EFASFMM: A Unique Approach for Early Prediction of Type II Diabetics using Fire Fly and Semi-supervised Min-Max Algorithm

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***Abstract*—Non-insulin-reliant, one of the most serious illnesses is diabetes mellitus, often known as type 2 diabetes, and it affects a large number of people. Between 2 and 5 million individuals worldwide die from diabetes each year. If diabetes is identified sooner, it can be managed, and catastrophic dangers including nephropathy, heart stroke, and other conditions linked to it can be avoided. Therefore, early diabetes diagnosis aids in preserving excellent health. Machine learning (ML), which has recently made strides, is now being used in a number of medical health-related fields. The innovative, nature-inspired Firefly algorithm has been shown to be effective at solving a range of numerical optimization issues. While using alliterations, the traditional firefly method employed a fixed step size models for semi-supervised learning (SSL). The firefly is effective for solving classification issues involving both a sizable number of unlabelled data and a limited number of samples with labels. The fuzzy min-max (FMM) family of neural networks in this regard provide the capability of online learning for tackling both supervised and unsupervised situations. Using a special mix of the two proposed algorithms, one of which is utilised for optimization and the other for making early predictions of type 2 diabetes. The findings for the training and testing phases for the parameter's accuracy, precision, sensitivity, specificity, and F-score are reported as 97.96%, 97.82%, 98.10%, 97.82%, and 97.95% which, when compared to current state-of-the-art methods, are finer.**

Keywords*—Fire Fly Algorithm (FFA); machine learning (ML); Semi-supervised Min-Max (SSMM)

I. Introduction

Diabetes mellitus (DM) is the collective metabolic disorder in which people have high blood sugar levels, either because their pancreas is incapable of producing enough insulin or because their cells are unable to react to the insulin that is generated. This leads to a number of medical conditions such polydipsia, polyuria, and polyphagia.DM is still a problem for public health everywhere in the world. This is increasingly the leading cause of death in affluent nations and is now ranked fourth or fifth among non-communicable diseases globally. In the entire world, 300 million people are predicted to have diabetes or be at risk for developing it by 2025. In the past few years, developing nations like India have had the highest growth in DM. There were 425 million diabetics worldwide as of 2017 [1], and research by the International Diabetes Federation in 2017 [2] predicted that number will rise to 625 million by 2045. Diabetes mellitus is a collection of endocrine disorders characterized by decreased glucose absorption and brought on by absolute or relative insulin deficiency. In addition to a chronic history, the disease is characterized by a disruption of all forms of metabolism. When our body's blood sugar, also known as blood glucose, is too high, we have diabetes mellitus (DM). People can develop diabetes at any age, and there are three main types: type 1, type 2, and gestational diabetes. Many hormonal and other changes that take place in the body during pregnancy are thought to be the cause of gestational diabetes, whereas other women see an increase in insulin resistance.

Type II diabetes is a chronic metabolic disorder that affects millions of people worldwide. It occurs when the body either does not produce enough insulin or is unable to use the insulin it produces effectively, resulting in high levels of glucose in the blood. Early detection of type II diabetes is crucial for effective management and prevention of complications. Predictive modeling techniques have shown great promise in identifying individuals who are at a high risk of developing type II diabetes before clinical symptoms appear. By leveraging machine learning algorithms and advanced analytics, healthcare professionals can identify individuals who are at risk of developing type II diabetes and implement preventative measures to reduce the likelihood of disease progression. This can ultimately lead to improved health outcomes and a reduction in healthcare costs associated with managing type II diabetes.

The entire paper is divided into five sections where Section I consists of introduction. Section II deals with related works, Section III deals with experimental results, Section IV deals with results of the work, and Section V deals with conclusion of the work.

II. Related Works

Mohebbi et al. demonstrated that it was possible to use CGM signals to detect T2D patients in [3], where they offered a unique deep learning approach for the identification of type 2 diabetes. To solve the difficulties of implementing DL approaches. The authors of [4] concentrated their talks on generalised approaches, reinforcement learning, natural

language processing, deep learning in computer vision, and healthcare today (Table I).

