

SS-FD: Internet of medical things-based patient health monitoring system

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ABSTRACT

Internet of Medical Things (IoMT) consists of connected devices used to collect patient health information in a real-time environment. The IoMT device effectively handles medical issues by using health wearable and medical-grade wearables. Although IoMT can process the collected data, it has few pitfalls, such as interoperability of data, standardization issues, and computation complexity while detecting disease. By considering these issues, in this work, IoMT is utilized in the field of the remote patient monitoring system. Initially, the IoMT devices are placed on the human body and collect their health information continuously. The gathered details are processed using a salp swarm optimized fuzzy deep neural network (SS-FD). This system supports the patient health monitoring process with minimum low-cost consumption. The SS-FD classifier processes the obtained data; primary and emergency data is classified according to the fuzzy rule. This process improves the remote patient health data analysis and reduces the difficulties involved in the patient health analysis. Then the efficiency of the system is evaluated using experimental results.

Keywords: Internet of Medical Things (IoMT), wearable device, interoperability data, salp swarm optimized fuzzy deep neural network (SS-FD).

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1. Introduction

Recent years, Chronic care management and remote patient monitoring (RPM) [1, 2] system placed a vital role because it minimizes the crowded waiting room in hospital. The RPM process uses the monitoring wearable device called Internet of Medical Things (IoMT) [3] to monitor the patient activities virtually. The data collects the patient real-time health data and transferred to the healthcare provider to minimize the serious impacts. From 2020, Covid-19 pandemic situation causes people to adopt the RPM system to reduce the unwanted disease spread. Therefore, the wearable devices are incorporated with the RPM technology [4, 5] for collecting and transferring data from patient to healthcare providers. The IoMT devices [6] are monitoring patient glucose level (glucose meter-diabetic management), heart rate monitoring (manage heart failure), blood pressure, oximeter (manage blood oxygen level), surveillance monitor, exercise logging program, calories logging program, grip strength sensor (Parkinson disease) etc. [7]. These sensors are bringing patient health details in 24/7 that is easily access by clinician to making the decision with lower cost. The collected health information is stored in cloud environment [8] via Internet which helps to access the data by family members, clinician and emergency health services. During the data transmission process, emergency data should be treated immediately to reduce the unwanted emergency situation. Therefore, several computer aided detection systems have been developed using machine learning techniques [9-10-11] to categorize the normal and abnormal data. The automatic analyze system uses the data pre-processing, feature extraction, selection and classification steps to investigating the characteristics of data. Among these steps' classification approaches are placed a critical role

because it identifies the exact data patterns from previous learned or trained data [12]. The classification process performed using artificial intelligence (AI) and machine learning (ML) [13] techniques. In which, deep learning [14, 15] techniques creates the great impact in machine learning task according to human brain function. This biological based learning process minimize the complexity while executing high-dimensional data. More ever, the deep learning model learn their classification directly from text, images and sounds[16]. This causes to improve the overall accuracy of the system that is maximum compared to the human-level performance. The network uses the multiple layers [17] that uses the specific function and process which reduce the computation complexity. By considering the advantage of deep learning model, several researcher utilizing the deep learning [18] concept to investigate their data. Although, the system still stuck while examining the interoperability data and standardization problem. Then the system maximizes the computation complexity and cost which reduce the overall IoMT based remote patient monitoring process. To overcome this research issues, in this work, optimization technique called Salp swarm optimization approach and fuzzy network is incorporated with deep learning model. Here, fuzzy approach utilizes the fuzzification and membership value identification process to reduce the overlapping data. This fuzzy value able to overcome the interoperability data issues and the network parameters are updated according to salp fish behavior. This continuous updating process minimize the deviation and improve the overall data status identification. The effectiveness of the system implemented using MATLAB tool and error rate, fit rate, accuracy metrics are used to determine the system performance.

Then the rest of the paper arranged as follows: Section 2 discuss the various research's opinion regarding the remote patient health monitoring. Section 3 elaborate the working process of SS-FD based remoted patient monitoring and excellence of the system discussed in section 4. Conclusion is derived in section 5

