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Internet of Things based Type 2 Diabetes Prediction using Enhanced Feed Forward Neural Network with Particle Swarm Optimization

S. Arulananda Jothi *[1], J.Abdul Samath [2]

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Abstract: The Internet of Things (IoT) is an emerging network that enables everyday objects to connect to the web and exchange and collect data. The IoT is crucial in healthcare because it allows for constant patient monitoring and informed decision making. Diabetic complications now impact a sizable fraction of the population. The elderly are disproportionately affected by type 2 diabetes, which is also the most prevalent form of the illness and which is associated with a wide range of serious health issues such as cardiovascular disease, renal failure, blindness, stroke, and even death. That's why knowing the patient's prognosis or receiving a diagnosis quickly may help. Improving the prediction model's accuracy takes time and work, but one of the biggest challenges is figuring out how to properly analyze the data to get the right conclusion. Many models may be employed for analysis; for instance, many Neural Network models have been used for clinical diagnosis. The problem is that these models haven't improved much, in terms of either accuracy or precision, whether in the training or testing stages of sickness diagnosis. This study offers an Enhanced Feed forwarded Neural Network (EFNN) that employs a chaotic-based particle swarm optimization model (EFNNCPSO) to analyze IoT-based datasets. The proposed method has the potential to improve the accuracy of predicting Type 2 diabetes in an IoT environment. The suggested network is able to learn all of the features in the dataset and performs efficient calculations. Finally, analogous models to the one proposed are compared. The proposed EFNNCPSO has a higher accuracy than state-of-the-art methods (99.9%).

Keywords: *Internet of Things, Type 2 diabetes, Enhanced feed forwarded Neural Network, Chaotic-based particle swarm optimization model*

1. Introduction

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The term "Internet of Things" (IoT) has recently gained traction in the IT industry, as was discussed before. Connecting sensors, microcontrollers, and transceivers to the internet is an example of this approach [1]. This improves the quality of communication and facilitates user interaction. There are many elements of people's everyday lives in which the Internet of Things (IoT) is now playing a significant role. As a result, there has been a rise in the number of IoT-based installations, in which every object is linked to the Internet through a wide range of sensor equipment's whose specifications vary from application to application [2]. Furthermore, IoT applications are growing daily in the healthcare sector, necessitating IoT to reduce costs associated with the maintenance of a wide range of convectional equipment [3].

In addition to being quite common, diabetes mellitus also attracts a lot of media attention [4]. Type 2 diabetes is a long-term metabolic illness that affects the pancreas. Because of this condition, the pancreas is unable to generate enough insulin, blood sugar levels rise, or the insulin that is produced is not used well, leading to diabetes [5]. If left untreated, diabetes may be lethal.

A diabetic patient with severe diabetes may have substantial medical consequences, some of which may go undetected for quite some time. Heart disease, kidney disease, and vision loss are only some of the serious outcomes that might result [6]. It has also been shown that diabetes is linked to a variety of other health problems [7], including hypertension, obesity, inactivity, poor nutrition, advancing age, and a family history of the disease. Although type 1 and type 2 diabetes mellitus account for

[1] Department of Computer Science, Government Arts College, Udumalpet, Tamilnadu, INDIA
[2] Department of Computer Science, Chikkanna Government Arts College, Tiruppur, Tamilnadu, INDIA
** Corresponding Author Email: amalrajevr@gmail.com*

the vast majority of cases, a third form, gestational diabetes, does exist [8]. Type 1 diabetes is distinguished from type 2 diabetes by the pancreas's failure to generate enough insulin to keep glucose levels in the body steady [9]. The inability to properly use insulin is what separates type 2 diabetes from type 1 [10]. Some of the symptoms and signs that are unique to high glucose include increased appetite, thirst, and urination, as well as itching and fatigue [11]. It seems that the very old are at greater risk than younger persons for contracting these diseases. As a result, there is a pressing need to improve diabetes care and early detection of the disease in order to stave off a host of potentially fatal consequences.

