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Edge-Based Health Care Monitoring System: Ensemble of Classifier Based Model

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Abstract— Health Monitoring System (HMS) is an excellent tool that actually saves lives. It makes use of transmitters to gather information and transmits it wirelessly to a receiver. Essentially, it is much more practical than the large equipment that the majority of hospitals now employ and continuously checks a patient's health data 24/7. The primary goal of this research is to develop a three-layered Ensemble of Classifier model on Edge based Healthcare Monitoring System (ECEHMS) and Gauss Iterated Pelican Optimization Algorithm (GIPOA) including data collection layer, data analytics layer, and presentation layer. As per our ECEHMS-GIPOA, the healthcare dataset is collected from the UCI repository. The data analytics layer performs preprocessing, feature extraction, dimensionality reduction and classification. Data normalization will be done in preprocessing step. Statistical features (Min/Max, SD, Mean, Median), improved higher order statistical features (Skewness, Kurtosis, Entropy), and Technical indicator based features were extracted during Feature Extraction step. Improved Fuzzy C-means clustering (FCM) will be used for handling the Dimensionality reduction issue by clustering the appropriate feature set from the extracted features. Ensemble model is introduced to predict the disease stage that including the models like Deep Maxout Network (DMN), Improved Deep Belief Network (IDBN), and Recurrent Neural Network (RNN). Also, the enhancement in prediction/classification accuracy is assured via optimal training. For which, a GIPOA is introduced. Finally, ECEHMS-GIPOA performance is compared with other conventional approaches like ASO, BWO, SLO, SSO, FPA, and POA.

Keywords- Edge Computing, Deep Maxout Network, Improved Deep Belief Network, Recurrent Neural Network

I. INTRODUCTION

Edge computing is a powerful processing model that allows computing and storage resources near IoT devices as well as sensors at the edge. Edge computing can manage security and privacy issues, reduce latency and delay, boost scalability, and reduce bandwidth utilization [1]. Various wireless technologies, including Long range (LoRa), Bluetooth Low Energy (BLE), ZigBee, etc., are used by edge computing to connect to edge devices. Edge-based system model can interface with overall edge devices and make a variety of Internet of Things (IoT) services possible even in cases where there is an intermittent Internet access. The expansion of Edge [2] [3] necessitates the lot of healthcare organizations to provide the societal medicating population with top-notch security services. Edge provides a variety of tools to monitor a patient's healthcare information [4], making this the most popular approach for health monitoring. Additionally, it is beneficial for both first aid medicine as well as the elderly. Recently, many health-related concerns have been reported from far-off places [5] [6]. For the development of intelligent healthcare systems, Deep Learning (DL), a specialized kind of data mining, is accomplished utilizing Machine Learning (ML) [7] [8].

To learn or develop the system's intelligence to properly forecast variations in the system, ML-based approaches must classify the data and the feature values are entered into the classifier [9] [10], which return a class. In ML [11], techniques were selected based on reliable outcomes where, testing as well as training of data is the primary issue. Frequently, it becomes practically hard to remove errors due to the size of the data. These errors might give users frustration and require a significant amount of time to fix because the data is so large [12]. The system will require time if the data is complex and huge, this might result in a higher CPU power requirement. Machine learning models are the commonly used methods to handle data more effectively. However, the system will be complex because of the error that occurs during the training phase. So to reduce the complexity of the system, the DL technique is more focused by the researchers. In Deep learning, some classification techniques are considered like DMN, RNN and DBN. Moreover, by using the Deep maxout technique the sparse features are extracted and the Recurrent Neural Network reduces the complexity of parameters and improves the accuracy of predicted values. Further the deep belief network can handle various types of data and their fitness. This paper intends to propose a new ECEHMS-GIPOA model, and its major contributions are as follows:

- **Handling the 'curse of dimensions'**: By adopting an Improved FCM clustering to reduce the dimensions via clustering the appropriate features from the extracted feature set.
- **Proposing an ensemble model:** It comprises the DMN, RNN, and Improved DBN for disease classification, which is the main source of making decisions related to that.
- **A new training model - GIPOA**: The DMN, RNN and Improved DBN weight are optimally tuned.

The paper is organized into 7 sections. Section 1 describes the introduction. Section 2 discusses the review on existing classifier models for health monitoring. Section 3 describes the architecture of ECEHMS. Section 4 describes the GIPOA optimization concept. Section 5 offers data sets for decision making system. Section 6 provides the result and discussion. Section 7 concludes the prosed model.

NOMENCLATURE

Abbreviation	**Description**
IoT	Internet of Things
LoRa	Long range
BLE	Bluetooth low energy
kNN	k-Nearest Neighbors
NB	Naïve Bayes
SVC	Support Vector Classification
WSN	Wireless Sensor Network
NDN	Named Data Networking
EC	Edge Cloud
SHS	Smart Healthcare System
PPSE	Privacy-Preserving Searchable Encryption
MCST-CNN	Multi Channel Spatio-Temporal Convolutional Neural Network
SHIN	Secure Healthcare data communication framework integrating NDN-based IoT with Edge cloud
CH	Cluster Head
ML	Machine Learning
DL	Deep Learning
UI	User Interface
ADOSC	Accumulation/Distribution Oscillator
STOCHOSC	Stochastic Oscillator
RSI	Relative Strength Index
PROC	Price Rate of Change
TSMOM	Time-Series Momentum
FCM	Fuzzy C Means
RBM	Restricted Boltzmann Machines
HMS	Healthcare Monitoring System
WSD	Wearable Sensor Devices
MR	Medical Records
DMN	Deep Maxout Network
NN	Neural Network
AI	Artificial Intelligence

II. LITERATURE REVIEW

Researchers have introduced the concept of edge computing in several articles in the context of the present health monitoring system. Samira Akhbarifar et al [13] created a healthcare monitoring system for the IoT environment that enables early disease diagnosis. This model uses data mining methods to examine biological data gathered by IoT-enabled smart medical devices in order to forecast important events and evaluate patients' health conditions. The safeguarding of critical patient data is provided via a simple secure block encryption method. The suggested paradigm is effective in delivering a safe IoT data foundation for cloud-based IoT platforms which offers a reliable model for remote diagnosis. Proposed K-star classification method achieves the best results among RF, MLP, SVM, and J48 classifiers. Priyan Malarvizhi Kumar et al [14] developed a novel deep learning algorithm called MCST-CNN incorporated with the proposed healthcare monitoring system for predicting the disease level efficiently. The experiments have been conducted for evaluating the performance of health monitoring system according to the particular diseases such as heart and diabetic diseases. The author considered the UCI medical dataset and the data collected from patients remotely through IoT devices. The proposed system is evaluated based on sensitivity, specificity, F-measure and prediction accuracy. Proposed healthcare system in terms of prediction accuracy as 99.45% and security level is 99.72% than other healthcare systems.

Ankush Manocha et al [15] proposed e-healthcare framework utilizing the advantages of IoT and fog technology to conclude the abnormalities related to health, behavioral, physical posture, and environmental conditions of the individual. The weighted K-mean Clustering technique-Artifcial Neural Network assisted (WKMC-ANN) hybrid methodology is

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proposed on the cloud layer for the early prediction of health severity. The experimental results achieved 94.51% of accuracy, 93.75% of sensitivity, 91.32% of specificity, 91.58% of precision, and 92.78% of f-measure compared to existing methods. IoT based smart edge system for remote health monitoring with two novel software engines, namely RASPRO and CMI alerts, both of which takes data from sensors were proposed by Rahul Krishnan Pathinarupothi et al [16] and carried out both clinical validation and performance evaluation of smart edge system. The clinical validation on 183 patients demonstrated that the IoT smart edge is highly effective in remote monitoring, advance warning and detection of cardiac conditions, as quantified by three measures, precision (0.87), recall (0.83), and F1-score (0.85). Furthermore, performance evaluation showed significant reductions in the bandwidth (98%) and energy (90%), thereby making it suitable for emerging narrow-band IoT networks.

Coronary Heart Disease (CHD) risk prediction method proposed based on two DNN models and applied it to the KNHANES dataset by Tsatsral Amarbayasgalan et al [17]. The proposed method addressed preparing an efficient training dataset by distinguishing and enriching the highly biased subset that degrades the model performance using the Principal Component Analysis (PCA) and Variational Autoencoders (VAE) models. The first one proved how PCA and VAE models of the proposed method improves the performance of a single deep neural network. The second experiment compared the proposed method with existing machine learning algorithms, including Naïve Bayes, Random Forest, K-Nearest Neighbor, Decision Tree, Support Vector Machine, and Adaptive Boosting. The experimental results show that the proposed method outperformed conventional machine learning algorithms by giving the accuracy of 0.892, specificity of 0.840, precision of 0.911, recall of 0.920, f-measure of 0.915, and AUC of 0.882. An intelligent classification and prediction model uses modified DBN as classification algorithm to predict the kidney related diseases Shahinda et el [18]. The evaluation of the proposed model shows that the model can predict the Chronic Kidney Disease (CKD) with accuracy 98.5% and sensitivity 87.5 % comparing with existing models for the dataset from UCI's machine learning.

