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Cloud-Centric IoT based Decision Support System for Gestational Diabetes Mellitus using Optimal Support Vector Machine

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Abstract: Recently, the healthcare applications using Internet of Things (IoT) provide diverse functionalities and real time services. Introducing IoT devices in healthcare leads to the generation of massive amount of medical data and is investigated on the cloud rather than depending on available memory and processing capability of handheld devices. In this way, an IoT and cloud based decision support system is developed to diagnose the presence of disease. In this paper, we develop a particle swarm optimization (PSO) based support vector machine (SVM) model for medical data classification. The presented PSO based SVM classification method has the ability to optimize the SVM parameters to enhance the classification accuracy.This paper develops an efficient system model is developed for gestational Type II diabetes mellitus (GDM) diseases and the relevant data is used from UCI Repository as well as from the use of medical sensor from the patients. The validation of the proposed method takes place using the benchmark dataset and a detailed comparative analysis is also made with the existing models. The experimental values ensure that the proposed method performs well and accurately predicts the presence of the disease.

Keywords: IoT; Cloud; Machine learning; Decision Support System; e-Healthcare

I. INTRODUCTION

Internet of Things (IoT) defines the way to design and mould the Internet-connected Things via computer networks. IoT indicates that rather than using few computation devices like laptop, tablets and mobile phones, it is effective to use a high number of low power components like wrist band, watched, umbrella and refrigerator. The regularly used objects like air freshener and home appliances are intellectually programmed using microprocessors, sensors and provides outcome in real time. So, the interlinked devices or things have the capability to process and communicate data apart from the requirements of common devices like average lamp and umbrella that connects the building using network communication. The delighted IoT objects hold some technical reasoning capability to perform the allocated process with no requirement of a name and personality.

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IoT and Cloud Computing are advantageous once they are combined to one another. The monitoring module integrates the technologies to monitor the patient data efficiently even at remote areas which is helpful for doctors. The IoT is generally supported by Cloud platform to improve the results interms of effective resource usage, memory, energy and processing ability. In addition, cloud computing gets benefit from IoT to enhance the scope to manage with the present scenario and to offer various new services in active and collaborativeway. These IoT based Cloud models can be elaborated to develop and apply new services in the smart surroundings. The integration of cloud and IoT based online applications performs well compared to traditional oneswith respect to effectiveness. The rising applications likehealthcare, military and e-commerce applications make use of these integrations. Specifically, the IoT based Cloud model will be helpful to provide effective services to the healthcare applicationto monitor and access the patient details from distantareas. The IoT based healthcare applications assist to gather the required details like often modifications in medical data and it update the severity of the healthcare detailsin predefined time duration. However, the IoT devices and healthcare related sensor readings are effectively used to diagnose the diseases at proper time. Machine learning algorithms play a vital part on the decision making procedurewhile managingmassive quantity of data. The procedure of implementing data investigation methods to the particular domains involves the use of different datatypes such as velocity, variety and volume. The traditional methods used to analyze data are feature selection, classification and clustering methods which employ efficient techniques. Data can be created from different causes with specific datatypes and it is essential to develop methods which have the capability to manage various characteristics of data. In IoT, massive amount of resources generates the required data with no issues like scalable, velocity and to find the optimal data model. In this study, we have generated a massive amount of big data using IoT devices as input data. Then, the data are saved in the cloud platform in a secured manner and accessed by the use of healthcare applications. In this context, we employ a new algorithm which undergo training process and test the input data to predict two classes 'Normal' and the 'Disease Affected'. Based on these ideas, several research works has been carried out and found in the literature [1–5]. [5] developed a novel method to monitor and diagnose disease by the use of IoT and cloud.