2. Related works

T. Zhang et al. [19] introducing the deep learning model (DLM) to monitoring the elder patients health by using Internet of Medical Things (IoMT). This method uses the sixth fold process to manage the device energy efficient while capturing patient cardiac information. The collected details are transmitted to the healthcare center via the wireless channel that used to predict the body postures. Khan, et al. [20] diagnosing patient heart disease by IoMT based patient monitoring using modified salp swarm optimization (MSSO) with adaptive neuro-fuzzy inference system (ANFIS) (MSSO-ANFIS). The sensor device collects age, sex, blood pressure, cholesterol, chest pain and blood sugar level which transmit to the health care center. The fuzzy inference system predicts the patient health condition from the collected data and the performance of the system optimized according to the fish behavior. This process ensures 99% of accuracy while investigating patient IoMT based collected data..Krech, et al. [21] applying big data analytics and machine learning concept to monitoring patient health by using internet of medical things (IoMT). This system aims to improve the overall accuracy of virtual patient monitoring process. During the analysis system uses 4600 respondents to predict how IoMT monitor the patient's health with quality aspects. AlShorman, et al. [22] creating remote patient health monitoring system using IoMT. The system aims to manage the security, privacy, data availability, energy efficient and computation cost while monitoring patient diabetic details. RM, SwarnaPriya et al. [23] introducing the grey wolf optimization with deep neural network (GWO-DNN) approach to monitoring the intrusion activities in the IoMT based patient monitoring process. This system extracts the features according to principle component analysis process that is processed by defined neural network which predicts the intermediate attacks with effective manner. According to the above researchers, the deep learning model effectively works on the Internet of Medical Things (IoMT). By considering their opinion, in this work, optimized deep learning approach is applied to investigating the patient data to predict the normal and abnormal details. The detailed description of problem statement and respective process is discussed as follows.

3. IoMT based patient health monitoring system

This section discusses the Internet of Medical Things (IoMT) based remoted patient health monitoring process. Traditional systems can investigate the patients remotely, but they have computation complexity while examining a greater number of patients. The standardization and interoperability of data cause to reduce the accuracy of the patient monitoring process. Therefore, the optimized system has been developed to overcome the problem definition and enhance patient monitoring accuracy. The overall IoMT remote patient monitoring process is illustrated in figure 1.