As a result, many hospitals and other medical facilities have adopted the use of several Internet of Things (IoT) devices, all of which produce copious amounts of data on a regular basis. The right decision can't be put off any longer without first doing the proper evaluation of these recently obtained facts [12]. Prediction systems built on the Internet of Things have the potential to aid in the early detection and prevention of chronic diseases like type 2 diabetes. This is because they enable clinical staff to preserve accurate records of individual patients even when interrupted by humans, and because they enable clinical staff to make the right choice more quickly and with fewer errors [13]. Although these prediction systems have come a long way, they still have space for improvement and might benefit from the use of appropriate Machine Learning (ML) techniques. These methods provide a substantial contribution to the data collection for the research of type-2 diabetes. Supervised learning, semi-supervised learning, and unsupervised learning are the three main types of machine learning approaches [14, 15]. However, the author evaluates the technique identification in larger data sets and finds that these methods have a tendency to perform consistently by generating advantages connected to the accuracy and measurement [16]. This is because these techniques are designed specifically for predictive research.

To better track and predict the beginning of type 2 diabetes, the authors of this study are focusing on machine learning-oriented approaches and subsequent optimizations. As a result, the early diagnosis of such a significant illness and the right care of diabetic patients will prevent the disease from progressing into more serious health concerns and will lower the cost of medical treatment. Here is a rundown of all the work has accomplished as follows.

- Using the suggested Enhanced Feed forward Neural Network with Chaotic based Particle Swarm Optimization model (EFNNCPSO) to diagnose people with type-2 diabetes.
- To effectively include an Internet-of-Things-based dataset into the proposed approach for predicting cases of type-2 diabetes

The rest of the report is summarized as follows: Section 2 provides a literature overview of recent studies focusing on Internet of Things-based diabetes prediction. The suggested algorithms are discussed in detail in Section 3 of this article. Comparing the suggested technique against existing algorithms is the focus of Section 4. In Section 5, the final conclusion is reached.

2. Related Works

Several works are presented previously over IoT based diabetics prediction some of them can be summarized below, Type 2 diabetes (T2D) patients were sorted into several groups using machine learning methods [17]. The diabetic patient's records came from the Prima Indian Dataset, which was deposited in the Kaggle Machine Learning competition's data repository. Machine learning-based classification and feature selection methods were used to organize the data and extract the characteristics of interest. The results were analyzed by contrasting them with one another using many different performance criteria. A centralized system was used to validate roughly 35 different machine learning methods, with and without a feature selection procedure, for the purpose of predicting type 2 diabetes [18]. Two methods were used to do this: with and without a feature selection procedure. Three different diabetes datasets and nine different feature selection algorithms were employed during validation. Several more metrics were used for cross-comparisons. The authors [19] used real-world data in their analysis of the machine learning method for predicting Type 2 Diabetes (T2DM). Eight popular machine learning techniques were employed to predict diabetes and to discover additional factors, such as latent characteristics of patients, attributes of patients, and socio-demographic data.

The use of artificial intelligence was mentioned as one of several technologies that may be housed in the proposed framework [20]. Early diagnosis of diabetes is crucial since it may considerably lessen the severity of the disease's effects on an individual's career, social, and personal life. The suggested method employs supervised machine learning for both classification and feature selection. The prediction rate was considerably enhanced once the Weighted Voting LRRFs ML strategy was established.

A method for calculating the diabetes rate in the general population was given in [21]. Machine learning algorithms were used to make predictions of diabetes, and 952 participants' answers to 18 questions about their families, health, and lifestyles were used to conduct the experiment. Using a technique called machine learning, [22] created a framework to forecast T2D cases in Korea during the next 12 months. Using this method, the disease may be detected many years in advance. The information required to build the dataset was housed in the digital repository from 2013 to 2018. Researchers in a recent research [23] used a hybrid of the decision tree method and logistic regression to estimate the number of Indian women who suffer from type 2 diabetes. With an error rate of around 21.74 percent, the method achieves an accuracy of about 78.26 percent. While [24] doesn't conduct any experiments of its own, it does highlight the wide variety of machine learning methods that have been employed in the past to make T2DM predictions. Accuracy attained across all ML approaches was noted, along with an evaluation of the various types of data acquired by each technique.