This method is solely employed to identify the severity levels of the diseases. introduced a new framework using cloud and IoTto diagnose and monitor the level of the disease. They have used a systematic medical data from student aspects has been created by the use of UCI Repository and some sensors in the healthcare domain to identify different diseases among students. The results are determined by the use of different evaluation parameters like F-measure, specificity and sensitivity. At the end, it is ensured that the present model is efficient over the available ones interms of prediction accuracy. [6] presented an efficient energy model solely developed for the cloud based IoT platform. This energy model has been employed to analyze the video stream generated by the cameras mounted in vehicles. These models have been validated on real-time test bed for particular applications and perform the simulations by the use of popular simulation tool to analyze the improvements with IoT devices. A survey on Cloud and IoT approaches with the security issues are made in [7]. In addition, the contributions made by the cloud and IoT has also mentioned. It is also demonstrated the process of the cloud in IoT. Tao et al. [8] developed an efficient multi-layer cloud model to enable the efficiency and continuous interaction over the heterogeneous services offered by different vendors in smart homes. Furthermore, ontology has also been employed to solve the challenges present in the heterogeneity. [9] introduced new and scalable 3-tier architecture to store massive quantity of sensor data. The 3-tiers involve data collection, storage and prediction. At the end, an investigation is made using the ROC curve to identify the symptoms to get heart diseases. [10] introduced a new method particularly developed for cloud to manage the real time IoT data and the scientific data. [11] developed an effective Cyber Physical System model to support multiple sites and product manufacturing. A new smart application is introduced in cars which make use of the cloud and deep learning concepts [12]. It identifies the objects from the saved videos, decides and selects the specific portion of videos that has to be saved in the cloud to preserve the local memory. [13] intended to develop a cloud based parallel ML approach for machinery prognostics. Random forest (RF) classifier is used to predict the tool wear in dry milling operation. In addition, a parallel RF technique is also designed utilizing MapReduce and it also implemented on the Amazon Cloud. The simulation outcomes ensured that the RF classification method precisely predict the presence of diseases. [14] performs the case study to monitor the voice pathology of people utilizing cloud and IoT. An efficient new local binary pattern based identification model is also developed to detect the voice pathology in the monitoring model and this model is effective over the available methods interms of accuracy.

Gelogo et al. [15] discussed the fundamentals of IoT with its appropriate applications in the future directions of healthcare. An efficient healthcare model is developed that is helpful for the IoT dependent u-healthcare services. In [3], the patient data can be gathered and observed by the use of compact and cheap sensor network. In addition, they have assumed the security needs to design the efficient healthcare model. [16] discussed the direction of the architecturecomponents and the future scope of IoT technology. [17] presented an online monitoring model known as Healthcare Industrial IoT to observe the health of the patients. This model has the capability to analyze the patient's medical data to prevent from the occurrence of death. In addition, it gathers the related medical data needed for investigation purposes by the use of sensing elements.

At the same time, the clinical errors and different identity thefts are also prevented by the use of security approaches. A discussion of different approaches exist to develop m-healthcare applications are made. [18] introduced a people centric sensing model for elder people and people with disabilities. The major intention is to offer a service based response case during the emergency situations. An intellectual and collaborative security model is developed in [2] to minimize the risk factors in the IoT based healthcare platform. Additionally,a detailed investigation is made with the advancements in the IoT healthcare domain. Sethukkarasi et al. [1] developed an intelligent diseasediagnosis model known as neuro-fuzzy temporal knowledge representation approach to predict and diagnose different deadly diseases. Another fuzzy based classification method is presented in Ganapathy et al. [19]. Kakria et al. [20] developed a new online medical monitoring model to monitor the heart patients in remote areas by the use of smartphones as well as wearable sensors. [21] devise an efficient monitoring method to offer emergency situationsto monitor servicesutilizing context of motion to track the patients.

In this study, we aim to develop an IoT and Cloud based diagnosis and disease prediction model to identify the presence of Gestational diabetes mellitus (GDM). System architecture has been developed to carry out this work. Furthermore, PSO based SVM classification method is also developed, where PSO algorithms has been presented to optimize the SVM parameters for enhancing the classification accuracy. For experimental purposes, GDM data is accessed from the UCI repository and the medical sensors to predict the patients affected by GDM.

The remaining part of the part is arranged as follows: The presented classification model with its system architecture is explained in Section 2. The validation of the proposed model takes place in Section 3. And, the conclusions are made in the last section.

II. PROPOSED METHOD

1.1. System model

The system modelof the proposed method is illustrated in Fig. 1. It comprises of various elements like wearable which generates the real time medical data, benchmark dataset, healthcare data, Cloud, Diagnosis model, Knowledge base and alert system. The wearable are employed to gather the healthcare data from remote places. The direct readings from the patients are gathered through the wearable connected via IoT devices from the human body. A benchmark GDM dataset from UCI Repository is also used. The medical dataset holds the patients details gathered from healthcare centers. Then, these dataset are saved in the cloud database.