TABLE I. VIEWS OF VARIOUS AUTHORS

Author	Contribution	Methodology	Advantages	Limitations
DPML [5]	Prediction of Type 2 diabetics	SVM, XGBoost, RF , LR	Early prediction	Works for only specific datasets not for all existing datasets
FFCSA [6]	Classification of diabetics	KNN Classifier	Notable accuracy of considered parameters	Works for static datasets not for existing
ADNNC [7]	random test and trail	DNN	High accuracy	Computation time
EDDN [8]	Prediction and classification	DNN	High accuracy	Works for limited size of data

EFA: Firefly algorithm

Begin

Objective function $f(x), x = (x_1, x_2, \dots\dots\dots\dots x_d)^T$

Light intensity $f_p = f(x_p)$ *i.e.,* $I(r) = I_0 e^{-\gamma r^2}$

Light absorption coefficient γ

While (t<Max generation) do

For $sx_p \in P$ *do*

For each $x_q \in q$ *do*

If $(x_p) < f(x_q)$, *firefly p towards q*

Vary β with distance r via exp(-γr_{pq}*)*

$$||X_p - X_q|| = \sqrt{\sum_{k=1}^{d}(x_{p,k} - x_{q,k})^2}$$

$$X_{p,t+1} = X_{p,t} + \beta_0 . e^{-\gamma r_{pq}^2} . (X_{q,t} - X_{p,t})$$

$$X_p = X_p + \beta_0 . e^{-\gamma r_{pq}^2} . (X_q - X_p) + \alpha\,(rand - \frac{1}{2})$$

Evaluate the solution and update the light intensity

end

end

Fireflies are ranked and current global best x_p^{max}

end

end

In population-based optimization techniques, efficient global exploration and local exploitation control is essential for locating the ideal solution. Therefore, during the initial stages of optimization, it is preferable to encourage individuals to roam around the whole search space rather than grouping around local optima. In order to quickly locate the best solution, it is crucial to increase convergence toward the global optima during the last stages.

EFA: Firefly algorithm

Input : UCI diabetic dataset

Output : Type 2 diabetic classification

For each considered sample do

Hyperbox membership is computed

$$b_j(A_h, V_q, W_q) = \frac{1}{2d}\sum_{p=1}^{d}[\max(0,1 - \max(0, \gamma \min(1, a_{hp} - w_{qp}))) + \max(0,1 - \max(\gamma \min(1, V_{pq} - a_{hp}), 0))]$$

For the criteria to be satisfied

$$\sum_{p=1}^{d}(\max(w_{q*p}, a_{hp}) - \min(V_{q*p}, a_{hp})) \le d\theta$$

All hyperboxes belonging to other classes are represented as

If $v_{q*p} < v_{qp} \le w_{q*p} < w_{qp}$, *then* $\delta^{new} = min\,(min\,(w_{rp} - v_{q*p}, w_{q*p} - v_{q*p}), \delta^{old})$

else if

$v_{qp} < v_{q*p} < w_{q*p} < w_{qp}$, *then* $\delta^{new} = min\,(w_{q*p} - V_{qp}, \delta^{old})$

else if

$v_{q*p} < v_{kp} \le w_{q*p} < w_{kp}$, *then* $\delta^{new} = min\,(min\,(w_{q*p} - v_{rp}, w_{kp} - v_{q*p}), \delta$

if

Overlap exists then contraction begins

If $V_{q*p} < V_{rp}$ then , $v_{q*p} < V_{rp} < w_{q*p}, \delta^{new}$

If $V_{qp} < V_{q*p} < W_{q*p} < W_{rp}$ then $w_{q*2}^{new} = v_{rp}^{new} = \frac{v_{rp}^{old} + w_{q*p}^{old}}{2}$

else

If $v_{qp} < v_{q*p} < w_{q*p} < w_{qp}$, *then* $\delta^{new} = min\,(w_{q*p} - V_{qp}, \delta^{old})$

else

If $v_{q*p} < v_{kp} \le w_{q*p} < w_{kp}$, *then* $\delta^{new} = min\,(min\,(w_{q*p} - v_{rp}, w_{kp} - v_{q*p}), \delta^{old})$

else

If $V_{rp} < V_{q*p} < W_{rp} < W_{q*p}$ then, $w_{rp}^{new} = v_{rp}^{new} = \frac{w_r^{old} + v_{q*p}^{old}}{2}$