Seven state-of-the-art deep learning algorithms were implemented for the prediction and classification of CKD by Shamima Akter et al [19]. The proposed algorithms were applied based on artificial intelligence by extracting and evaluating features using five different approaches from pre-processed and fitted CKD datasets. While classifying CKD, algorithms such as ANN, Simple RNN, and MLP provided high accuracy of 99%, 96%, 97% respectively, and a good prediction ratio along with reduced time. Huitao Qi et al [20] developed PCA-ANN and DBN-ELM-BP prediction models. The training set of PCA-ANN provides 35.29% sensitivity, 98.36% specificity, 97.01% accuracy, and AUC 0.7245, the testing set of PCA-ANN provides 37.50% sensitivity, 98.33% specificity, 97.85% accuracy, and AUC 0.7221; while the training set of DBN-ELM-BP gives 58.83% sensitivity, 98.31% specificity, 98.03% accuracy, and AUC measuring 0.7747 respectively, the testing set of DBN-ELM-BP gives 62.50% sensitivity, 98.52% specificity, 98.24% accuracy, and AUC measuring 0.7238 respectively.

A system architecture with integrated artificial intelligence that combines Edge/Fog computing, LPWAN technology, IoT and deep learning algorithms to perform health monitoring tasks. J. Pena Queralta et al [21] implemented a fall detection system from the sensor node and Edge gateway to cloud services and end-user applications. The system uses inertial data as input and achieves an average precision of over 90% and an average recall over 95% in fall detection. Adaptive hybridized Deep Convolutional Neural Network (AHDCNN) has been proposed for the early detection of Kidney disease efficiently and effectively Guozhen Chen et al [22]. The experimental process on the Internet of medical things platform (IoMT) concludes, with the aid of predictive analytics that advances in machine learning which provides a promising framework for the recognition of intelligent solutions to prove their predictive capability beyond the field of kidney disease.

Ihnaini, Baha, et al [23] proposed SHRS-M3DP model to predict and recommend multidisciplinary diabetes disease in the patients quickly and efficiently. The proposed model efficiently predicted and recommended whether the patient is a victim of multidisciplinary diabetes disease or not and also identify the effect of human body parts: Neuropathy, Retinopathy, Nephropathy, or Heart. Finally, the study of this research concluded that the SHRS-M3DP model's overall performance is 99.6%, which is outstanding compared to previously published approaches using Python language. Deep Belief Network (DBN) was used to represent and select more efficient and effective features of the recorded dataset called LSTM-DBN by Sina Dami et al [24]. The prediction results of the proposed LSTM-DBN were compared with other deep learning approaches (simple RNN, GRU, CNN and Ensemble), and traditional classification approaches (MLP, SVM, Logistic Regression and Random Forest). In addition, DBN performance was compared with other methods of feature selection and representation such as PCA and Auto-Encoder. Experimental results showed that the proposed LSTM-DBN (88.42% mean accuracy) had significantly better performance in comparison with all other deep learning approaches and traditional classifications.

To improve the accuracy of the traditional methods, cluster-based bi-directional long-short term memory (C-BiLSTM) has been proposed by Dileep, P et al [25]. The UCI and real time heart disease dataset are used for experimental results, and both the datasets are used as inputs through the K-Means clustering algorithm for the removal of duplicate data, and then, the heart disease has been predicted using C-BiLSTM approach. The conventional classifier methods such as Regression Tree, SVM, Logistic Regression, KNN, Gated Recurrent Unit and Ensemble are compared with C-BiLSTM, and the efficiency of the system is demonstrated in terms of accuracy, sensitivity and F1 score. The results show that the C-BiLSTM proves to be the best with 94.78% accuracy of UCI dataset and 92.84% of real time dataset compared to the six conventional methods for providing better prediction of heart disease. Shimpy Goyal et al [26] has presented a lung diseases detection in the period of covid-19 from the chest X-ray images. The lung specific features were enhanced with the minimum computational. Also improve the classification performance the F-RNN-LSTM models was consider and it provide the superior accuracy, recall, precision, F1-score and specificity with less computational. The final outcomes were verified by the soft computing as well as the machine learning techniques. Also the suggested approach can be improved further in terms of adaptive model generation and severity analysis for more datasets with multiple classes (more than 5) and deep models.

Kahyun Lim et al [27] has developed an optimized Deep Belief Network and GA, to evaluate the prediction of Coronary Heart Disease. The optimized –DBN was able to predict the coronary disease in advance and it was supported to the medical staff. If there was adequate patient medical data to train and validate the prediction model, it can also be applied to any other diseases. And using a genetic algorithm, we were able to get around DBN's constraints and it was subjected to derive the optimal value of the number of layers and nodes. Once the process of genetic algorithm was finished, the layer and node values with the lowest error rate were chosen as the optimal value. Further despite its superiority, the accuracy of the prognosis not ideal so in advance more prognosis and classification were needed. Cen Wan et al [28] has presented a protein function prediction method STRING2GO which effectively training the downstream classifiers for prediction purpose. It gives the better performance in the operation of protein function. The Deep Maxout Neural Networks (DMNNs) were employed for learning the functional representations at the same time protein-protein iteration and predictive information was encoded. Also in prediction biological process it exhibit highest accuracy. Further in advance, uses the other data sources for enhancing the accuracy.

III. PROPOSED SYSTEM MODEL OF ECEHMS

The ensemble of Classifier model on Edge based Healthcare Monitoring System (ECEHMS) model is an essential tool that employs edge-IoT to deliver the patient data. As per this work the UCI repository dataset were used. Based on the validation of patient’s stage, assistance can be given by the doctors or practitioners to deal with it. The model includes the given three aspects:

- **Patient:** Collect the healthcare dataset from the UCI repository.
- **Monitoring system:** The modeled monitoring system includes the processes like preprocessing, feature extraction, dimensionality reduction, and classification. These steps are followed to classify the diseases (based on the collected patient data). For this, the ensemble model is introduced.
- **Decision Making (Doctors):** Finally, based on the prediction/classification result of the enhanced ensemble model, the doctor evaluates the patient's condition and make suggestions accordingly. Fig.1 shows system model of ECEHMS-GIPOA.

The following are the three layers of the model.

- Data collection layer
- Data analytics layer
- Presentation layer

A. *Data Collection layer*

Patient data collection is the major work in this layer. Here the healthcare dataset from the UPI repository (Heart disease, Lung cancer, and Respiratory disease) were collected.