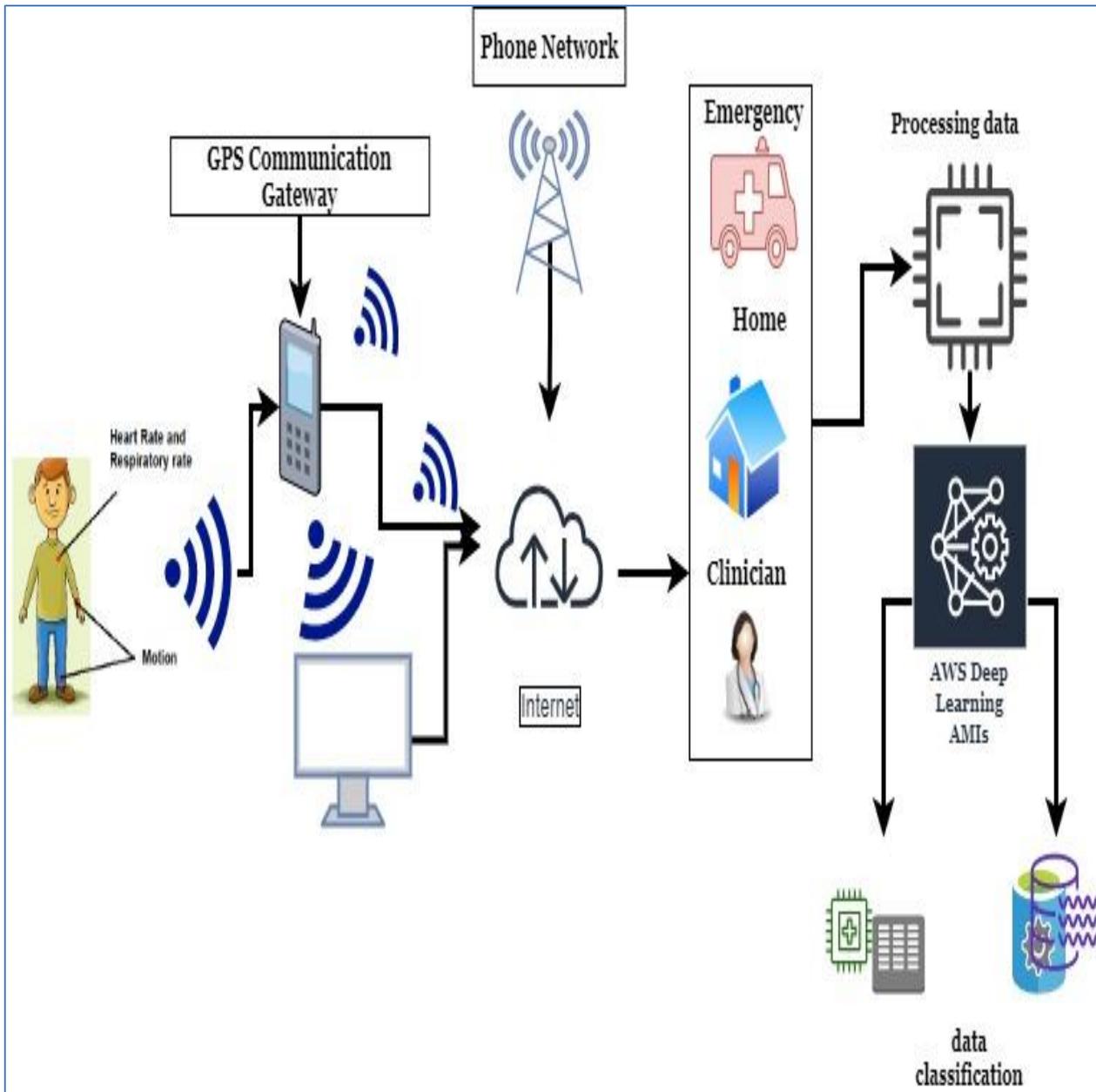


Figure 1. IoMT based patient remote health monitoring

Figure 1 illustrated that the working process of IoMT based patient remote health monitoring system. Here, IoMT medical device placed on the patient body and different information like heart rate, respiratory, motion and other details is continuously recorded. The collected details are transmitted to clinicians, family members and the emergency center via the Internet. These shared details help identify the patient's normal and emergency information, reducing the critical medical situation. The gathered details are processed by machine learning techniques to recognize the normal and abnormal data because emergency patients require immediate treatment. This process consumes more complexity in traditional systems due to the interoperability and standardization problem. These problems cause to minimize the accuracy of the patient remote monitoring process. Therefore, an optimized fuzzy deep learning network is applied to investigate the IoMT data normal and abnormal. This approach recognizes and categorizes the data using three phases: fuzzification, identification, and learning phase. In the first phase, each attribute is fuzzified using the clustering process and detecting the membership grade value for every attribute. In the second phase, a different α - cut approach is applied to identify the new features and finally, using learning phase is performed with the help of the deep learning technique. The overall working process of a fuzzy deep learning network is illustrated in figure 2.

