sensitivity or recall shows the capacity to identify a patient at risk for HD and was assessed as expressed in the equation.

$$Sensitivity = \frac{TP}{TP+FN} \qquad (16)$$

Specificity was calculated by dividing the total true negatives by the total count of negatives, as illustrated. The best specificity was determined as 1.0, while the poorest was denoted as 0.0.

$$Specificity = \frac{TN}{TN+FP} \qquad (17)$$

The F-measure evaluates test accuracy and is described as the test recall and precision's weighted harmonic mean. The accuracy does not consider how the data was distributed. The f-measure was hence used to precisely handle the distribution issue [17].

$$Fmeasure = \frac{2 \times Precision \times Recall}{Precision+Recall} \qquad (18)$$

4.3. Performance Analysis

This section presents a detailed analysis of the performance evaluated using the research model BBOA-SNDAE and the comparison of its results with current models derived from the related works. Table 4 presents the results of the research model assessed utilizing both sensor data and the dataset data. The results were evaluated individually on both the data as shown in the table. According to the attained results, the results based on the dataset data have a higher performance rate compared to the results from the sensor data. This indicates that the sensor data must be further processed and optimized to attain a higher result.

Table 4: Performance Results of the BBOA-SNDAE Model

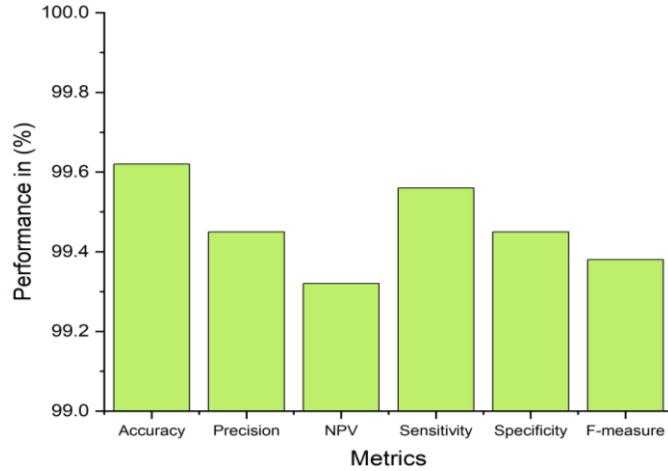| Metrics	Dataset Data	Sensor Data
Accuracy	99.62	98.84
Precision	99.45	98.73
NPV	99.32	98.34
Sensitivity	99.56	98.62
Specificity	99.45	98.21
F-measure	99.38	98.27

Figure 6. Results of the BBOA-SNDAE Model using Dataset Data

As shown in the table, the model has an accuracy rate of 99.62% for external data and 98.84% for sensor data. There is a 0.78% difference between the accuracy values. The precision of the model is 99.45% for external data and 98.73% for sensor data, in which the result obtained using the external dataset is 0.72% higher than the result of sensor data. The NPV of the research model is 99.32% for the external dataset and 98.34% for the sensor data, in which the result attained using the external dataset is 0.98% higher than the result of the sensor data. The sensitivity of the research model is 99.56% for the external dataset and 98.62% for the sensor data, where the result achieved using the external dataset is 0.94% higher than the result of the sensor data. The specificity of the research model is 99.45% for the dataset and 98.21% for the sensor data, where the result obtained using the dataset is 1.24% higher than the sensor data's result. The f-measure of the research model is 99.38% for the dataset and 98.27% for the sensor data, in which the result attained using the dataset is 1.11% higher than the result of the sensor data. Figures 6 and 7 represent the graphical plot of the results obtained using the dataset and sensor data separately.
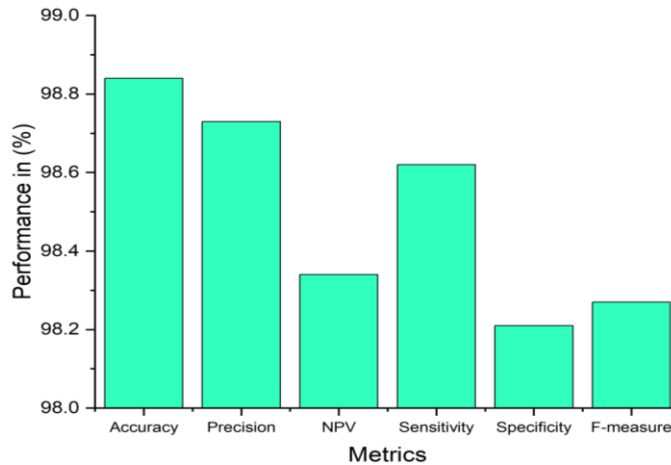