3. Proposed Work

Below, we describe in further depth how the proposed model for predicting T2DM works. Extensive details on the datasets used and the prediction and feature extraction techniques used are provided. IoT-based prediction of Type 2 diabetes illness utilizing a Feed-forward Neural Network and a Chaotic-based Particle Swarm Optimization algorithm is shown as a technique diagram in Fig. 1. Data collection, feature selection, and illness prediction are the three stages shown in the methodology diagram presented above. Similar to what was suggested for EFNNAO, the proposed approach of EFNNCPSO consists of three stages. To get to the innovative element of the work - the optimization bypass the first three stages. In this study, chaotic maps are fed into the same Feed forward network used in the previous work's Adam optimization.

In order to take use of PSO-Particle Swarm Optimization's superior searching capabilities and faster convergence, we have begun to hybridise Feed forward Neural Networks with it. In addition, the use of PSO for the hybridization of Feed forward Neural Network might enable the prediction even under the most unfavorable conditions. For the sake of training a feed-forward neural network, chose the Torus distribution as our starting point. To improve convergence use circular chaotic maps [25].

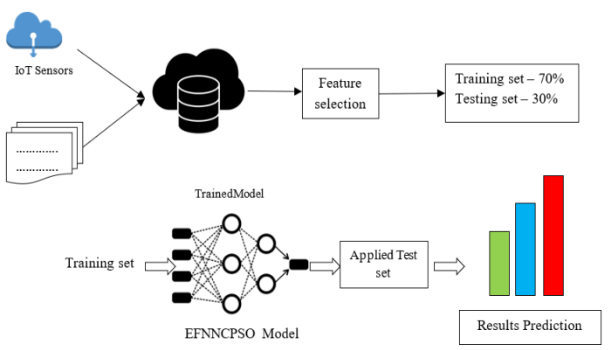

Fig. 1. Pictorial depiction of the proposed methodology

Below will show how the suggested technique estimates G_{chao}. It is possible to make an approximation of the circular chaotic map, y_j^F, for any vector solution by

$$y_{j+1}^F = y_j^F + a - (b - 2\pi) * Sin\left(2\pi * Torus\ (0,1)\right) \quad (1)$$

In the above equation 1, y_{j+1}^F generates the distribution of circular chaotic containing $a = 0.5$ and $b = 0.2$. Now, estimate G_{chao} by deploying the below equation 2,

$$G_{chao} = \begin{cases} Maximum\ \left((Q_g * P_g), (Q_g * y_{j+1}^F)\right) \quad if \\ \quad \left(Itr < \frac{itr}{3}\ ||\ C < \frac{C}{3}\right) \\ (Q_g * y_{j+1}^F) \quad if\ \left(Itr > \frac{itr}{3} \&\&\ itr < \frac{iter}{1.5}\right) \\ Minimum\ \left((Q_g * P_g), (Q_g * y_{j+1}^F)\right)\ Else \end{cases} \quad (2)$$

G_{chao}used circular chaotic maps to be adaptable to our Feed forward Neural Network. Then, Donor vector $u_{x,y}^H$is given by

$$u_{j,k}^F = Q_{g1}.u_{iss1}^F - u_{iss2}^F \quad (3)$$

The Equation 4 produces u_{iss1}^F, while Equation 6 produces u_{iss2}^F, making the procedure simpler. Q_g, the estimated average dot vector, is equal to 0.4 once the procedure is performed. This calculated mean value will be used as a search intermediary between $u_{iss1}^F$and u_{iss2}^F to maintain the balance. The following is a description of the

$$u_{iss1}^F . u_{iss1}^F = y_{iss1}^F + G_{chao}.\left(y_{iss1,p_1}^F - y_{iss1,p_2}^F\right) + G_{chao}.\left(y_{iss1,p_2}^F - y_{iss1,p_4}^F\right) \quad (4)$$