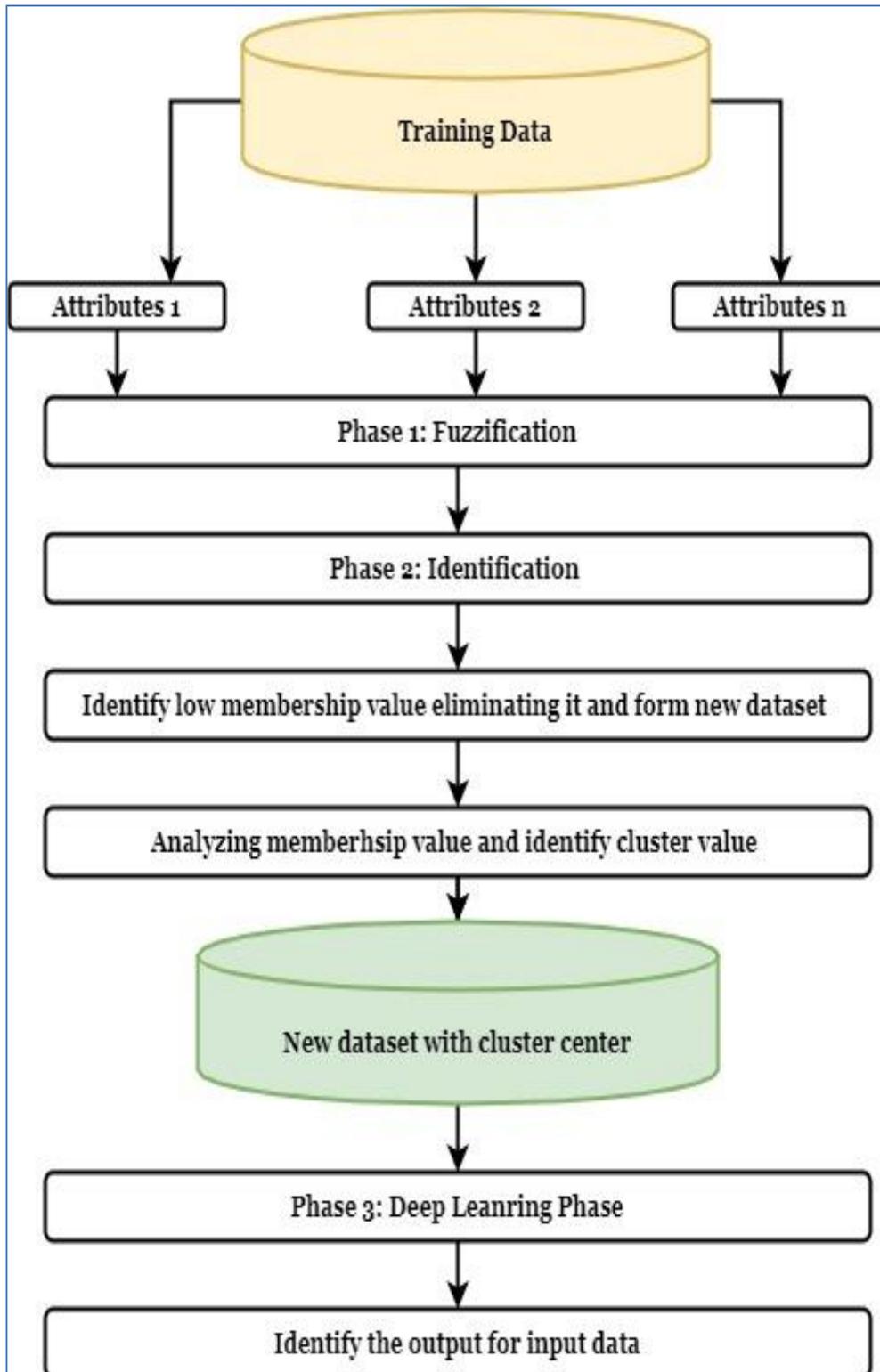


Figure 2. Process of fuzzy deep neural network in remote patient monitoring system

3.1. Phase 1: Fuzzification

The intention of this phase is to reduce the overlapping issues by doing the fuzzification process to non-categorical features. This is achieved by identifying the overlapping degree and respective clustering class. Here the collected data is processed with the help of K-means clustering process because every data is belonging to particular class that helps to identify the normal and abnormal data. The clustering approach is able to detect

the membership grade value for every cluster successfully. The fuzzification process performed in terms of three steps: first, the c-means clustering process is applied to attributes in training dataset. According to the number of datasets, number of clusters are selected for gathering the non-category data. Second step is to identifying the degree of membership value for every attribute in cluster. If the system has three clusters, then three membership values are computed. In third step, the membership values are arranged in the descending order and the high values are considered to form the new training dataset. Consider, the IoMT device collected n input records that has k number of attributes. Therefore, the input and output space has been represented in the matrix (X and Y) format (Eq. 1).

$$y_i = x_{i1}, x_{i2}, \dots, x_{ik} \tag{1}$$

In Eq. (1), i denoted as collected IoMT dataset records. Here X is represented as follows,

$$X = \begin{bmatrix} x_{11} & x_{12} & \dots & x_{1k} \\ x_{21} & x_{22} & \dots & x_{2k} \\ \dots & \dots & \dots & \dots \\ x_{n1} & x_{n2} & \dots & x_{nk} \end{bmatrix} \tag{2}$$

$$Y = y_1 y_2 \dots y_n \tag{3}$$

During the degree of membership value identification process, clustering approach considering each column in X. Then the new matrix is formed from new input attributes that is defined in Eq. (4).

$$W = \begin{bmatrix} \mu_{11}(x_{i1}) & \mu_{11}(x_{i2}) & \dots & \mu_{11}(x_{ik}) \\ \mu_{12}(x_{i1}) & \mu_{12}(x_{i2}) & \dots & \mu_{12}(x_{ik}) \\ \dots & \dots & \dots & \dots \\ \mu_{n3}(x_{i1}) & \mu_{n3}(x_{i2}) & \dots & \mu_{n3}(x_{ik}) \end{bmatrix} \tag{4}$$

In Eq. (4), membership grade value is denoted as μ_{ik} , i.e., μ_{12} is denoted as, membership value of first attribute of second cluster of first record in the dataset. Here the matrix is changed into W that is represented as Eq. (5).

$$W_n = \begin{bmatrix} w_1 \\ w_2 \\ \dots \\ w_n \end{bmatrix} \tag{5}$$

Here, record i membership value is denoted as W_n . Finally, combining the W_i to generate the input to the dataset.

3.2. Phase 2: Identification

Next phase is identification of new attributed from the given fuzzy based input value. The new attributes are identified from the cluster center and $\alpha - cut$ assignment process. Here, the overlapping issue is resolved by applying the $\alpha - cut$ that is done by using Eq. (6).

$$W_\alpha = \{u \in U / \mu_{ik} \geq \alpha\} \tag{6}$$

This $\alpha - cut$ process is performed on W_n to identify the threshold value. universe discourse is denoted as U and membership grade is μ_{ik} [0,1]. The computed membership degree value is compared with the threshold value, if it is very low then it has to be discarded and formed new attribute set. Then the cluster center is chosen for every cluster instead of using membership grade. Then the cluster matrix is defined as follows,

$$C_n = [C_1 C_2 C_3 \dots C_n]^T \tag{7}$$

Suppose, the records do not remove any information from W_n , then $\alpha - cut$ value is 0. Therefore, the cluster center matrix is defined as,

$$C_i = \begin{bmatrix} C_{11} & C_{12} & \dots & C_{1k} \\ C_{21} & C_{22} & \dots & C_{2k} \\ \dots & \dots & \dots & \dots \\ C_{j1} & C_{j2} & \dots & C_{jk} \end{bmatrix} \tag{8}$$

In Eq. (8) k denoted as number of attributes and number of clusters is j.