Figure 7. Results of the BBOA-SNDAE Model using Sensor Data

Table 5 presents the comparison of the research model BBOA-SNDAE's results with the current models based on all the metrics used for the performance evaluation. For this comparison, the results achieved using the external dataset are used. As shown in the table, the proposed BBOA-SNDAE model has outperformed all the current models in every metric with improved performance. The accuracy of the research model is 99.62%, which is 0.33% to 15.79% higher than the other models. The CNN-LSTM model has the second-best performance with 99.29% and the least performed model was PS-GWO-DBN with 83.83%. The precision of the research model is 99.45%, which is 0.55% to 7.45% improved than the compared models. The FIS-BiLSTM model has the second-best performance with 98.90% precision and the least performed model was MSABA with 92%. The NPV of the research model is 99.32%, which is 0.02% to 2.45% enhanced than the compared models. Most of the compared models did not evaluate this metric; however, the MDCNN model has a close performance of 99.30% NPV. The sensitivity of the research model is 99.56%, which is 0.03% to 37.49% higher than the compared models. The CNN-LSTM model has a close performance rate of 99.53% and the least performed model was IoTDL-HDD with 62.07%. The specificity of the research model is 99.45%, which is 0.37% to 13.97% improved than the compared models. The CNN-RNN model has the second-best result with 99.08% and the least performed model was LSTM-DBN with 85.48%. The f-measure of the research model is 99.38%, which is 0.52% to 19.72% higher than the compared models. The FIS-BiLSTM model has the second-best result with 98.86% and the least performed model was PS-GWO-DBN with 79.66%. Figures 8 to 12 represent the graphical plot of the results compared individually.