Current sample encoding using new hyperbox , $V_{q+1} = W_{q+1} = A_h$

End

The algorithm provided appears to be a variant of the Fuzzy ARTMAP algorithm, which is a type of artificial neural network that uses fuzzy logic to perform pattern recognition and classification. The algorithm takes as input the UCI diabetic dataset and aims to perform classification to predict whether an individual is likely to have type II diabetes. For each sample, the algorithm computes hyper box membership using a formula that takes into account the attributes of the sample and the weights associated with the hyper boxes. The

hyper boxes represent regions in the input space that are assigned to a particular class (in this case, type II diabetes or not). The criteria for a hyper box to be considered a member of a class is that it must satisfy a certain threshold (represented by the value Θ in the algorithm). If a hyper box overlaps with a hyper box belonging to a different class, the algorithm performs a contraction step to adjust the boundaries of the hyper boxes to reduce overlap. If the hyper box is not a member of any class, the algorithm creates a new hyper box to represent the current sample. This new hyper box is initialized with the attributes of the current sample, and the classification decision is based on whether the new hyper box satisfies the classification criteria. Overall, the algorithm is a type of supervised machine learning algorithm that uses fuzzy logic and neural networks to perform classification of the input data. It is designed to be able to adapt to new input data and adjust the hyper boxes accordingly.

Over the past ten years, machine learning and data categorization have paid a lot of attention to semi-supervised learning (SSL). Finding the target class (i.e., label) to which a data sample belongs is referred to as data classification. To do this, a collection of labelled data samples are used for model training, and the input samples are then mapped to the associated classes using the underlying learning technique. The new, unseen test samples are then categorized into the appropriate classes using the trained model. A hyper box membership function is defined as

$$f(x,\gamma) = \begin{Bmatrix} 1, if\ x\gamma > 1 \\ x\gamma\ if\ 0 \le x\gamma \le 1 \\ 0\ if\ x\gamma < 0 \end{Bmatrix}$$

Each supervised and unsupervised FMM network has a different topology made up of a variety of hyper boxes that were built up gradually (see Fig. 1). Each hyper box creates a feature boundary in a d-dimensional unit cube and is represented by a set of minimum and maximum vertices (I^d). The value of [0, 1] determines the hyper box size; a tiny result in several hyper boxes, each of which has a small size, and vice versa.

Early prediction of Type 2 Diabetes is a growing area of research and many studies have been conducted to explore this topic. One unique approach for early prediction of Type 2 Diabetes is the use of artificial intelligence and machine learning algorithms. For example, a recent study by Wang et al. [9] (2021) used machine learning algorithms to predict the risk of Type 2 Diabetes in a Chinese population based on demographic and lifestyle factors. Another study by Noh et al. (2021) [10] used artificial intelligence to predict the risk of Type 2 Diabetes based on clinical data from electronic health records.

In addition, several studies have explored the use of biomarkers for early prediction of Type 2 Diabetes. For instance, a study by Senn et al. (2020) [11] investigated the use of a blood-based biomarker called plasma branched-chain amino acids (BCAAs) to predict the risk of Type 2 Diabetes in a cohort of Finnish individuals. Similarly, another study by Li et al. (2020) [12] explored the use of urinary metabolites as a biomarker for early prediction of Type 2 Diabetes in a Chinese population. Furthermore, there has been research into the use of genetic information for early prediction of Type 2 Diabetes. A study by Wang et al. (2020) [13] investigated the use of genetic risk scores to predict the risk of Type 2 Diabetes in a Korean population. Another study by Bancks et al. (2021) [14] used a genetic risk score and lifestyle factors to predict the risk of Type 2 Diabetes in a diverse population in the United States. Overall, these studies demonstrate the potential of various approaches for early prediction of Type 2 Diabetes, including the use of artificial intelligence and machine learning algorithms, biomarkers, and genetic information.