After identifying the new dataset with respective cluster center, the attributes in the dataset should be trained using learning phase to classify the normal and abnormal data. The above two phases are investigating the collected IoMT information and formed as cluster according to their membership value.

3.3. Phase 3: Learning Phase

The final phase is learning which is done by using Deep Learning Neural Networks (DNN). The second phase output is fed as input (fuzzified) to this stage and the DNN learning process is done according to the new cluster centers and categorical attributes. Here, the DNN approach utilizes to perform the high volume of data processing to predict the status of the collected IoMT details. The network uses the dilation layer to improve

the feature learning process that improves the overall remote patient monitoring. During the learning process, salp swarm optimization algorithm is incorporated with this network to minimize the computation complexity also reduce the difficulties in parameter updation. The network uses three dilated hidden layer to investigating the IoMT collected data related features. As discussed above, the highly correlated i.e., high membership degrade inputs are considered in the learning phase. Each dilation layer has 32 nodes and the ranges are 1,2 and 4. The last layer is interconnected with the fully connected nodes to accomplish learning process that is done by using vanilla RNN function.

$$h_t^l = \text{vanilla RNN}(h_t^{\text{length}-1}, h_{t-d^1}) \tag{9}$$

The vanilla RNN function helps to accomplish the feature or input learning in many to one strategy process it has been rewrite as,

$$h_t^{\text{length}} = \varphi(w_{hh}h_{t-d^1} + w_{hh}^{\text{length}-1}h_{hh}^{\text{length}-1} + b^{\text{length}}) \tag{10}$$

$$\tanh(x) = (e^x - e^{-x}) / (e^x + e^{-x}), \tag{11}$$

Here tangent activation function helps to predict the output value of inputs in each node. The output is performed according to input, hidden node weight value $w_{hh}h_{t-d^1}$, specified dilation ranges $w_{hh}^{\text{length}-1}h_{hh}^{\text{length}-1}$ and bias value b^{length} . The computed $\tanh(x)$ values are belonging to -1 and 1. These values are indicating that status of the collected patient monitoring data. therefore, the output value is obtained using Eq. (12) which is computed based on learned feature value.

$$O_t = \Delta D + D_j^i \tag{12}$$

In Eq. (12), predicted IoMT data status at time t is denoted as O_t which is computed from addition of identified patient monitoring health feature status (D_j^i) and current health status feature value (ΔD). This process is performed continuously until to detect the status of collected data. Suppose the data is not satisfy the tanh condition, the network propagate the values for updating process. Here, the parameter updation is performed according to SSO algorithm which maximize the computation and gives accurate convergence. The SSO algorithm works according to the food searching behavior salp fish. The leader salp fish updating every swarm's behavior while hunting prey in their search space. According to this process, network weight and bias values are updated to improve the feature learning process. consider, S is the number of input features taken from the previous fuzzification based created dataset. $S = \{S_1, S_2, \dots, S_n\}$ which is treated as the salp fish population. The Salp fish position updating criteria is defined in Eq. (13).

$$S_j^1 = \begin{cases} Fit_j + c_1((S_{max} - S_{min})c_2 + S_{min}c_3 \geq 0 \\ Fit_j - c_1((S_{max} - S_{min})c_2 + S_{min}c_3 < 0 \end{cases} \tag{13}$$

The computation of Eq. (13) helps to update the deep network feature learning process and the best value is allocated in S_j^1 . The selected fitness values Fit_j used to update the collected data related feature weight. Minimum and maximum value of input feature is represented as S_{min} and S_{max} which is chosen from input batch size. Then this process has been regularized according to random coefficients such as $c_1, c_2, \text{ and } c_3$ (range from 0 and 1). If the c_3 value is ≥ 0 then $Fit_j + c_1((S_{max} - S_{min})c_2 + S_{min}c_3)$ value is used to compute the new network weight value else, $Fit_j - c_1((S_{max} - S_{min})c_2 + S_{min}c_3)$ value is used. From the Eq. (13), the coefficient c_1 value is estimated as $c_1 = 2e^{-\frac{(4 * \text{current iteration})^2}{\text{Maximum iteration}}}$. Here the initial weight values updating process is performed according to current iteration exponential value and maximum iteration. The remaining values are updated using Eq. (14).

$$D_j^i = \frac{1}{2}at^2 + v_0t, \quad i \geq 2, D_j^i \tag{14}$$

Here, i indicates the number of the input features in batch size ($i=2, 3, \dots, n$). The a, v and t are represented as acceleration, initial speed, and time. The acceleration and speed of the weight of the input features are computed using the $a = \frac{v_{end}}{v_0}$, and $v = \frac{S-S_0}{t}$. The v_0 and v_{end} attains the initial and end of the speed limit of the model.