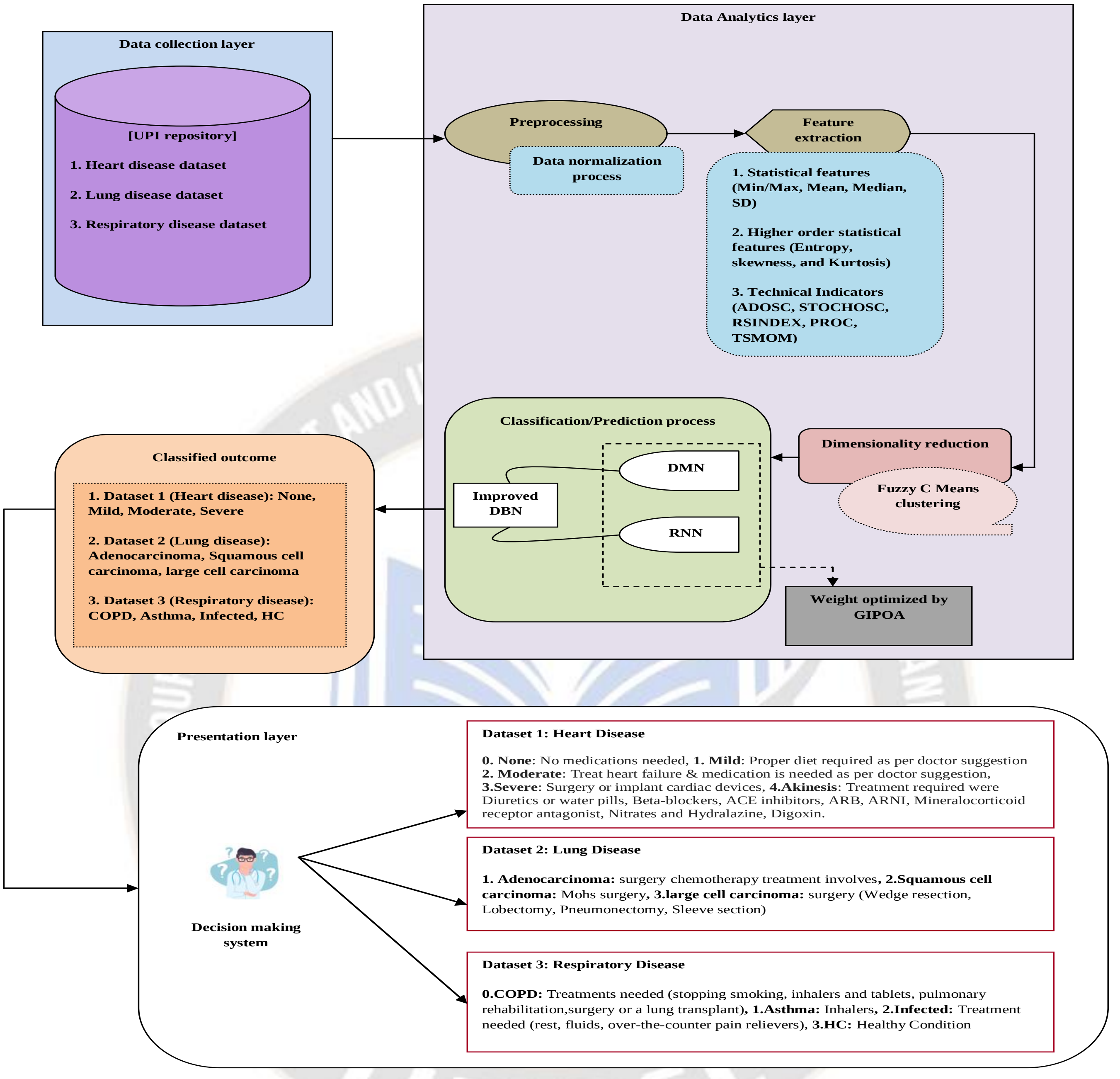

Figure 1. Proposed Architecture of ECEHMS-GIPO

Heart disease dataset description: This directory contains 4 databases concerning heart disease diagnosis. All attributes are numeric-valued. The data was collected from the four following locations:

- Cleveland Clinic Foundation (cleveland.data)
- Hungarian Institute of Cardiology, Budapest (hungarian.data)
- V.A. Medical Center, Long Beach, CA (long-beach-va.data)
- University Hospital, Zurich, Switzerland (switzerland.data)

Each database has the same instance format. While the databases have 76 raw attributes, only 14 of them are actually used. **Lung cancer dataset description:** Number of Instances: 32, Number of Attributes: 57 (1 class attribute, 56 predictive), Attribute Information: attribute 1 is the class label. All predictive attributes are nominal, taking on integer values 0-3, Missing Attribute Values: Attributes 5 and 39 (*), Class Distribution: 3 classes: 9 observations, 13 observations, 10 observations.

Respiratory diseases dataset description: The Exasens dataset includes demographic information on 4 groups of saliva samples (COPD-Asthma-Infected-HC) collected in the frame of a joint research project, Exasens ([Web Link]), at the Research Center Borstel, Biomaterial Bank Nord (Borstel, Germany).

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The sampling procedure of the patient materials was approved by the local ethics committee of the University of Luebeck under the approval number AZ-16-167 and a written informed consent was obtained from all subjects. A permittivity biosensor, developed at IHP Microelectronics (Frankfurt Oder, Germany), was used for the dielectric characterization of the saliva samples for classification purposes

Definition of 4 sample groups included within the Exasens dataset:

- Outpatients and hospitalized patients with COPD without acute respiratory infections (COPD).
- Outpatients and hospitalized patients with asthma without acute respiratory infections (Asthma).
- Patients with respiratory infections, but without COPD or asthma (Infected).
- Healthy controls without COPD, asthma, or any respiratory infection (HC).

B. Data Analytics layer

Here, the data collected from patients were analyzed to classify the diseases by following the processes like preprocessing, feature extraction, dimensionality reduction, and classification. The description regarding the processes is given below: **Preprocessing**: In this stage, the collected patient data I^D is normalized. One of the fundamental components of data mining is data normalization. It entails converting the data, namely transforming the original data into a different format that enables efficient data processing. Data normalization's primary goal is to reduce or even eliminate redundant data. Preprocessed data is p^D . **Feature extraction**: From p^D , features are obtained by some methods and they are: Statistical Features SF [29], higher order statistical features HOS [30], and technical indicator based features TI .

Statistical features: Dataset features that may be specified and calculated by statistical analysis are known as statistical features. The statistical features include Min/Max, Mean Median, SD. Statistical feature set SF is defined in eq. (1).

$$SF = [Min/Max \;\; Mean \;\; Med \;\; \sigma] \tag{1}$$

$$Mean = \frac{Sum of \; p^D}{Number of \; p^D} \tag{2}$$

$$Med = \left[\frac{p^D + 1}{2} \right] \tag{3}$$

$$\sigma = \sqrt{\frac{\sum (x - Mean)^2}{p^D}} \tag{4}$$

Higher Order Statistical (HOS) features: In contrast to more traditional lower-order statistical methods, which employ linear, constant, and quadratic terms, HOS uses the 3rd or higher power of sample. HOS feature set HOS is defined in eq. (5).

$$HOS = [Entropy \;\; Iskewness \;\; Kurtosis] \tag{5}$$

$$Entropy = -\sum_{i=0}^{n-1} p_i \log p_i \tag{6}$$

$$ISkewness = \left(\frac{E(x - Mean)^3}{\sigma^3} + V \right) \Big/ 2 \tag{7}$$

Where V is given by

$$V = \frac{1}{N-1} \sum_{i=1}^{N} |x - \mu|^2$$

$$Kurtosis = n \times \frac{\sum_i^n d_i - \bar{d}}{\sum_i^n (d_i - \bar{d})^2} \tag{8}$$

Technical indicator based features: Technical indicator based features TI is defined in eq. (9). The final extracted feature set F_ex is defined in eq. (10). Table 1 shows the Technical Indicators.

$$TI = [ADOSC \;\; STOCHSC \;\; RSI \;\; PROC \;\; TSMOM] \tag{9}$$

$$F\_ex = [SF \;\; HOS \;\; TI] \tag{10}$$

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TABLE 1: TECHNICAL INDICATORS

$ADOSC$	Implying the accumulation ratio over distribution, the $ADOSC$ produces a value between 0 and 100.
$STOCHOSC$	$STOCHOSC$ A stochastic oscillator is used to show when a data has moved into a higher or lower position.
RSI	RSI The Relative Strength Index (RSI), is a momentum oscillator that measures the speed and change of data movements.
$PROC$	$PROC$ A momentum-based technical indicator called the Price Rate of Change determines how much the proportion of data has moved in a particular period.
$TSMOM$	$TSMOM$ The strong positive predictability data is captured using the time series momentum.

Dimensionality reduction: Extraction of many features may cause the issue of ‘curse of dimensionality’. Hence there needs the processing to reduce the dimensions, in the sense selecting the appropriate feature set. In this work, Dimensionality reduction can be done by improved FCM clustering process [30]. By objective function O_{FCM} minimization, as shown in the below Eq. (11), the FCM's primary goal is to generate a fuzzy c-partition for the specified data set, where $F\_ex = \{f_1, f_2, ..., f_n\}$ indicates number of features, T indicates the membership degree matrix, S indicates the cluster centroid, c indicates the cluster count, m indicates the fuzziness index, d indicates the Euclidean distance and u indicates the hard cluster

$$D^f = O_{FCM}(F\_ex, T, S) = \sum_{i=1}^{c}\sum_{j=1}^{n} s_{ij}^{m} d \tag{11}$$

As per ECEHMS-GIPOA, improved FCM is calculated in eq. (12), here d_{new} indicates the improved Minkowsi distance [31] which is determined as the extension of both the Manhattan and Euclidean distance calculated in eq. (13). After that, apply Principal Component Analysis (PCA) to each cluster and combine the output of PCA. Using the correlation among features in PCA, the patterns in data can be obtained. In high-dimensional data, PCA seeks to identify the maximum variance directions and projects the data into a new subspace with the similar or several numbers of dimensions. Dimensionality reduced features is indicated as D^f .

$$D^f = O_{FCM}(F\_ex, T, S) = \sum_{i=1}^{c}\sum_{j=1}^{n} s_{ij}^{m} d_{new} \tag{12}$$

$$d_{new} = \frac{\left(\sum_{i=1}^{n} |p_i - q_i|^{p_1}\right)^{1/p_1}}{\min\left(\left(\sum_{i=1}^{n} p_i^{p_1}\right), \left(\sum_{i=1}^{n} q_i^{p_1}\right)^{1/p_1}\right) + \gamma} \tag{13}$$

Here, $p_{1=1}$, and $\gamma = 0.6$

Ensemble classification: DMN, RNN, and Improved DBN: Dimensionality reduced features D^f is given as an input to the ensemble model. The proposed ensemble model combines the models like: DMN, RNN, and improved DBN. The progress of ensemble model is as follows: D^f will be given as an input to DMN and RNN classifier. The processed output from those classifiers will be subjected to the improved DBN to determine the final classification outcome. Fig. 2 shows the proposed ensemble model.