Next, the diagnosing model has the capability to predict the disease using the PSO based SVM classifier. This module involves both training and testing phases. Once the training process is carried out, then testing phase will begin. At the end, the medical data is classified into normal and disease affected.

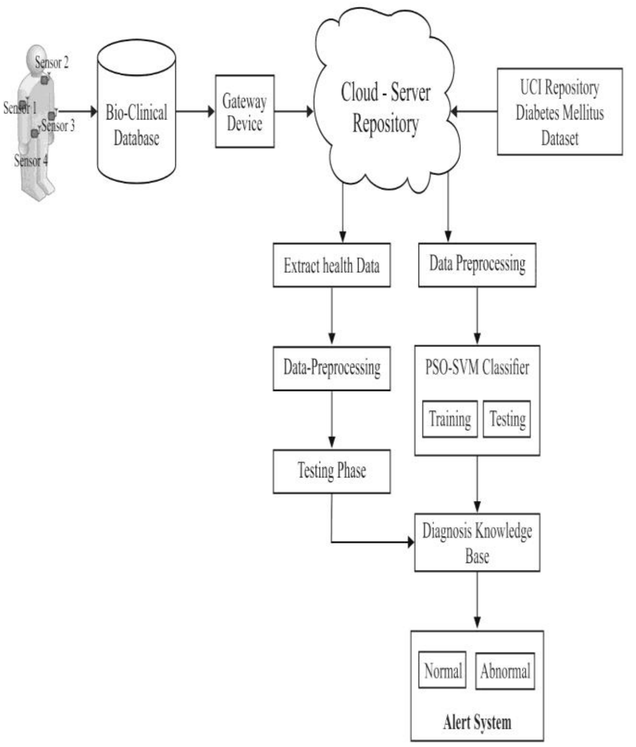

Fig. 1. System Architecture

The IoT and Cloud based healthcare model comprises of two stages. In the first stage, required medical data is gathered from the IoT devices, UCI Repository and Medical details. In the second stage, diagnosis and classification process takes place. During the data gathering process, the patient details will be extracted by wearable's which are placed on the human body to collect some specific information seamlessly. Generally, these devices will examine the healthcare data with the normal one. When the personal healthcare data exceeds the standard values in crucial variables, the device will alert the physician by transmitting the measured values of the patients. At the same time, UCI repository dataset values are also employed to map the present data that has been generated by the IoT devices.

1.2.Support Vector Machine (SVM)

SVM is introduced by Vapnik in the year of 1995, and it has become one of the importance classifier. An important benefit of SVM is the features of global optimization andhigh generalization ability. In addition, it eliminates overfitting issues and provides a sparse solution when comparing with traditional approaches like artificial neural network (ANN).

SVM classifier can be formulated as follows: For a training set $T = \{(x_1, y_1), .., (x_n, y_n)\}$, with $x_i \in \mathbb{R}^m$ *and* $y_i \in \{\pm 1\}$ considering n examples from m real time variables, learning a hyperplane $< w, x > +b = 0$, with $w \in \mathbb{R}^m$ *and* $b \in \mathbb{R}$.For a linear classification problem, it is needed to separate the collection of training data, $(x_i, y_i), i = 1,2, \ldots, m$ where m is the number of given observations, where $x_i \in R_n$are feature vectors and $y_i \in (-1, +1)$are label vectors. A binary classification issue can be treated as an optimization problem and is defined in Eq. (1):

$$Min = \frac{1}{2}\|w\|_2^2 + C\sum_{i=1}^{m}\xi_i \qquad (1)$$

Subject to $y_i < w, x > +b \geq 1 - \xi_i, \xi_i \geq 0, i = 1,2, .., m$

Where C is the regularization parameter and ξ_i is the penalizing relaxation parameter. The above equation indicates that

$$w \times \phi(x_i) + b \geq +1 \qquad \text{when } y_i = +1$$
$$w \times \phi(x_i) + b \geq -1 \qquad \text{when } y_i = -1 \quad (2)$$

The non-linear classification model in the input space is represented as

$$f(x) = sign(\textstyle\sum_{i=1}^{m}\alpha_i^* \times y_i \times K(x_i, y_i) + b^*) \qquad (3)$$

For attaining optimal results, few of the SVM parameters has to be chosen correctly, includes regularization parameter C and the kernel parameter γ.