The S_0, S are attaining the first and last point of compute node weight.

$$S_j^i = \frac{1}{2}(S_j^i + S_j^{i-1}) \tag{15}$$

According to Eq. (15), the status of the input features is predicted during the feature learning process. With the help of these derived patterns, the new incoming features are successfully classifying the normal and abnormal condition of data.

4. Results and discussion

This section discusses the effectiveness of salp swarm optimized fuzzy deep neural network (SS-FD) approach to monitoring the patient remotely. During this analysis, system uses the BPCO dataset based GANs for IoMT[24] for evaluating the effectiveness of the system. The database uses the wearable devices such as electrocardiogram (day and night movements), pulse information (oximetry monitoring), weight, sphygmomanometer (blood pressure monitoring) and spirometer (FEV1 parameter and peak flow information. These devices collect patient health information in every data for continuous three months: blood pressure, MAP, Body mass index, heart rate, body temperature, oxygen, heart rate master, diastolic blood pressure, systolic blood pressure. The collected data is processed by applying SS-FD approach which uses 32 hidden nodes, 0.002 learning rate, 1,2 and 4 ranges of dilations and 500 batch size information. The discussed system compared with existing literature reviews such as DLM [19], (MSSO-ANFIS)[20], and GWO-DNN[23] because it provides the effective results while examining clinical data. Then the introduced system excellence is evaluated using different metrics such as mean absolute error, mean square error rate, fit rate and accuracy. These metrics are computed as follows. Mean absolute percent error (MAPE),

$$MAPE = \frac{100}{no.of\ class} \sum_{i=1}^{no.of\ class} \frac{|Acual\ abnormal\ condition\ class_i - Predicted\ abnormal\ condition\ class_i|}{Acual\ abnormal\ condition\ class_i} \tag{16}$$

$$Mean\ square\ error,\ MSE = \frac{\sum_{i=1}^n (Acual\ abnormal\ condition\ class_i - Predicted\ abnormal\ condition\ class_i)^2}{no.of\ class} \tag{17}$$

$$Root\ mean\ square\ error,\ RMSE = \sqrt{MSE} \tag{18}$$

$$Fit\ rate = \left(1 - \frac{RMSE}{\sqrt{\frac{1}{number\ of\ samples} \sum (actual\ class - predicted_mean)}} \right) * 100\% \tag{19}$$

$$ACC = \frac{Correctly\ predicted\ True\ abnormal\ class + Wrongly\ predicted\ True\ abnormal\ class}{Correctly\ predicted\ True\ abnormal\ class + Wrongly\ predicted\ True\ abnormal\ class + Correctly\ predicted\ False\ abnormal\ class + Wrongly\ predicted\ False\ abnormal\ class} \tag{20}$$