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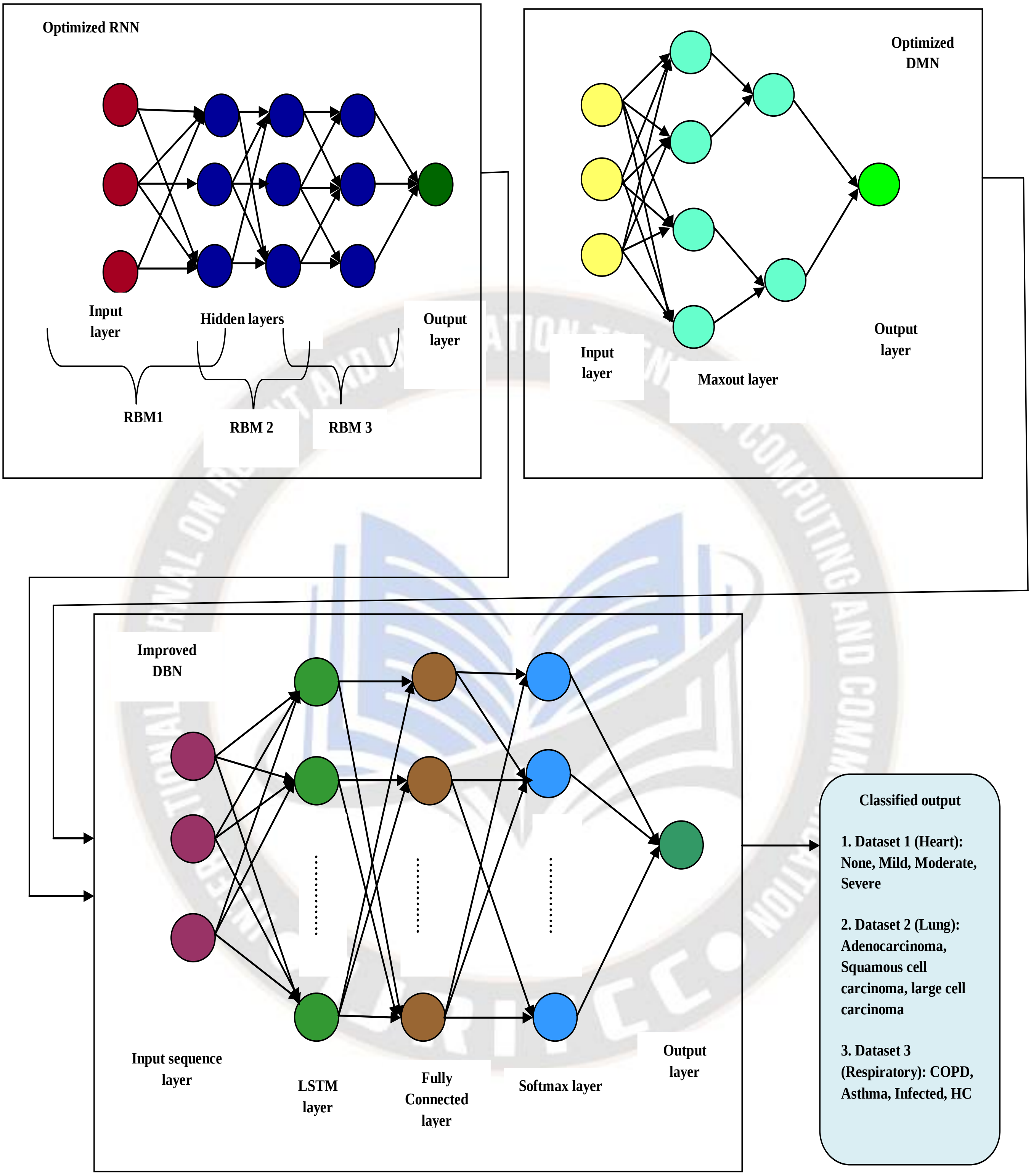

Figure 2. Ensemble classification combining DMN, RNN, and Improved DBN.

Training of DMN and RNN: During training phase, a new training algorithm termed as GIPOA is proposed, by which the weights of both the classifiers will be tuned optimally.

Testing: During testing phase, the classification output will be validated by calculating the difference of actual and predicted value. Finally, the classified outcome will be:

- For data set 1 (Heart), the classified output will be 4 classes: 0,1,2,3 (0 means none, 1 means mild or moderate,

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2 means moderate or severe, and3 means akinesis or dyskmem).

- For dataset 2 (Lung), the classified output will be 3 classes (Adenocarcinoma, Squamous cell carcinoma, and large cell carcinoma).
- For dataset 3, the classified output will be 4 classes (COPD-Asthma-Infected-HC).

DMN [32]: DMN's input is D^f . Multiple layers of DMNs use the maxout function to achieve hidden activations. A maxout network's discontinuous group layer is where the hidden units were partitioned. Here, A indicates overall unit groups, k indicates overall units per group. Each unit group is subjected to the maxout function to create the activations $M_i^l = \left[M_1^l, M_2^l, M_3^l, ..., M_A^l\right]$ for this layer. Each component is calculated as shown in equation (14), where $B^l = W_l M_{l-1} + g_l$ indicates the linear pre-activation value. The maxout function in this case performs a max pooling on B^l .

$$M_i^l\left(D^f\right) = \underset{j}{Max}\left(B_j^l\right), \ (i-1)\times k + 1 \le j \le i \times k \qquad (14)$$

Here, $h \in D^{f^T} D^*$

Here l^{th} layer is regarded to be the highest value inside each group. A DMN can be built by sequentially connecting several maxout layers and then include the softmax layer. By layer-wise stacking autoencoders that relate to the maxout layers, the entire DMN could be pre-trained. DMN weight is indicated as D^* which is optimally tuned by GIPOA. DMN output is indicated as DMN^{out}

3.2.4.2 RNN [33]: Input of RNN is D^f . RNN is the simplest fundamental and appropriate for the changing of time in a NN's structure for different sorts of AI.Particularly, an RNN with symmetric links ensures that it can converge. A RNN's operational model is built via nonlinear activation function synthesis and is dependent on linear data pairs. The layers followed in RNN as per the work is described as follows:

- **LSTM layer:** In sequence data as well as time series, an LSTM layer develops long-term connections among time steps. The hidden state also referred to as the output state, and the cell state make up the layer's state.
- **Fully connected layer:** Fully-connected layers, often referred to as linear layers, are frequently employed in NN since they link every input neuron to each and every output neuron.

Softtmax layer: In a multi-class scenario, Softmax gives decimal probability to each class. The sum of their decimal probabilities must be 1.0. Training converges faster than it would without this extra constraint.A NN layer that comes before the output layer is used to implement Softmax. RNN weight is R^* which is optimally tuned by GIPOA. RNN output is indicated as RNN^{out}.

Improved DBN [34]: RNN^{out} and DMN^{out} is given as an input to improved DBN. A powerful generative NN known as a DBN generates output using an unsupervised ML approach. This kind of network highlights some latest work on developing unsupervised models utilizing relatively unlabeled input. According to some experts, the DBN consists of several RBMs layered on top of one another. Generally, a variety of lesser unsupervised NN make up DBN. Although connections exist among layers, including a DBN's common characteristics is the lack of connections within a single layer. This specific kind of unsupervised ML model illustrates how engineers might pursue less organized, more robust systems where there is less data classification and the technology must construct outcomes based on random inputs and repetitive procedures.