Table 5: Comparison of Results

| Models	Accuracy	Precision	NPV	Sensitivity	Specificity	F-measure
PS-GWO-DBN [17]	83.83	94.94	96.87	68.61	96.87	79.66
χ^2-DNN [16]	93.33	NA	NA	85.36	NA	NA
MDCNN [18]	98.20	95.10	99.30	97.80	92.60	95.00
CSO-CLSTM [19]	97.26	NA	NA	98.62	96.94	NA
CNN-RNN [20]	98.50	NA	NA	97.96	99.08	NA
IoTDL-HDD [23]	93.84	94.13	NA	62.07	NA	88.65
CNN [24]	92.89	94.00	NA	94.00	NA	94.00
FIS-BiLSTM [25]	98.86	98.90	NA	98.81	98.90	98.86
MSABA [26]	90.00	92.00	NA	91.00	NA	95.00
LSTM-DBN [27]	88.74	95.50	NA	82.52	85.48	91.09
LSTM-DNN [28]	97.13	98.44	NA	98.21	NA	NA
CNN-LSTM [29]	99.29	NA	NA	99.53	97.77	NA
Proposed BBOA-SNDAE	99.62	99.45	99.32	99.56	99.45	99.38
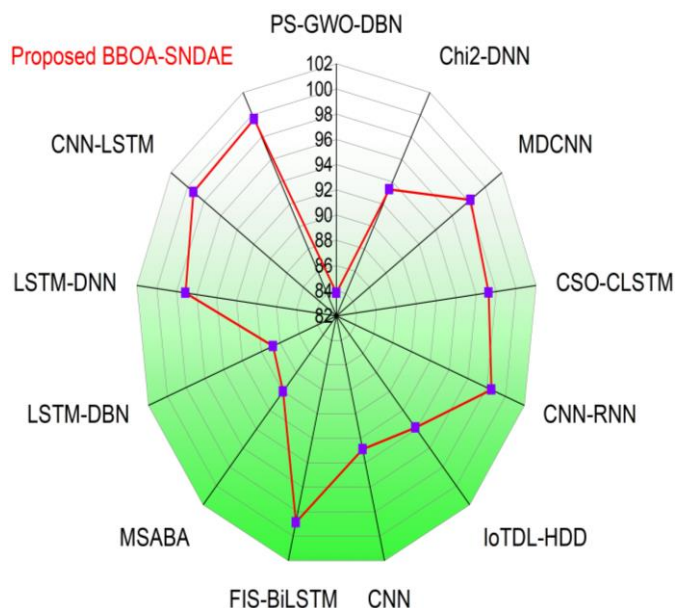
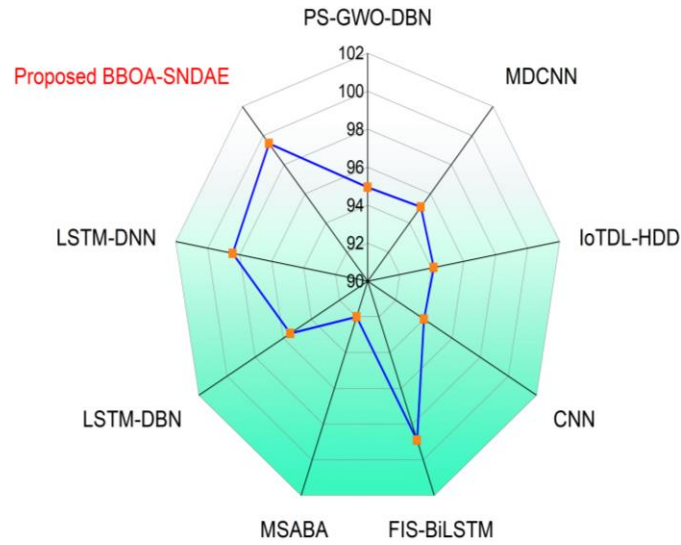**Figure 8.** Accuracy Results Comparison

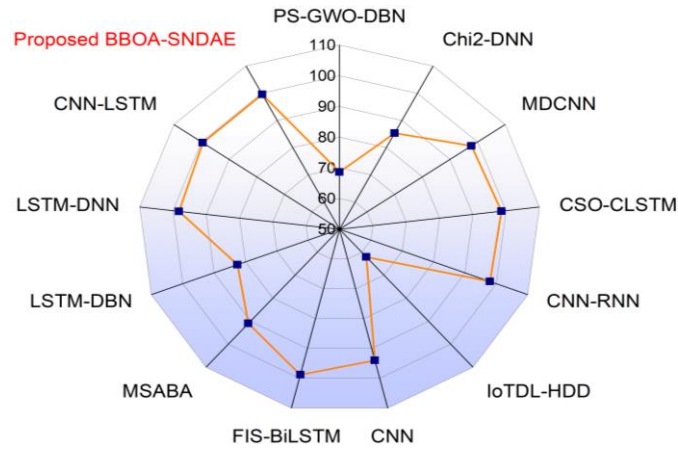**Figure 9.** Precision Results Comparison

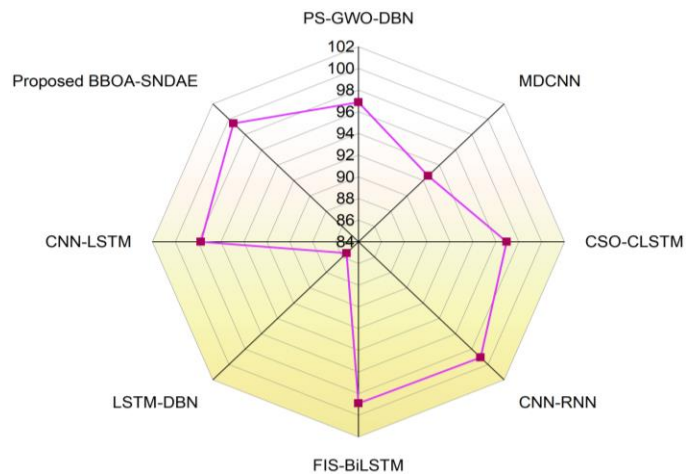**Figure 10.** Sensitivity Results Comparison