The above u_{iss1}^F will be giving rise to four mean solutio vectors that are indexed at $y_{iss1,p_1}^F, y_{iss1,p_2}^F, y_{iss1,p_2}^F$and y_{iss1,p_4}^F. Because of this, the hybridization of the already-deployed feed-forward neural network will proceed more smoothly. The similar thing occurs with u_{iss2}^F as described for u_{iss1}^F to give rise to $y_{iss2,p_1}^F, y_{iss2,p_2}^F$, y_{iss2,p_3}^F, and y_{iss2,p_4}^F. iss1 can be given by

$$iss1 = \begin{cases} iss1\%2 * k + 1 \quad for\ (k = 1,2, and\ 3) \\ k = 1\ and\ iss1\%2 * k + 1\ \ when\ k == 3 \end{cases} \quad (5)$$

$$u_{iss2}^F = y_{iss2}^F + G_{chao}.\left(y_{iss2,p_1}^F - y_{iss2,p_2}^F\right) + G_{chao}.\left(y_{iss2,p_3}^F - y_{iss2,p_4}^F\right) \quad (6)$$

$y_{iss2,p_1}^F, y_{iss2,p_2}^F$, y_{iss2,p_3}^F, and y_{iss2,p_4}^Faided $y_{iss1,p_1}^F, y_{iss1,p_2}^F, y_{iss1,p_2}^F$ and y_{iss1,p_4}^F and the average difference between them raise the convergence. iss2 can be given by

$$iss2 = \begin{cases} iss2\%3 * k + 1 \quad for\ (k = 1,2, and\ 3) \\ k = 1\ and\ iss2\%3 * k + 1 \quad when\ k == 3 \end{cases} \quad (7)$$

In each and every production, ISS1 and ISS2 are put through an iterative process for 2*k+1 and 3*k+1 times, respectively, in order to produce the 8 vectors that are ultimately selected. These vectors, when used further in equation 3, give birth to a donor vector that is both more powerful and more carefully chosen; it is denoted by u_(j,k)F. The procedure for running the PSO with circular chaotic maps that include the torus distribution and a throughput range of [0,1] is outlined in the following paragraphs. For every vector $y_j = \left(y_{j,1}, y_{j,2}, y_{j,3}, \dots, y_{j,C}\right)$The condition listed below will be validated when iteration j is performed on production f along the dimension C.

$$G\left(y^F_{j,k}, a_{greatest}\right) = \begin{cases} a_{greatest} \leftarrow y^F_{j,k} \quad obtain_{10^{th}_{power\left(y^F_{j,k}\right)}} - obtain_{10^{th}_{power}} \\ \left(y^a_{j,k}\right) < Fit_p \\ y^F_{j,k} \text{ Else} \end{cases}$$

(8)

$G\left(y^F_{j,k}, a_{greatest}\right)$ is the hybridising function that, inside the Feed forward Neural Network, controls the shifting operation. At each stage of construction, the feed-forward neural network's input vectors were independently verified. $y^F_{j,k}$ determined to be worse than $y^F_{j-1,k}$ with the estimation of

$$obtain\_10^{th}\_power\left(y^F_{j,k}\right)\ obtain\_10^{th}\_power\left(y^a_{j,k}\right) < Fit_p \quad (9)$$

At this time, the particle with the highest PSO score is given preference in every feed-forward neural network solution.as the$a_{greatest} \leftarrow G\left(y^F_{j,k}, a_{greatest}\right)$.This is going to show that the optimisation procedure was carried out successfully. This optimisation will continue till it is complete.

$$obtain\_10^{th}\_power\left(y^F_{j,k}\right) - obtain\_10^{th}\_power\left(y^a_{j,k}\right) < Fit_p \quad (10)$$

It is determined false and the vector solution for the complete iteration j will be defined as $y^F_{j,k} \leftarrow G\left(y^F_{j,k}, a_{greatest}\right)$.Here, additional shifting also takes place, and the value of 'Fit'(p) will end up being equal to 30. As a result, the convergence will be maintained for the duration of the training of the feed forward neural network to make type 2 diabetes predictions. This training will follow the same format as the conventional EFNNAO method, the details of which are laid out in the following section. The dataset was divided such that 70% of it would be used for training and 30% would be utilised for testing. In order to handle the training data, a neural network with three hidden layers was employed. The BCE function was used to calculate the sample's predictive loss, and the BP approaches were then used to reduce that loss to an acceptable level. The model's parameters are adjusted with the help of a programme called Particle Swarm Optimizer. The model is trained using a learning rate of 0.001 over the course of 300 iterations.