In the case that each RBM has n neurons inside the visible layer and m neurons inside the hidden layer, eq.(15) defines the energy function, where Eg indicates the energy function, vl indicates the visible layer, hl indicates the hidden layer, W indicates the weight function of hidden and visible layer bias, and u, e indicates the offset vectors.

$$Eg(vl, hl) = -\sum_i u_i vl_i - \sum_j v_j hl_j \qquad (15)$$

As per the proposed concept, for improved DBN, improved error function IE is calculated in eq. (16), where AV depicts the actual value, PV depicts the predicted value, WPV^C depicts the wrongly predicted value count, OPV^C depicts the overall predicted value count. Also, $OPV^C = length(AV)$, $WPV^C = Sum(AV - PV)$

$$IE = abs\left[(AV - PV)\right] + \frac{WPV^C}{OPV^C} \qquad (16)$$

Objective function and solution encoding: ECEHMS-GIPOA discovered that the DMN and RNN weights D^* and R^* were tuned using the GIPOA method, with the objective of minimizing of errors Er as modelled in Eq. (17). Weight D^*

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and R^* is provided to GIPOA method as an input solution. Er Indicates the error between the classified outcome and actual value.

$$obj = Min\ [Er] \tag{17}$$

IV. GAUSS ITERATED PELICAN OPTIMIZATION ALGORITHM (GIPOA) FOR OPTIMAL TRAINING OF DMN AND RNN WEIGHT

As per the GIPOA algorithm. For fine-tuning DMN and RNN weight D^* and R^*, we introduced a GIPOA. As per the proposed logic, arithmetic crossover operations is been added in the existing strategy of POA [35], and this improvement ensures better convergence rate when compared to existing logic. The procedure of proposed GIPOA is as follows:

A. Initialization phase[36]

Depending on the lower/upper bound of the problem, equation (18) is employed for randomly initialize population members, where m denotes the count of problem variables, N denotes the count of problem member, $J_{i,j}$ denotes the value of the j variable determined using the i^{th} candidate solution, u_j, l_j denotes lower/upper bound, z denotes random value.

$$J_{i,j} = l_j + z * \left(u_j - l_j\right), \quad i = 1,2,....,N, \quad j = 1,2,...,m \tag{18}$$

As per GIPOA, z is estimated by the Gauss Iterated map provided in eq. (19), where $n = [0,1]$, $\lambda = 4.90$, and $\partial = -0.58$.A Gaussian function-based nonlinear iterated map of real into a real interval is known as a Gauss iterated map.

$$z = \exp\left(-\lambda n^2\right) \tag{19}$$

Exploration step: The pelican can now update its position often due to ϑ which is a dynamic weight factor. Here, ϑ has a big value at the starting of the iteration, whenever the pelican is ready to execute a optimal global search, and it drops adaptively at the completion of the iteration, whenever the pelican is ready to execute a optimal local search while accelerating convergence. Eq. (20) explains this activity.

$$J_{i,j}^{t+1} = \begin{cases} J_{i,j}^t + z * \left(o_j^t - J_{i,j}^t\right) * \vartheta & F(J_o) \prec F(J_i) \\ J_{i,j}^t + z * \left(J_{i,j}^t - o_j^t\right) * \theta & F(J_o) \geq F(J_i) \end{cases} \tag{20}$$

Here, $\vartheta = \dfrac{e^{2\left(1-t/T\right)} - e^{-2\left(1-t/T\right)}}{e^{2\left(1-t/T\right)} + e^{-2\left(1-t/T\right)}}$

According to GIPOA, the Pelicans' updated position is defined as in eq. (21).

$$J_{i,j}^{t+1} = \begin{cases} \dfrac{J_{i,j}^t + z * \left(o_j^t - J_{i,j}^t\right) * \vartheta + o_j^t}{2} & F(J_o) \prec F(J_i) \\ \dfrac{J_{i,j}^t + z * \left(J_{i,j}^t - o_j^t\right) * \vartheta + o_j^t}{2} & F(J_p) \geq F(J_i) \end{cases} \tag{21}$$

Exploitation phase: In this step, pelicans spread their feathers on the water's surface to push fish upward, catch the prey, and then lock it away in their neck pouches. The method must mathematically examine the areas close to the pelican area for converging to an ideal solution. Equation (22) mimics this feature of pelican hunting behavior, where $J_{i,j}^{o2}$ denotes the i^{th} pelican new update in j^{th} dimension, t denotes iteration count, constant parameter is denoted as L which is 0.2, and T denotes maximal iteration count.

$$J_{i,j}^{o2} = J_{i,j} + L \times \left(1 - \frac{t}{T}\right) * \left(2 * z - 1\right) \times J_{i,j} \tag{22}$$

Arithmetic crossover (AC) [37]: In AC, arithmetic produces offspring which are the weighted average of their two parents. With regard to linear constraints as well as boundaries, children are feasible. The method returns the child if parent1 as well as parent2 seem to be the parents as well as parent1 has the higher fitness value. Equation (23) determines the AC operation; where P indicates the parent, and α indicates the random integer ranges from 0 to 1.

$$offspring = \left(\alpha \times P_1\right) + \left(1 - \alpha\right) \times P_2 \tag{23}$$

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V. PRESENTATION LAYER (DECISION MAKING SYSTEM)

At this phase, based on the patient's condition using the enhanced ensemble model, the decision will be taken by the doctors. As per the proposed monitoring system, the decision made by doctors for dataset 1, dataset 2, and dataset 3 were:

A. *For dataset 1 (Heart disease)*

0. None:No medications were required
1. Mild: Proper diet required as per doctor suggestion
2. Moderate: Treat heart failure & medication is needed as per doctor suggestion
3. Severe: Surgery or implant cardiac devices
4. Akinesis: Treatment required was given below:
    a. Diuretics or water pills (Treats swelling of feet and abdomen)
    b. Beta-blockers (Slows heart rate and regulates blood pressure)
    c. ACE inhibitors, ARB, ARNI (Widen blood vessels)
    d. Mineralocorticoid receptor antagonist (Rids the body of excess salt and fluid but retains potassium)....
    e. Nitrates and Hydralazine(Relaxes and further widens blood vessels)
    f. Digoxin(Assists in the pumping process of the heart)

B. *For Dataset 2 (Lung Disease)*

1. Adenocarcinoma: surgery is done to remove cancer and some of the surrounding tissue. And Chemotherapy treatment involves using drugs to kill cancer cells.
2. Squamous cell carcinoma: Mohs surgery is the most effective technique for removing SCCs.
3. Large cell carcinoma: Surgery is needed including:
    a. Wedge resection: Involves removing the tumor and some of the normal tissue around it
    b. Lobectomy: Removes the whole lobe or section of the lung
    c. Pneumonectomy: Involves removing one entire lung
    d. Sleeve section: A surgeon will remove part of the bronchus

C. *For Dataset 3 (Respiratory Disease)*

0. COPD: Treatments needed (stopping smoking, inhalers and tablets, pulmonary rehabilitation, surgery or a lung transplant)
1. Asthma: Inhalers
2. Infected: Treatment needed (rest, fluids, and over-the-counter pain relievers)
3. HC: Healthy Condition

VI. RESULTS AND DISCUSSION

A. *Simulation Procedure*

MATLAB tool was utilized to implement the proposed healthcare monitoring system. Consequently, the efficacious of the ECEHMS-GIPOA was measured over standard models such as Atom Search Optimization (ASO), Black Widow Optimization (BWO), Sea Lion Optimization (SLO), Slap Swarm Optimization (SSO), Flower Pollination Algorithm (FPA) and Pelican Optimization Algorithm (POA) regarding wide-ranging metrics. In addition, statistical, convergence and ablation analyses were made to represent the reliability of the ECEHMS-GIPOA.

B. *Performance Analysis on ECEHMS-GIPOA*

Performance investigation on ECEHMS-GIPOA is conducted for distant learning percentages, as regards to measures like accuracy, f-measure, specificity, precision, MCC, NPV, FNR and FPR and also the findings were correlated with approaches like ASO, BWO, SLO, SSO, FPA and POA, which is indicated in fig 3, fig 4 and fig 5. Here, three different types of datasets are utilized in this assessment. On examining the fig 3(a), it is apparent that using the ECEHMS-GIPOA results in a higher accuracy value at the 70th learning percentage (92.84%). Despite having significantly lower ratings for accuracy than other techniques, ASO, BWO, SLO, SSO, FPA and POA has much lower ratings of 82.48%, 83.36%, 85.54%, 81.62%,

Algorithm 1: Pseudocode of GIPOA

Input is D^*, R^*, **Result is** Optimal weight
Determine GIPOA population size as N and the maximal iteration count as T
Initialization of pelicans location using the eq. (18) with Gauss iterated map randomization as per GIPOA
for $t = 1:T$
  Randomly prey location randomly
  for $I = 1:N$
Exploration Step
    for $j = 1:m$
Calculate current location of pelicans using the equation (21) as per GIPOA
    end for
Exploitation Step
    for $j = 1:m$
      Calculate current location of pelicans equation (22)
    end for
    Update Optimal weight
  end for
Arithmetic crossover is performed as per GIPOA algorithm
end for

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84.79% and 80.18%, respectively. In accordance with the fig 3(b), the precision of the ECEHMS-GIPOA is 93.96% in the 80^{th} learning percentage, this is terrific than ASO=81.46%, BWO=84.68%, SLO=83.54%, SSO=82.66%, FPA=78.19% and POA=88.32%, respectively. Similarly, the ECEHMS-GIPOA attained the sensitivity of 89.62%, although it reached the greatest sensitivity in the 90^{th} learning percentage is 94.91%. Moreover, the specificity of the ECEHMS-GIPOA is 88.46%, 90.62%, 92.58% and 95.34% at the 60, 70, 80 and 90% of learning percentage.