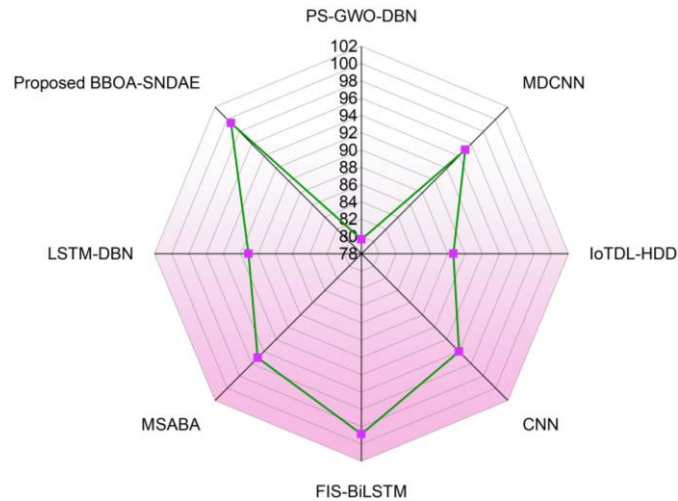**Figure 11.** Specificity Results Comparison

Figure 12. F-measure Results Comparison

Based on the comparison, it is evident that the proposed research model BBOA-SNDAE model has outperformed all the other current models in each metric with superior performance in this research. This indicates that the research model is highly efficient in predicting HD based on the clinical data. The BBOA-SNDAE model has many advantages as it achieved efficient results in correctly predicting HD. The integration of BBOA with SNDAE enables the model for optimized feature selection and effective classification. This integration improves the model's ability to manage high-dimensional and complex data, which enhances the prediction and minimizes the false positives and negatives. However, the model has a few limitations to consider, as the interpretability of the research model remains a challenge and the model's performance is highly reliable on the quantity and diversity of the training data. The training process can be time-consuming, specifically with large datasets.

5. Conclusion

This research proposed a novel hybrid DL model called BBOA-SNDAE for the prediction and classification of HD based on medical IoT technology. The BBOA was integrated with the SNDAE for the classification of clinical data. The data were collected using the sensors and sampled at 100Hz. Data were transferred and stored in cloud storage. In this work, the IoT device collects data from the human body and patient's records. The data were transmitted and stored in the cloud for further access and diagnosis. The data stored in the cloud was given as the input to the research model in a .csv format and preprocessed initially. The research model was trained before testing the real-time data utilizing the Statlog and Cleveland datasets. In the training process, the data was preprocessed and normalized using the Min-Max normalization. The BBOA technique was employed to perform the feature selection to choose the best optimal features for classification. Based on the selected optimal features, the SNDAE technique was used for the classification. The predicted outcome is based on a binary class classification, where the results will be either predicted as disease present or not. The research model was assessed based on accuracy, specificity, precision, sensitivity, NPV, and F-measure. The model attained 99.62% accuracy, 99.45% precision, 99.32% NPV, 99.56% sensitivity, 99.45% specificity, and 99.38% f-measure using the HD dataset, and the model attained 98.84% accuracy, 98.73% precision, 98.34% NPV, 98.62% sensitivity, 98.21% specificity, and 98.27% f-measure using the sensor data. The results of the research model were compared with the current model for validation, where the research model outperformed all the compared models. In future, the research will focus on improving the BBOA-SNDAE model's real-time applicability by optimizing its computational efficiency and reducing training time. Additionally, the model can be trained and tested with other disease datasets for predicting various diseases. The integration of additional IoT devices and sensors can be added to the system for prediction that is more accurate and remote monitoring.

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