1.3. Particle Swarm Optimization (PSO) algorithm

In this paper, we employ PSO algorithm for the optimization of these two variables. PSO algorithm is stimulated from the social and cooperative nature of different species to satisfy the requirements in the search space. It is based on the personal experience $Pbest$, total experience $Gbest$, and the current motion of particles to make decision about their upcoming positions in the search space.In addition, the experiences gets multiplied by two factors c_1 and c_2 with two arbitrarily created numbers r_1 and r_2 lies between [0,1]; whereas, the current motion is accelerated by w. In a mathematical way, the updated positions of every particle in the search space can be defined as follows. The initial population (swarm) of size N and dimension D is indicated as $X = [X_1, X_2, .., X_N]^T$ where T is the transpose operator. Every individual particle $X_P(p = 1,2, .., N)$ is represented by $X_P = [X_{p,1}, X_{p,2}, .., X_{p,D}]^T$. Next, the initial V is represented as $[V_1, V_2, V_3]^T$. Hence, the V of every particle $X_P(p = 1,2, .., N)$ is represented as $V_P = [V_{p,1}, V_{p,2}, .., V_{p,D}]$. The index p ranges between1 to N whereas the index q varies from 1 to D.

$$V_{p.q}^{k+1} = w \times V_{p.q}^{k} + c_1 r_1 (Pbest_{p.q}^{k} - X_{p.q}^{k}) + c_2 r_2 (Gbest_q^k - X_{p.q}^{k}) \qquad (4)$$

$$X_{p.q}^{k+1} = X_{p.q}^{k} + V_{p.q}^{k+1} \qquad (5)$$

$Pbest_{p.q}^{k}$ is the personal best of the q^{th} component of p^{th} individual, whereas $Gbest_q^k$ is the q^{th} component of the best individual of population up to iteration k. Fig. 2 represents the searching process of PSO algorithm in a multi-dimensional search space. The $Pbest$ and $Gbest$ of every particle gets updated as follows. At the round number k,

$$\text{When } f(X_p^{k+1}) < f\left(Pbest_p^k\right) \ then\ Pbest_p^{k+1} = X_p^{k+1}\ else\ Pbest_p^{k+1} = Pbest_p$$
$$\text{When } f(X_p^{k+1}) < f\left(Gbest_p^k\right) \ then\ Gbest^k = X_p^{k+1}\ else\ Gbest_p^{k+1} = Gbest^k \quad (6)$$

Where $f(X)$ is the objective function subjected to minimization. The updating process will be iterated till the termination criterion is satisfied like fixed iteration count is reached. Once the process is stopped, $Gbest^k$ and $(Gbest^k)$are provided as the solution of PSO algorithm.

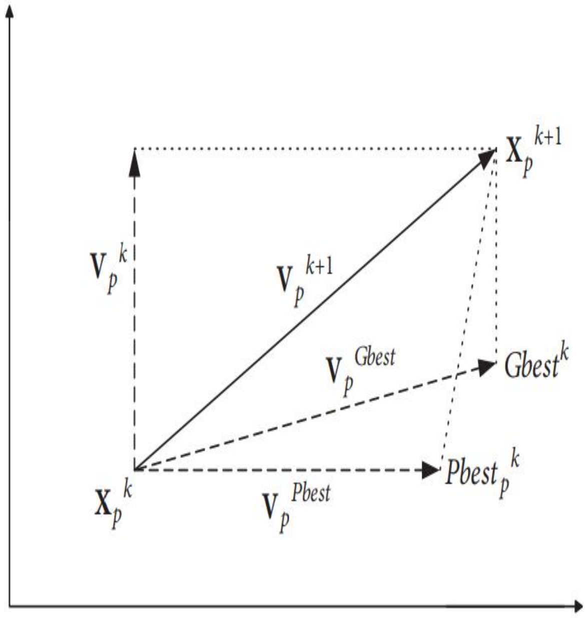

Fig. 2. PSO searching mechanism

1.4. Optimal SVM parameter tuning using PSO algorithm

The effectiveness of the SVM classifier is liable to γ and C, hence, these two parameters should be chosen properly to enhance the classification performance of SVM. Here, PSO algorithm is applied to choose the SVM parameters. The results are computed based on the classification accuracy on unknown testing data. During the learning process, the PSO based encoding SVM approach undergoes training process to reduce the error rate. During the enhancement of training error, the parameters γ and $C$are controlled using PSO algorithm. These controlled parameters with reduced error are considered as the appropriate variables. Consequently, the optimumparameters (C and γ) have to be attained. When the optimal parameters of the SVM are found, it is employed to retrain the SVM model. During the training process, SVM is used to predict new samples in the testing stage. The testing stage gives the input to the trained SVM classification model to detect the presence of disease. The process involved in the PSO based SVM classifier is listed as follows.