In particular, the ECEHMS-GIPOA retained a lowest FDR of 0.07 for the 60% of learning percentage, meanwhile the ASO is 0.198, BWO is 0.172, SLO is 0.191, SSO is 0.194, FPA is 0.193 and POA is 0.167, respectively. The ECEHMS-GIPOA model FNR ranges from 0.08 to 0.06, which is significantly lesser than previous approaches in nearly all learning percentages. From the fig 4(c), we can determine that not only for 90^{th} learning percentage, for other learning percentages our ECEHMS-GIPOA sustained lower FPR ratings.

Similarly we have analyzed the measures like F1-score, NPV and Matthews Correlation Coefficient of ECEHMS-GIPOA with other approaches, and the results from figure 5(a) revealed that ECEHMS-GIPOA accomplished higher Matthews Correlation Coefficient rating that is 93.69% for 90^{th} learning percentage, though the other algorithms ASO=82.64%, BWO=84.58%, SLO=85.35%, SSO=83.66%, FPA=84.93% and POA=86.19%, respectively.

The other datasets for the ECEHMS-GIPOA over the conventional procedures are exposed in fig 6 to fig 11. Similar to the dataset1, the ECEHMS-GIPOA increased positive and other metrics while also achieving the lowest negative measure values. This signifies that the other standard approaches for Healthcare Monitoring System is amateurish over the ECEHMS-GIPOA.

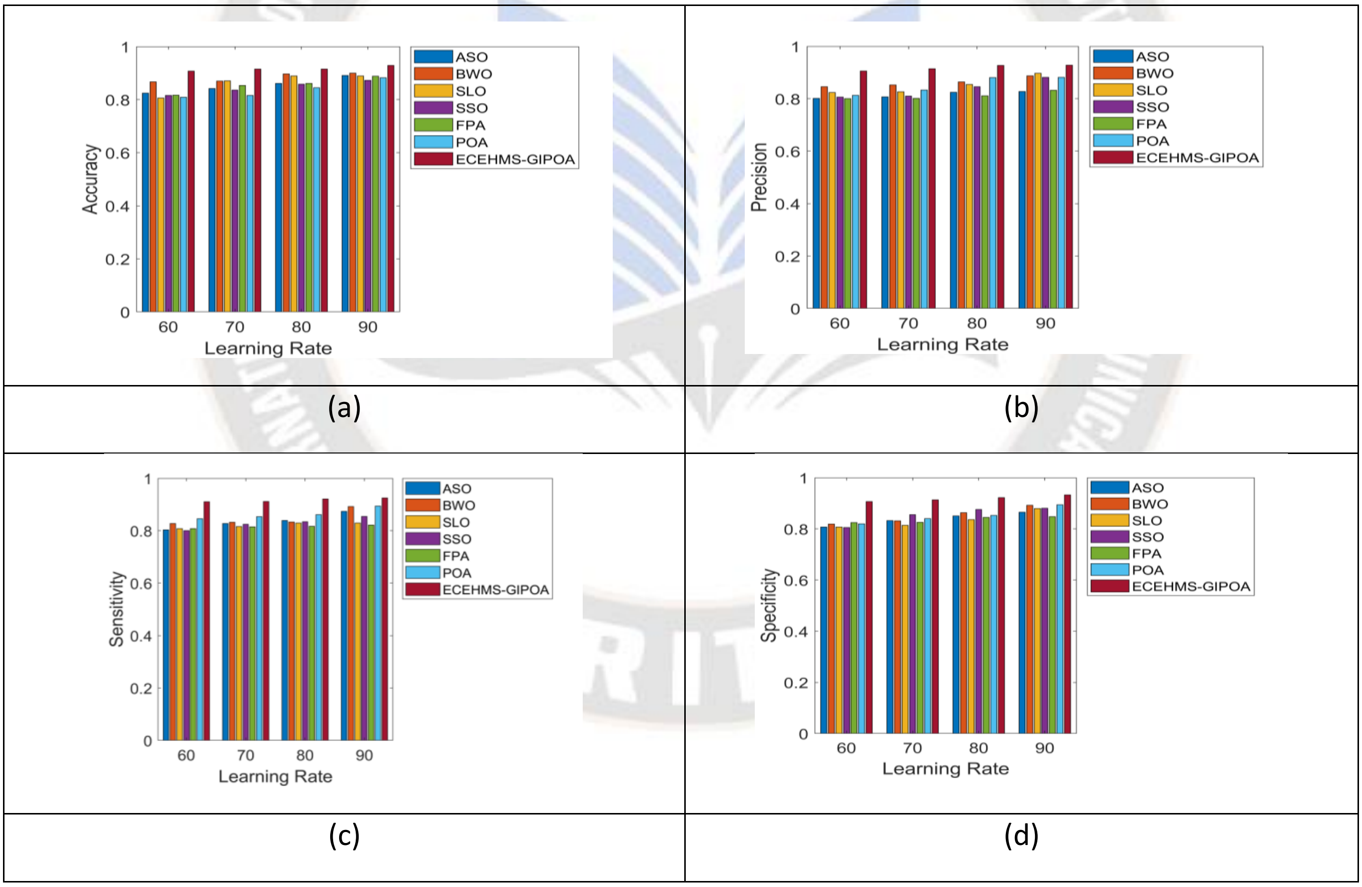

Figure 3. Comparison on ECEHMS-GIPOA with other conventional approaches a) Accuracy b) Precision c) Sensitivity d) Specificity for dataset1

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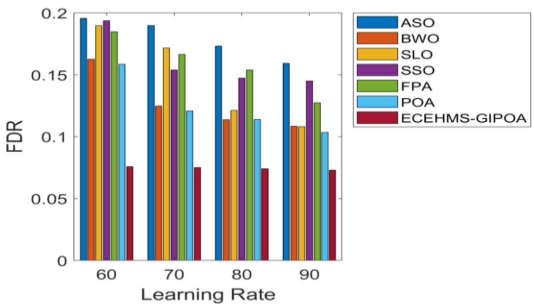

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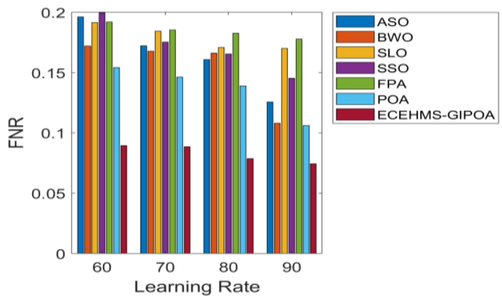

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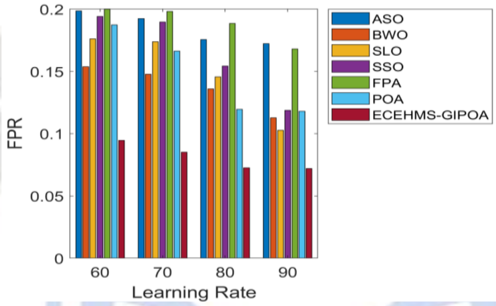

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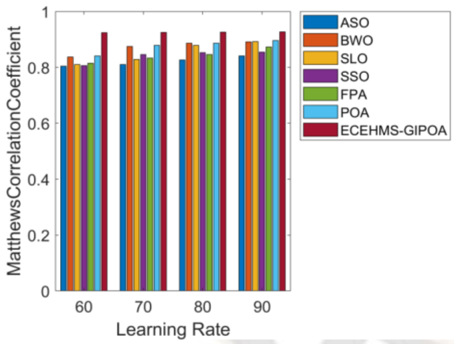
Figure 4. Comparison on ECEHMS-GIPOA with other conventional approaches a) FDR b) FNR c) FPR for dataset1



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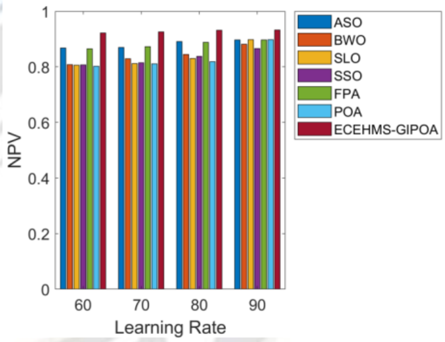