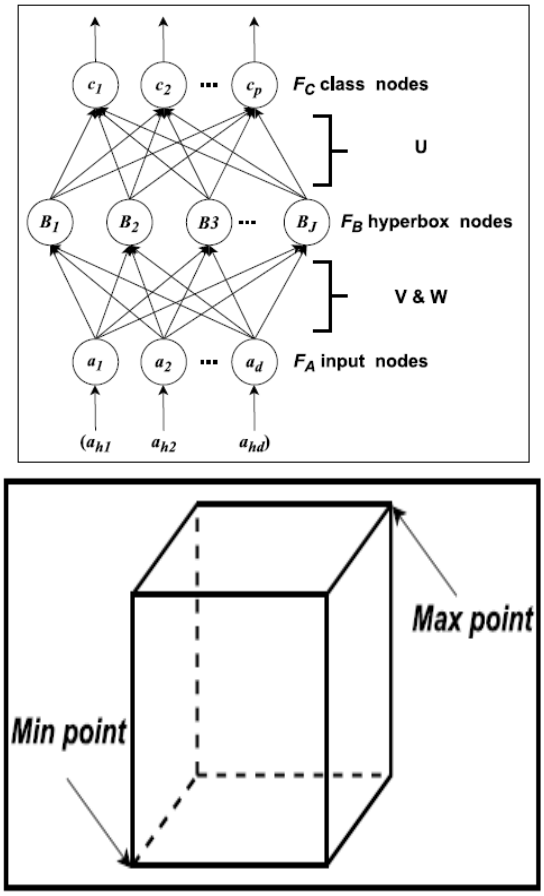

Fig. 1. (a), (b) Supervised FMM network and a 3D hyperbox.

III. Experimental Set Up

Utilizing the Visual Studio IDE, a specific User Interface (UI) is created in order to connect to the server and obtain performance metrics for both existing and suggested methods. The proposed system is implemented in Visual C++ and the existing methods are implemented in Common Language Runtime (CLR) libraries. The UI is operated on a machine that connects to the server using an 8 GB RAM and an Intel Core i5-7200 processor operating at 2.7 GHz. Through the I2K2 cloud server intermediary infrastructure, Amazon Server is rented. The server has 100GB of High IOPS Solid State Hard Drive (SSD), 2GB of RAM, 2 Virtual CPU Computational Cores, and a 99.99% uptime guarantee. For Single Admin Windows Operating System and Single User Remote Desktop Server (RSD) Client Access License (CAL) included, the

software licenses are provided by the I2K2 service. Dataset [15] is considered to carry out the results (see Fig. 2).

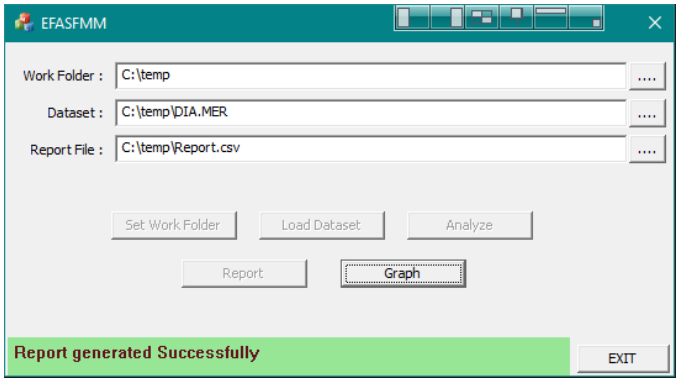

Fig. 2. UI for running the proposed approach.

IV. Results

The model is trained and tested with the dataset with a ratio of 60-40. The results are considered in terms of accuracy, precision, specificity, sensitivity and F-Score.

A. Accuracy

TABLE II. Accuracy Obtained during Training

Data (%)	DPMLA	FFCSA	DNNC	EDDN	EFASFMM
7	38.54	33.40	36.54	43.72	45
14	53.89	47.28	54.93	59.69	61.13
21	63.10	55.69	65.63	69.43	70.19
28	69.38	61.38	73.37	76.02	76.99
35	74.51	66.30	79.06	81.39	82.34
42	78.64	69.66	83.98	85.49	86.64
49	81.87	72.99	87.99	88.71	90.01
56	84.60	75.49	91.50	92.04	93.17
63	87.53	78.12	94.27	94.96	96.15
70	89.90	80.31	97.27	97.27	98.75