The values of many key elements, including as the number of epochs, the total number of neurons, and the layers, are susceptible to change throughout the process of determining the best configuration for the creation of the proposed model. To further examine whether or not the suggested model overfit or underfit the data, it was executed using a range of epoch values, from 100 to 300. Overfitting occurred in the proposed model after it had been run for more than 300 epochs, despite the fact that after just 300 iterations it had already achieved optimal results. This happened despite the fact that after just 300 epochs the model had already produced the optimal result. Following is a pseudocode representation of the suggested approach for the EFNNCPSO technique.

```
Pseudo-Code :EFNNCPSO Technique
Procedure EFNNCPSO
Input: IoT based Dataset
Output: T2DM Prediction
        Data initialization;
        Initialize Network DN;
   Define Variables
   Hidden layer,   X_O =>output layer
   DN = {X_I, X_H, X_O}
    Each item n from D is passed on to XI, where
n is the data
   item XH is a cost function, and
   XO is an
   activation function to process the data.
   Activate X_f;
   Optimize the DN with PSO;
   Start the training process
   Start the testing process
        Output generated from X_O
End
```

4. Performance Analysis

The purpose of this part is to analyze the performance of the suggested model in comparison to the performance of other models based on the accuracy. The suggested model's accuracy, as measured in terms of epochs, is shown in Fig. 2 and Fig. 3, respectively. This demonstrates that the model is able to acquire knowledge of the loss process and easily arrive at the global minimum. In addition to this, the loss of the model is reduced, while the precision of the results is improved, and there is neither under fitting nor over fitting.

Age	BS Fast	BS pp	Plasma R	Plasma F	Hb1Ac	Type	Class	Predictions	Probabilities
22	6.8	8.8	11.2	7.2	62	Type 1	1	Type 1	0.996
24	19	6.3	7.9	3.9	40	Normal	0	Normal	1.0
41	6.3	4.2	12.2	7.8	57	Type 2	1	Type 2	1.0
44	6.8	8.2	11.6	7.4	69	Type 2	1	Type 2	0.999
22	31	6.3	7.9	3.9	40	Normal	0	Normal	1.0
60	6.7	8.7	11.6	7.4	69	Type1	1	Type2	0.925
67	6.8	4.8	13.1	9.1	58	Type2	1	Type2	0.998
23	28	7.7	11.0	6.1	36	Normal	0	Normal	0.999
35	6.7	8.7	11.6	7.4	69	Type1	1	Type1	0.911
55	5.2	6.8	10.9	4.2	33	Normal	0	Normal	1.0
26	6.8	8.2	11.6	7.4	69	Type2	1	Type2	0.921
34	5.8	4.2	11.4	8.4	53	Type2	1	Type2	0.999
27	30	7.7	11.0	6.1	36	Normal	0	Normal	0.997
26	46	5.6	10.2	5.4	32	Normal	0	Normal	1.0

Fig. 2. Simulated output

The illness may be properly predicted using the model that was presented, as can be shown in Fig. 2. There are many different evaluation metrics, some of which, such as kappa statistics, AUROC, sensitivity, specificity, and Logloss, are utilized for the suggested model to evaluate the accuracy.

4.1. Accuracy

The ratio that exists between the number of right forecasts and the total number of predictions is what is meant to be understood by the word accuracy. The expression or formula for achieving precision is shown in the following.

$$\text{Accuracy} = \left(\frac{\text{TP+TN}}{\text{TP+FN+FP+TN}}\right) \tag{11}$$

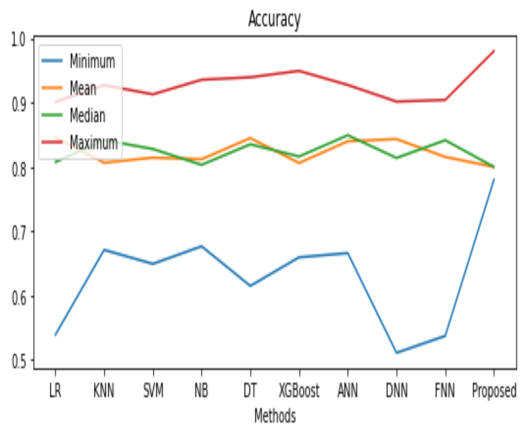

Fig. 3. Accuracy curves for all the existing and proposed methodologies

Fig. 3 provides an illustration of the accuracy curves for all of the previous research as well as the suggested technique. The accuracy curves for both the train data and the test data are shown in Fig. 4, which can be seen below.