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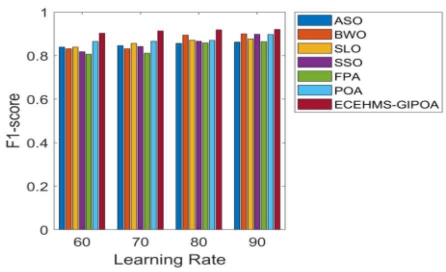

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Figure 5. Comparison on ECEHMS-GIPOA with other conventional approaches a) Matthews Correlation Coefficient b) NPV c) F1-score for dataset1

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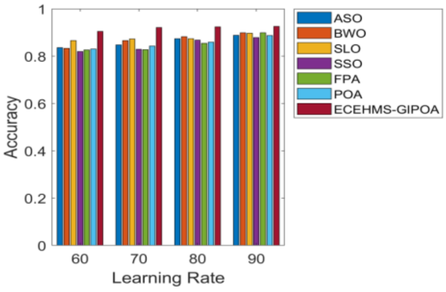

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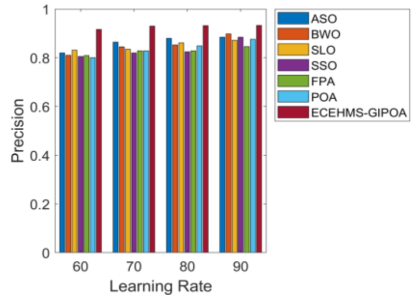

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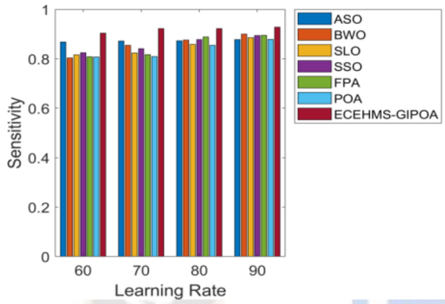

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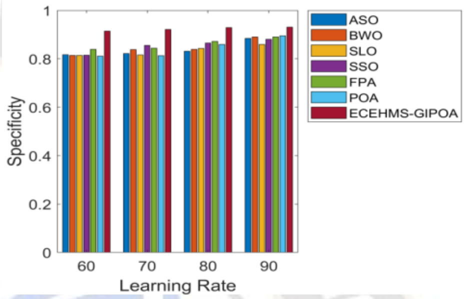

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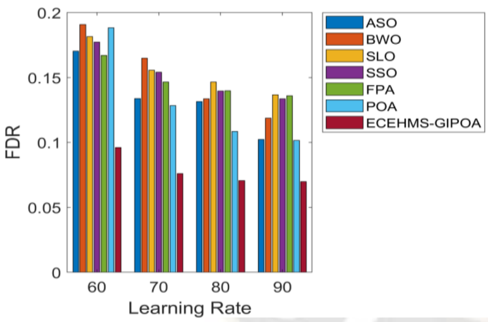
Figure 6. Comparison on ECEHMS-GIPOA with other conventional approaches a) Accuracy b) Precision c) Sensitivity d) Specificity for dataset2



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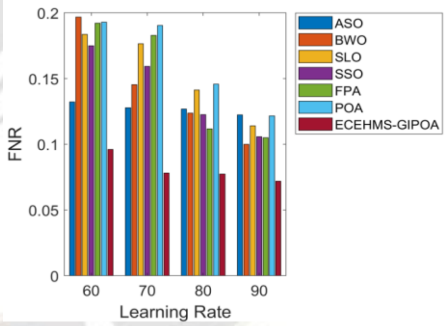

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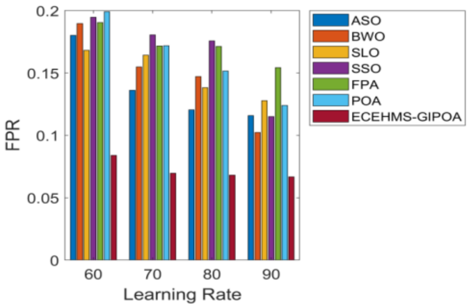

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Figure 7. Comparison on ECEHMS-GIPOA with other conventional approaches a) FDR b) FNR c) FPR for dataset2

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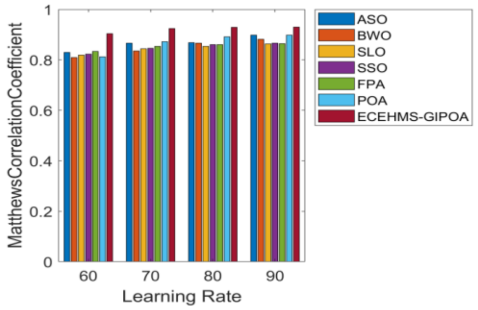

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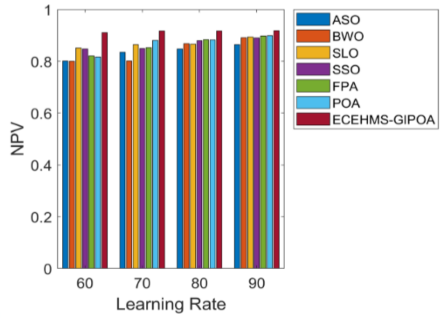

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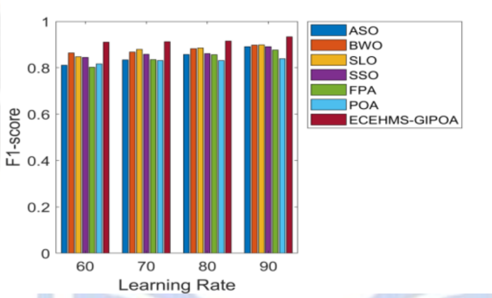

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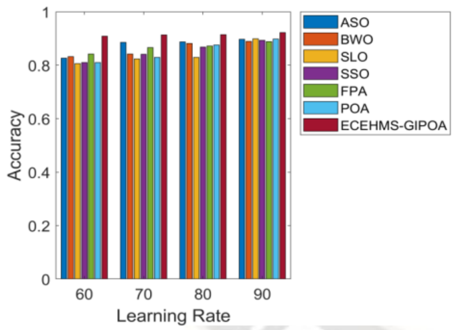
Figure 8. Comparison on ECEHMS-GIPOA with other conventional approaches a) Matthews Correlation Coefficient b) NPV c) F1-score for dataset2



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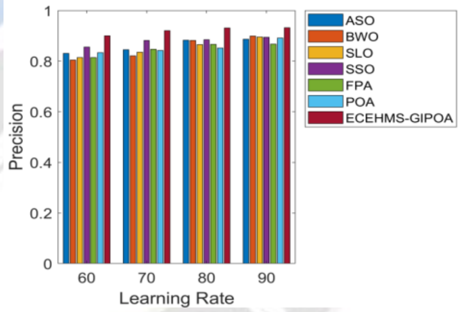

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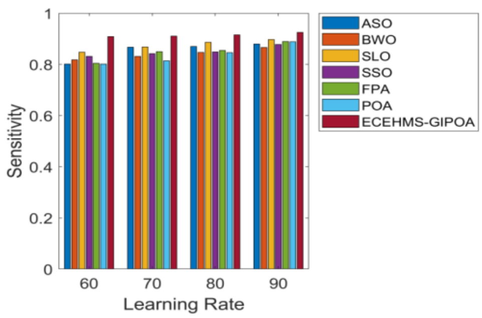

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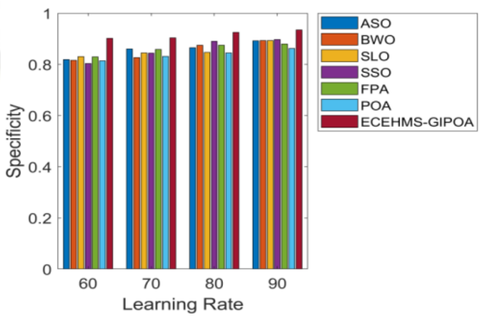

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Figure 9. Comparison on ECEHMS-GIPOA with other conventional approaches a) Accuracy b) Precision c) Sensitivity d) Specificity for dataset3

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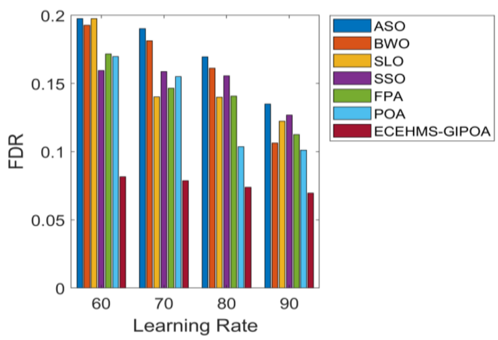