- Read the entire data and initialize $w, c_1\ and\ c_2$ parameters.
- Initialization of X and V for every particle.
- Initialization of SVM parameters.
- Develop SVM utilizing train data and initialize the P of every particle.
- Determine the fitness of every particle $F_p^k = f\left(X_p^k\right), \forall p$ and identify the best particle index b.
- Choose $Pbest_p^k = X_b^k$
- Initialize iteration count $k = 1$
- $w = wmax - (wmax - wmin) \times ite / \max ite$
- Updates V and P of every particle
- Estimate updated fitness of every particle $F_p^{k+1} = f(X_p^{k+1})\ \forall p$ and identify the best particle index b_1.
- Update Pbest$\forall p$
  When $F_p^{k+1} < F_p^k$ then $Pbest_p^{k+1} = X_p^{k+1}$; else $Pbest_p^{k+1} = Pbest_p^k$
- Update Gbest
  When $F_{b_1}^{k+1} < F_b^k$ then $Gbest^{k+1} = Pbest_{b_1}^{k+1}$ and set $b = b_1$; else $Gbest_p^{k+1} < Gbest^k$
- When k max itethen $k = k + 1$ and jump to step 6 else jump to step 14
- Once the optimal results are attained, display the output as $Gbest^k$
- Train the SVM with optimal parameters and find the unknown samples from test dataset

The overall processes are illustrated in Fig. 3.

III. PERFORMANCE VALIDATION

The proposed model has been simulated in RapidMiner and Amazon Cloud. In this paper, data classification is a main process which classifies the data into positive and negative. The set of experimental analysis have been carried out utilizing medical data and also to validate the proposed method by the use of accuracy, sensitivity and specificity. In addition, diverse classifiers such as fuzzy neural classifier (FNC), Logistic Regression (LR), RF and radial basis function (RBF) are used for comparison purposes. Furthermore, this paper focuses on the use of GDM dataset. For experimentation, 10-fold cross validation process is utilized to finalize the results of the proposed method.

1.5. Dataset used

The proposed method is tested against the benchmark GDM dataset from UCI repository. The GDM dataset comprises of a total of 768 instances with 8 attributes. The instances falls into two classes: positive and negative. Among the total of 768 instances, 500 instances comes under negative class (Normal) and 268 instances comes under positive class (Disease affected). The dataset description is provided in Table 1 and attributed used in the dataset are given in Table 2. The attributes used are number of times pregnant, glucose level, blood pressure level, and so on. Every attribute with its measurement unit for each attribute is given in Table 2.

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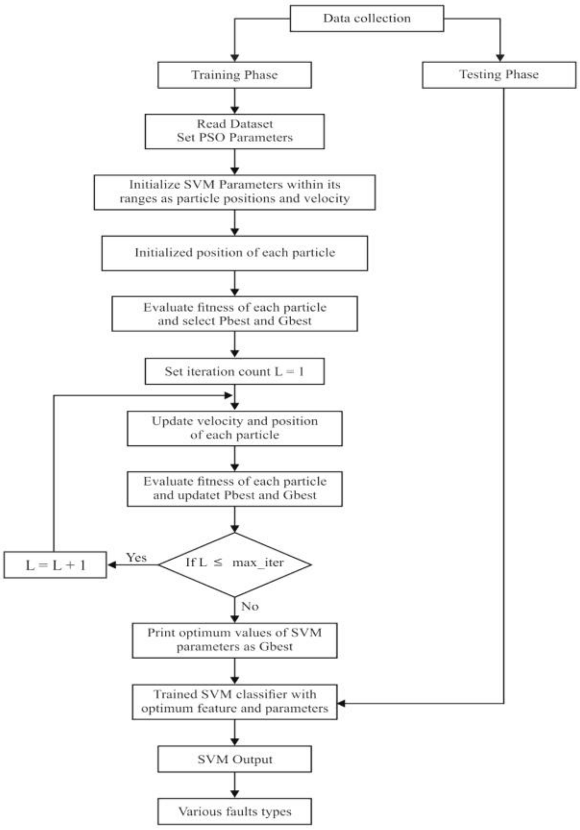