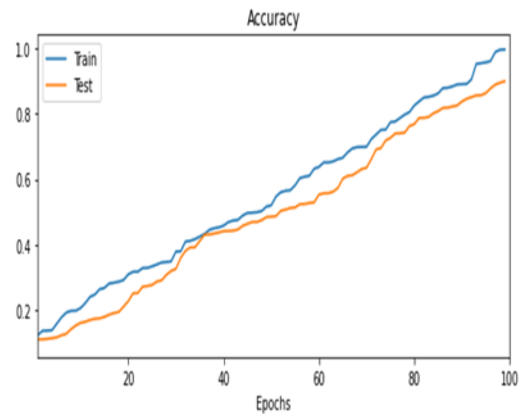

Fig. 4. Accuracy curves for train and test cases

4.2. Kappa coefficient

The term "Kappa Statistics" refers to a measure of the consistency between the judgments of different raters on the same set of data. Here is a formula for calculating kappa, a statistical term.

$$K_p = 1 - \frac{1-p_o}{1-p_e} \tag{12}$$

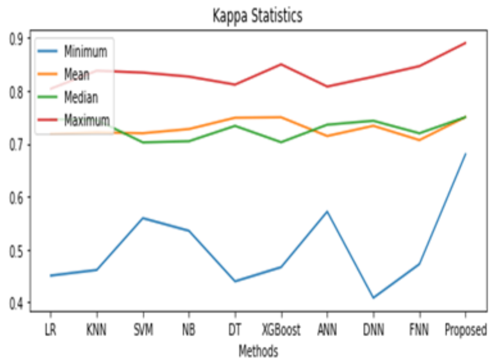

Fig. 5. Kappa Statistics for all the existing and proposed methodologies

4.3. AUROC

In its full form, "Area Under Receiver Operating Characteristics" (or "AUROC") refers to the typical value of the receiver's dynamic range. The true positive rate (TPR) and the 1-false positive rate (FP rate) are the building blocks for the calculation and expression for AUROC across all rankings. Let, $(t_n - t_{n-1})$ – time observation of concentrations C_n and C_{n-1} correspondingly. The expression or formula for kappa statistics is given below.

$$[\text{AUROC}]_{n-1}^{n} = \frac{C_{n-1}+C_n}{2}(t_n - t_{n-1}) \tag{13}$$

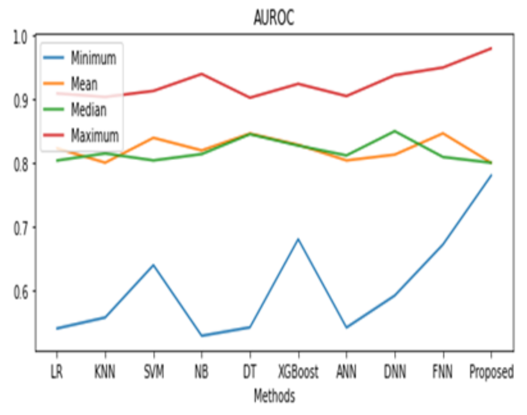

Fig. 6. AUROC for all the existing and proposed methodologies

4.4. Sensitivity

The term "sensitivity" might mean the proportion of correctly classified positive instances compared to the total number of positive examples. It might also be called the true positive rate. Here is the formula or equation that may be used to calculate sensitivity,