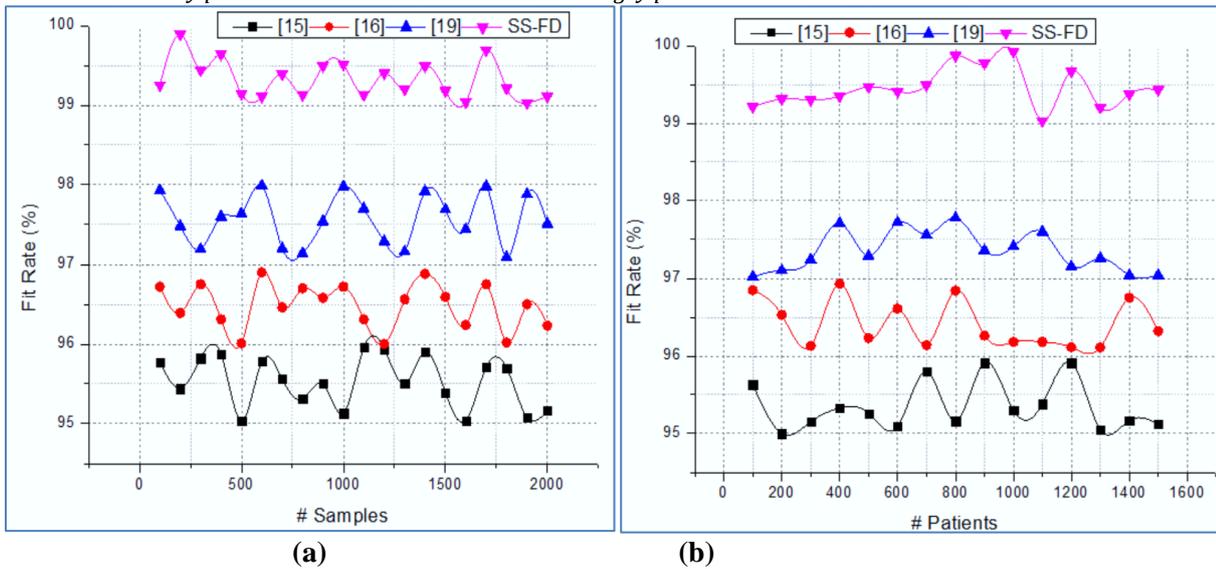


Figure 3. (a) Number of sample data (b) Number of Patients related Fit Rate

Figure 3 illustrated that the fit rate that is prediction accuracy while investigating the patient health information. The effective computation of fuzzy membership grade ($y_i = x_{i1}, x_{i2}, \dots, x_{ik}$) values help to determine the new attribute set and cluster center. This fuzzification process helps to identify the new attribute set according to $\alpha - cut$. This process improves the overall clustering of similar data while analyzing the collected IoMT data. In addition to this, the clustered data trained in third phase that improve the overall data status identification process (normal and abnormal). The tangent activation $(e^x - e^{-x}) / (e^x + e^{-x})$ function computes the new formed inputs, network weight and bias values correctly. This causes to improve the overall data status identification. In addition to this, the process minimizes the computation complexity due to the effective computation of fuzzy membership grade value. Not only this the system recognizes the abnormal data with

maximum accuracy. The effectiveness of the system analyzed with different number of samples and various number of patients. The obtained results are illustrated in figure 4.

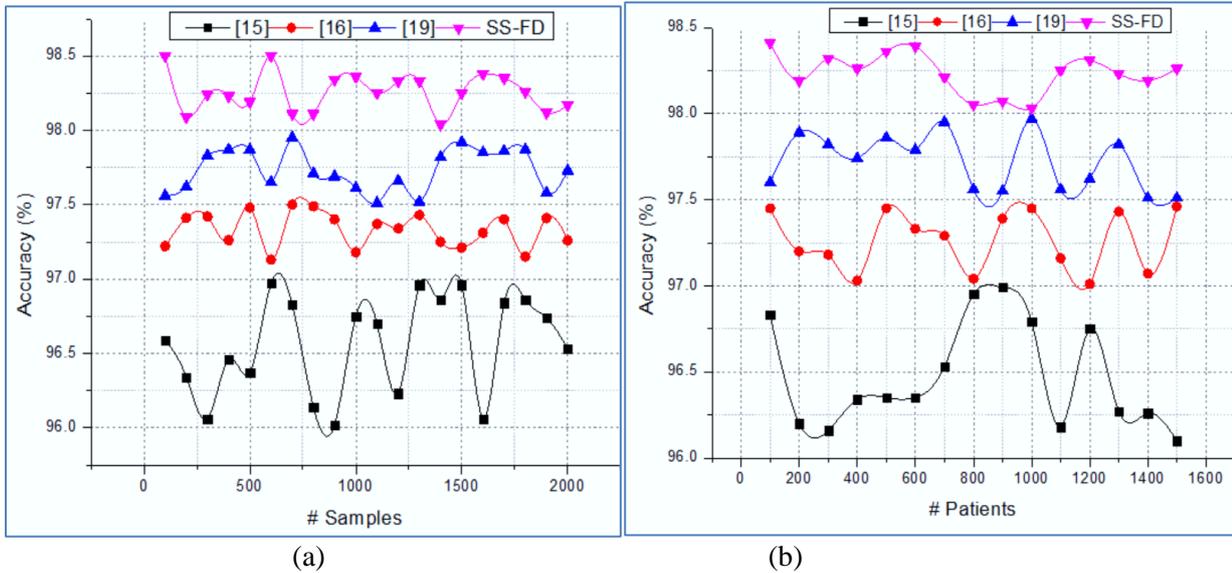


Figure 4. (a) Number of sample data (b) Number of Patients related Accuracy

Figure 4 illustrated that the accuracy of introduced SS-FD approach that is compared with the existing research works such as [18, 20, 23]. The introduced system uses the salp swarm optimization technique that resolve the parameter updating issues. Here, the network parameters are updated according to salp swarm food searching behavior. $(S_j^1 = Fit_j + c_1((S_{max} - S_{min})c_2 + S_{min}) / S_j^1 = Fit_j - c_1((S_{max} - S_{min})c_2 + S_{min}) S_j^i = \frac{1}{2}(S_j^i + S_j^{i-1}))$. More ever, the deep network hidden node functionalities are updated using this swarm optimization process which reduce the difficulties of classification and improve the overall recognition rate. Not only this, the system minimizes the overall categorization rate which is illustrated in figure 5.