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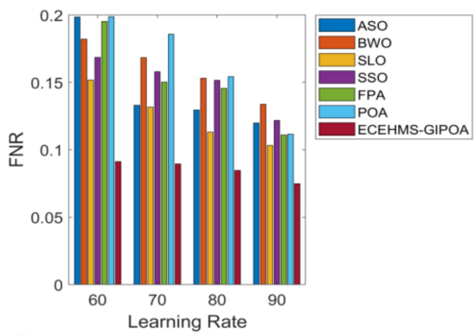

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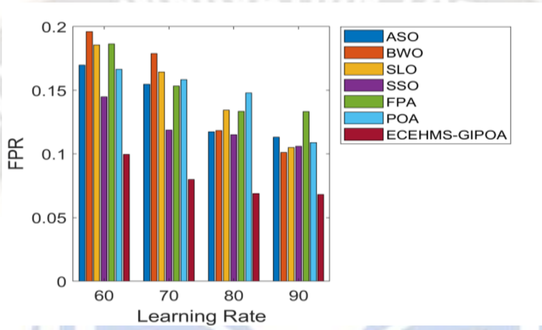

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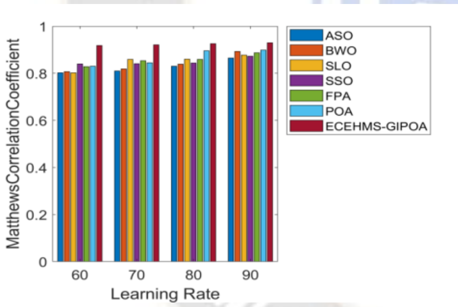
Figure 10. Comparison on ECEHMS-GIPOA with other conventional approaches a) FDR b) FNR c) FPR for dataset3



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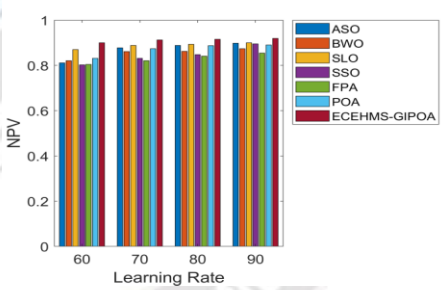

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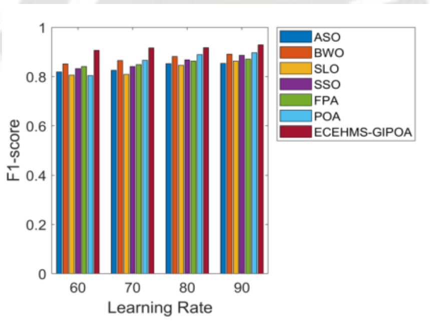

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Figure 11. Comparison on ECEHMS-GIPOA with other conventional approaches a) Matthews Correlation Coefficient b) NPV c) F1-score for dataset3

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C. Convergence Analysis

To assess the supremacy of the ECEHMS-GIPOA for the Healthcare Monitoring System, a convergence evaluation on ASO, BWO, SLO, SSO, FPA, and POA was performed. The results are presented in fig 12. This convergence analysis was evaluated for a range of iterations (0-100), and the comparison is made to those of other traditional approaches or techniques including ASO, BWO, SLO, SSO, FPA, and POA. As demonstrated by the acquired results, the ECEHMS-GIPOA has recorded least error rate (1.0418) from the iteration 38 to 100, while the current methods have established the error value as being higher, nevertheless, the ECEHMS-GIPOA is seems to be more advantageous than conventional schemes for all the datasets. Finally, the ASO, BWO, and SSO achieved the highest error scores compared to the others. Thus, the ECEHMS-GIPOA concept has consolidated into being potent for Healthcare Monitoring System.

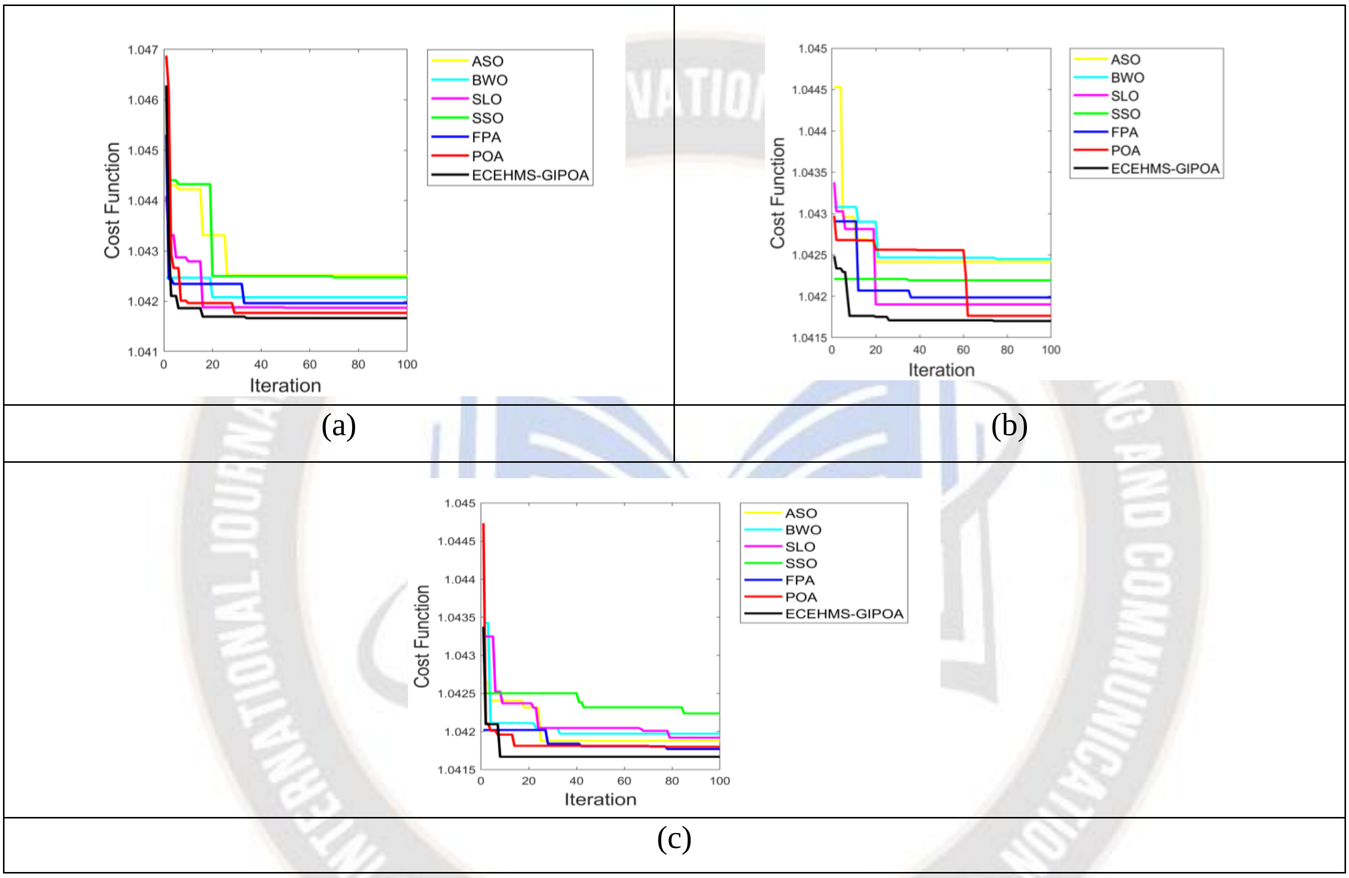

Figure 12. Convergence study on ECEHMS-GIPOA versus traditional classifier a) Dataset1 b) Dataset2 c) Dataset

VII. CONCLUSION

The major objective of this research is to develop a three-layer ECEHMS -GIPOA including data collection layer, data analytics layer, and presentation layer. As per our ECEHMS-GIPOA, healthcare dataset is collected from the UCI repository (Lung, Heart, and Respiratory). In the data analytics layer, ECEHMS-GIPOA with the steps like preprocessing, Feature Extraction, Dimensionality reduction, and classification are performed. Data normalization will be done in preprocessing step. Statistical features, improved higher order statistical features, and Technical indicator based features were extracted during feature extraction step. Improved FCM will be used for handling the dimensionality issue. Ensemble model is introduced to predict the disease stage that including the models like DMN, Improved DBN, and RNN. Also, the enhancement in prediction/classification accuracy is assured via optimal training. For which, a GIPOA is introduced. Finally, ECEHMS-GIPOA performance is evaluated and the output was verified successfully.

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