$$Sensitivity = \left(\frac{TP}{TP+FN}\right) \quad (14)$$

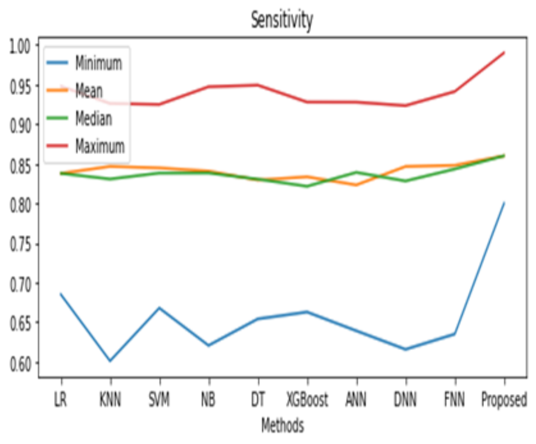

Fig. 7. Sensitivity for all the existing and proposed methodologies

4.5. Specificity

Specificity is defined as the ratio of correctly classified negative instances to the total number of occurrences in which a negative outcome was observed. The term "false positive rate" also describes this statistic. Below is the formula, or mathematical equation, for Specificity.

$$\text{Specificity} = 1 - \left(\frac{\text{FP}}{\text{FP+TN}}\right) \quad (15)$$

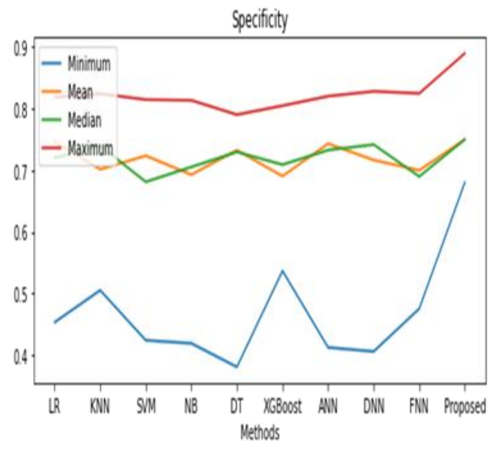

Fig. 8. Specificity for all the existing and proposed methodologies

4.6. Loss

The Logarithmic loss, often known as Logloss, is used to evaluate each classifier's performance on its own. The calculation or term for Logloss may be found down below.

$$\mathrm{L_g} = \frac{-\sum_{y=1}^{j}\sum_{x=1}^{n} f(x,y)\,log(p(x,y))}{n} \quad (16)$$

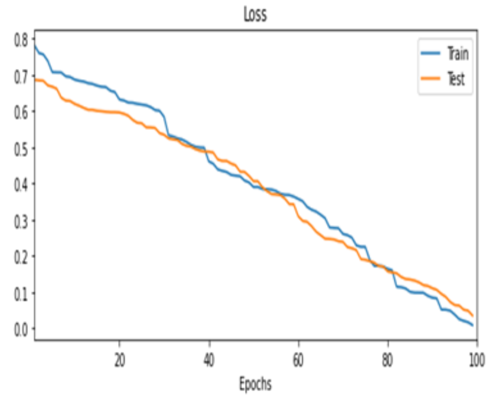

Fig. 9. Loss or Logloss for all the existing and proposed methodologies

From the result obtained it was revealed that the suggested methodology outperforms well when compared to other existing methods by obtaining high range of accuracy over type 2 diabetics prediction.

5. Conclusion

The authors propose the EFNNCPSO model for the early diagnosis of Type 2 Diabetes Mellitus using Internet of Things (IoT) technologies. Data was collected using a questionnaire and several sensors. Features were selected using the IG method, and then fed into the proposed EFNNCPSO model. The network of the proposed model consists of one input layer, four hidden layers, and one output layer; this structure was chosen since it maximizes the efficiency with which the model learns about the data's attributes. Particle swarm optimizers with a chaotic foundation improve upon the EFNNAO model's performance achieved in prior work. The proposed model outperformed its forerunners in terms of accuracy because to the use of an epoch cycle, which mitigated the effects of underfitting and overfitting. The model's cost function was also approximated and tweaked. When compared to previous models for the IoT-based prediction of the type-2 diabetes state, the accuracy of our model was shown to be superior. Next, a different method of optimization will be used, leading to enhanced outcomes achieved by means of this feed forward network.

Author contributions

S.Arulananda Jothi: Conceptualization, Software, Methodology, Field study, Data curation, Writing-Original draft preparation, Software, Validation, Field study. **J.Abdul Samath:** Visualization, Investigation, Writing-Reviewing and Editing.

Conflicts of interest

The authors declare no conflicts of interest.

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