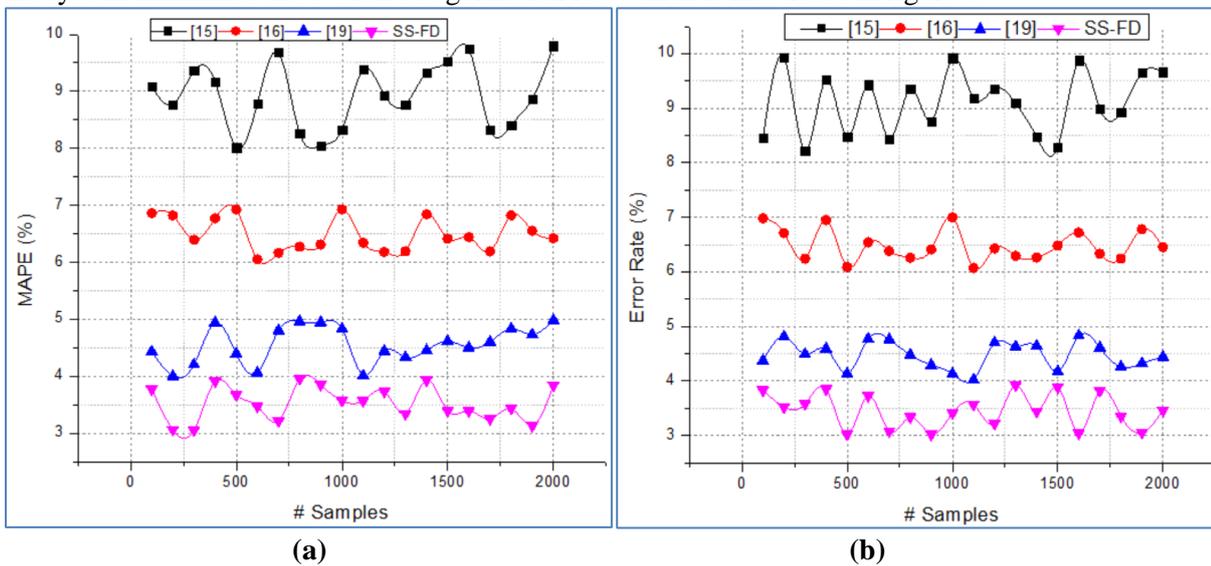


Figure 5. (a) MAPE (b) Error Rate

Figure 5 illustrated that the error rate value of while examining the IoMT data using SS-FD approach. The method consumes minimum 3% of error rate compared to the existing research work [19, 20, 23]. The effective deep learning process $(\varphi(w_{hh}h_{t-d^1} + w_{hh^{length-1}}h_{hh^{length-1}} + b^{length}) > -I)$ and $S_j^i = \frac{1}{2}(S_j^i + S_j^{i-1})$ based parameter updating process helps to reduce the deviations. The learning process generates the abnormal data patterns that used to identify the new testing data patterns successfully. The minimum error value directly indicates that overall effectiveness of the system which is illustrated in Table 1.

Table 1. Effectiveness of SS-FD System

Methods	MAPE (%)	MSE (%)	FitRate (%)	Accuray (%)
[19]	8.95	9.04	95.54	96.58
[20]	6.59	6.51	96.46	97.73
[23]	4.31	4.49	97.42	98.78
SS-FD	3.4	3.56	98.60	99.17

Thus, the table 1 clearly states that introduced salp swarm optimized fuzzy deep neural network (SS-FD) approach recognize the IoMT medical data status with 99.17% of accuracy with minimum error rate 3.4%. The obtained results are more effective compared to the other existing approaches.

On the other hand, compact microstrip filters and antennas [25-26], can be utilized to enhance portability of IoMT system with an efficient medical wireless communication. This proposed IoMT can be adopted as future work to develop intelligent wireless communication along with Node-MCU [27], Arduino [28], cloud computing, and e- government with effective performance [29] .

5. Conclusion

Thus, the paper analyzing the salp swarm optimized fuzzy deep neural network (SS-FD) approach based IoMT remote patient monitoring process. This system uses the BPCO dataset based GANs for IoMT information to examine the introduced system. The collected data is classified by determining the cluster center which is performed according to K-means clustering algorithm. the During this process, system computes the fuzzy membership grade value; this value used to identify the low importance of the data. The minimum value is eliminated from input dataset and new dataset has been formed. From that, cluster center is identified for every input attribute which is fed as input to the deep learning network. Here, the feature patterns are derived using deep learning process. Then the salp fish behavior is examined and the network parameters are updated for reducing the computation complexity. The discussed system implemented using MATLAB tool and the system recognize the normal and emergency data from IoMT with 99.17% accuracy. In future, optimized techniques are incorporated in feature extraction and selection stage to improve the overall accuracy of the remote patient monitoring process.

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