Fig. 3.Overall process of the PSO based SVM classifier

Table 1 Dataset used

Dataset	Source	# of instances	# of attributes	# of class	Negative/Positive
GDM	UCI	768	8	2	500/268

Table 2 Attributes in dataset

Dataset	Attribute Description	Measurement Unit
GDM	No. of times pregnant	Numeric
	Plasma glucose Level	Numeric
	Diastolic blood pressure	mm Hg
	Triceps skin fold thickness	mm
	2-Hour serum insulin	mu U/ml
	BMI	kg/m^2
	Diabetes pedigree function	Real
	Age	Years

1.6. Result analysis

To evaluate the results of the presented PSO based SVM classifier, the confusion matrix is initially determined. Once the values in the confusion matrix are obtained, different classification metrics are needed to validate the results and they are false positive rate (FPR), false negative rate (FNR), sensitivity, specificity, accuracy, F-score, false discovery rate (FDR), false omission rate (FOR) and error rate.Before explaining the definition of evaluation parameters, the fundamental concepts of confusion matrix should be defined. Confusion matrix is an important part in the classification algorithm. It is generally a 2x2 matrix and hold four elements namely true positive (TP), true negative (TN), false positive (FP) and false negative (FN). By the use of the four elements, the classification measures can be determined and the formulas are given in Table 3.

The obtained confusion matrix for the applied dataset is provided in Table 4. The 4 elements in the confusion matrix obtained by various classifiers are shown in Table 4. In the confusion matrix, the value of TP and TN should be as high as possible to indicate better classifier results.

Table 3 Evaluation parameters

Metric	Description	Formula
FPR	Wrongly identifies the presence of a condition	$\mathrm{FPR} = \mathrm{FP}/\mathrm{FP} + \mathrm{TN}$
FNR	Wrongly identifies the no presence of a condition	$\mathrm{FNR} = \mathrm{FN}/\mathrm{FN} + \mathrm{TN}$
Sensitivity	Correctly identifies the presence of a condition	$\mathrm{TP}/(\mathrm{TP} + \mathrm{FN})$
Specificity	Correctly identifies the no presence of a condition	$\mathrm{TN}/(\mathrm{TN} + \mathrm{FP})$
Accuracy	Measure of appropriate classification of dataset	$(\mathrm{TP} + \mathrm{TN})/(\mathrm{TP} + \mathrm{TN} + \mathrm{FP} + \mathrm{FN}$
F-score	Measure of test's accuracy	$2\mathrm{TP}/(2\mathrm{TP} + \mathrm{FP} + \mathrm{TN})$
Kappa value	Measure of agreement between expert's opinion and data mining technique	$\frac{\mathrm{Obs.Agreement} - \mathrm{Exp.Agreement}}{100 - \mathrm{Exp.Agreement}}$

where, Observed Agreement = %(Overall Accuracy)

Expected Agreement = (%(TP+FP)* %(TP+FN)) + (%(FN+TN)* %(FP+TN))

From the Table 4, it is clear that the PSO based SVM method successfully classifies all the 500 negative instances to negative. Similarly, among the 268 positive instances, the proposed method successfully classifies 200 instances. Next, the RF classifies 417 negative instances correctly out of 500 instances and 158 positive instances out of 268 instances. Likewise, the RBF classifies 434 negative instances correctly out of 500 instances and 145 positive instances out of 268 instances. In line with, the LR classifies 440 negative instances and 153 positive instances correctly. But, the FNC successfully classifies 492 negative instances and 238 positive instances. From these values, it is obviously clear that the FNC classifies more number of instances correctly compared to RF, RBF and LR. Though the FNC is found to be better than existing methods, it fails to show betterperformance over the presented method. Here, the RF classifier shows worse results by classifying only less number of instances in overall, the proposed PSO based SVM classifier successfully classifies more number of instances correctly. Table 4 also shows that the presented method attains a maximum kappa value of 88.74 which implies the effective classification results of the applied dataset.

Table 4 Confusion Matrix of different classifiers on GDM Dataset

Experts	Proposed			FNC			LR			RBF Network			Random Forest		
	Negative	Positive	Total	Negative	Positive	Total	Negative	Positive	Total	Negative	Positive	Total	Negative	Positive	Total
Negative	500	0	500	492	8	500	440	60	500	434	66	500	417	83	500
Positive	38	230	268	38	230	268	115	153	268	123	145	268	110	158	268
Total	538	230	768	530	238	768	555	213	768	557	211	768	527	241	768
Chance Agreement	56.06			55.74			56.72			56.80			55.62		
Kappa	88.74			86.46			47.34			43.02			43.37		

Table 5 Performance Evaluation of different classifiers on GDM Dataset

Dataset	Method	FPR	FNR	Sens.	Spec.	Accuracy	F-score	FDR	FOR	Error rate
Diabetes Mellitus	**Proposed**	0	07.06	92.94	100	95.05	96.34	0	14.18	0.05
	FNC	03.36	07.17	92.83	96.64	94.01	95.53	01.60	14.18	0.06
	Logistic Regression	28.16	20.72	79.27	71.83	77.21	83.41	12.00	42.91	0.22
	RBF Network	31.27	22.08	77.92	68.72	75.39	82.11	13.20	45.89	0.25
	Random Forest	34.44	20.87	79.13	65.56	74.87	81.21	16.60	41.04	0.25

An investigation of the classification results of different methods are made and are compared in Table 5. For the applied GDM dataset, the proposed PSO based SVM attains better performance with a least FPR and FNR values of 0 and 7.06 respectively. On comparing the applied methods, RF shows poor results with a highest FPR and FNR of 34.44 and 20.87 respectively. In line with, RBF also fails to effective results and attaining higher FPR and FNR values of 31.27 and 22.08 respectively. At the same time, LR tries to show effective classification and depicted lower FPR and FNR values compared to RBF and RF with the FNR and FPR value of 28.16 and 7.17 respectively. But, it exhibited its ineffectiveness over the FNC and proposed method. Though FNC attains lower FPR and FNR values of 3.36 and 7.17 respectively, it fails to show superior performance over the proposed method. While comparing the various methods, the proposed method produces better results than other classifiers with the lowest FPR and FNR values of 0 and 7.06 respectively. On the basis of accuracy, the proposed method shows maximum classification accuracy of 95.05 whereas the RF achieves minimum classification accuracy of 74.87. It is shown that RBF classifier does not attain enhanced classification and attained the lowest accuracy of 74 whereas the LR classifier obtained an accuracy of 77.21. Similarly, the FNC classifier exhibited better classifier results with an accuracy of 94.01 which is superiorto compared models except the PSO based SVM method. On comparing the classifiers in terms of sensitivity and specificity, the results revealed that the RFclassifier shows worse performance with the values of 79.13 and 65.56 respectively. Similarly, the FNC shows better performance with the higher sensitivity and specificity of 98.83 and 96.64 respectively. At the same time, FNC classifier tries to handle well with the compared methods. But, it shows its inefficiency over the compared methods. Interestingly, proposed method shows highest predictive results with the highest sensitivity and specificity values of 92.94 and 100 respectively. Fig. 4 shows the comparison of classification performance of diverse classifiers on the employed GDM dataset interms of FPR, FNR, FDR and FOR. All the values of these parameters should be as low as possible to represent better classification performance. From this figure, it is clear that the proposed method shows minimum values over the compared methods. Likewise, it is noted that the proposed and FNC methods shows competitive performance interms of FNR and FOR. But, the proposed method still achieves better performance with the lowest values of the FPR, FNR, FDR and FOR.

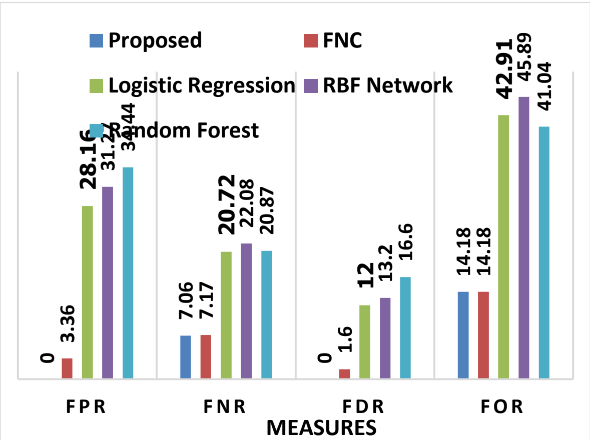

Fig. 4. Comparative results of different classifiers interms of FPR, FNR, FDR and FOR

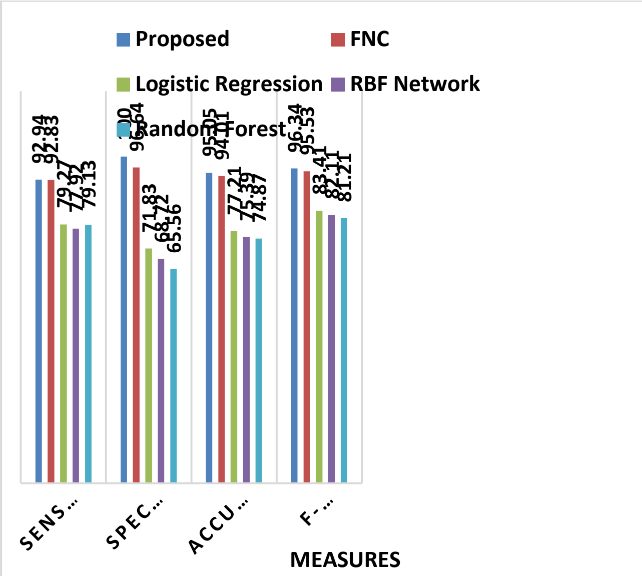

Fig. 5. Comparative results of different classifiers interms of different measures

Fig. 5 depicts the performance of different classifiers on the employed GDM dataset interms of sensitivity, specificity, accuracy and F-score. The values of these measures should be as high as possible to indicate better classification performance. From this figure, it is obvious that the proposed method shows maximum values over the compared methods. At the same time, it is noted that the proposed and FNC methods shows competitive performance interms of sensitivity. But, the proposed method still achieves better performance with the highest sensitivity value of 92.94. In the same way, the proposed method shows superior results over the compared methods.

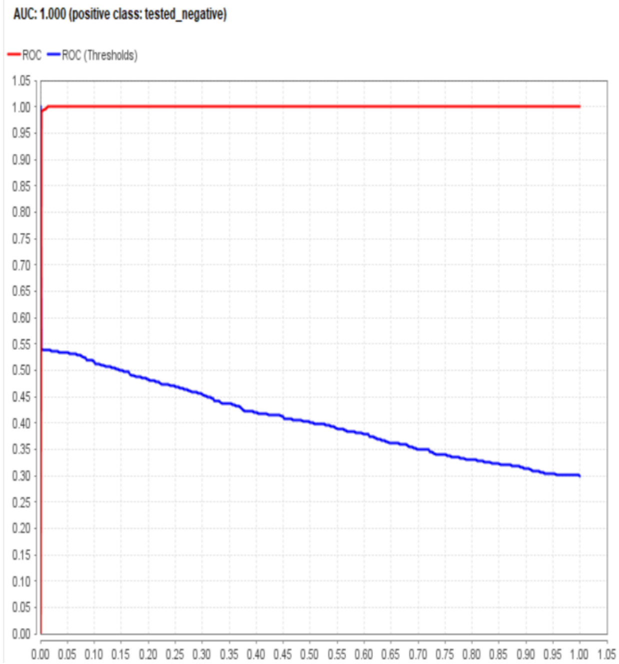

Fig. 6.AUC curve obtained by proposed method

Area Under Region of Curve (AUC) provides an aggregate measure of performance across all possible classification thresholds. A simple way to interpret AUC is the probability of a model ranks a random positive example highly than a random negative instance. Generally, the value of AUC ranges between 0 and 1. From the Fig. 6, it is clear that the proposed method achieves AUC of exactly 1 which implies the excellent classification performance.On observing the above figures and tables, it is clear that the proposed method achieves better classification performance with minimal error rate.

IV. CONCLUSION

In this paper, we have developed a novel IoT and Cloud based disease diagnosis model for GDM disease. The proposed model makes use of a benchmark GDM dataset and also the relevant medical data using IoT sensors. In this work, we have introduces a new PSO based SVM classifier for the identification of diseases. A set of experimental analysis has been made using the benchmark GDM dataset and a comparativeanalysis is also made with different classifiers. The experimental values depicted that the proposed method attains a maximum classification accuracy of 95.05 with the minimal error rate of 0.05. As a part of future scope, the presented method can be implemented in real time hospitals to assist physicians to make decisions quickly.

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