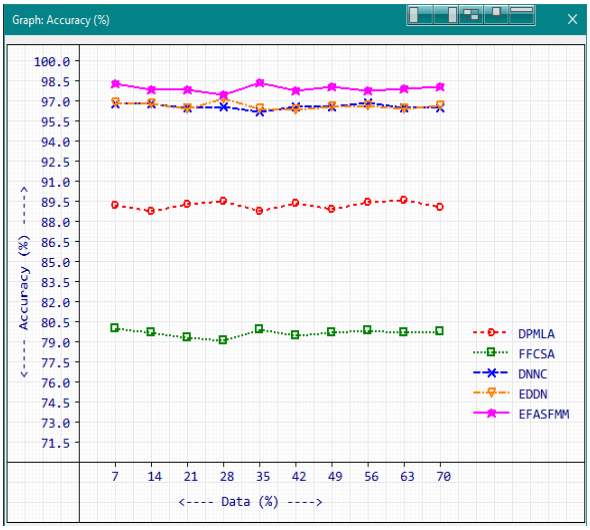

Fig. 3. Graphs of accuracy obtained during training.

TABLE III. Accuracy Obtained during Testing

Data (%)	DPMLA	FFCSA	DNNC	EDDN	EFASFMM
7	89.23	79.97	96.83	96.86	98.35
14	88.79	79.73	96.79	96.8	97.84
21	89.3	79.34	96.54	96.45	97.88
28	89.53	79.07	96.55	97.19	97.49
35	88.75	79.93	96.23	96.44	98.37
42	89.41	79.45	96.59	96.33	97.77
49	88.94	79.72	96.55	96.55	98.07
56	89.46	79.88	96.89	96.63	97.8
63	89.61	79.70	96.53	96.45	97.94
70	89.08	79.8	96.48	96.63	98.09

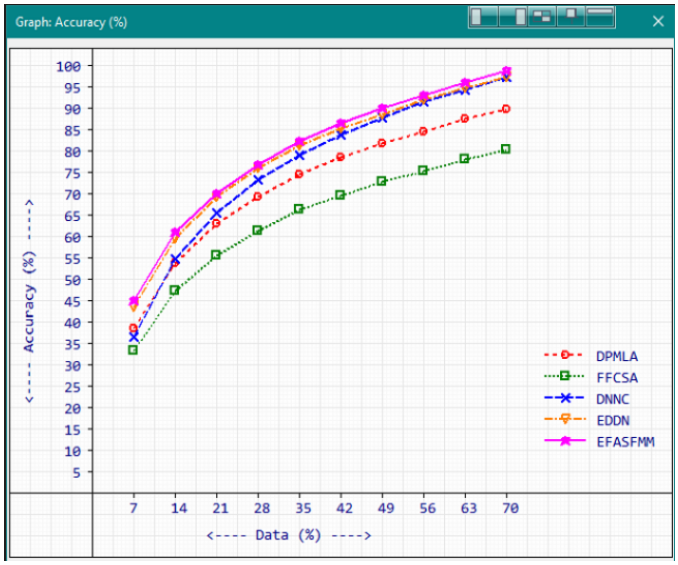

Fig. 4. Graphs of accuracy obtained during testing.

Accuracy values are referred in the Table II for training and Table III for testing. During training the average values of accuracy for the existing and proposed approaches such as DPMLA, FFCSA, DNNC, EDDN and EFASFMM observed are 72.20%, 64.06%, 76.45%, 78.87% and 80.04%. During testing the average values of accuracy for the existing and proposed approaches are given as 89.21%, 79.66%,96.60%, 96.63% and 97.96%. Acurracy graphs are shown in Fig. 3 and Fig. 4 during training and testing.

B. Precision

Precision values are referred in the Table IV for training and Table V for testing. The corresponsing graphs for precision during training and testing are shown in Fig. 5 and 6, correspondingly.

During training the average values of Precision for the existing and proposed approaches such as DPMLA, FFCSA, DNNC, EDDN and EFASFMM observed are 73.73%, 63.75%, 75.59%, 79.03% and 79.72%. During testing the average values of precision for the existing and proposed approaches are given as 90.68%, 79.63%,95.45%, 96.74% and 97.82%.

TABLE IV. PRECISION OBTAINED DURING TRAINING

Data (%)	DPMLA	FFCSA	DNNC	EDDN	EFASFMM
7	40	32.45	36	44	44.45
14	55.35	46.72	54.24	60.13	60.71
21	64.87	55.17	65.17	69.65	69.76
28	70.88	60.98	72.48	76.09	76.51
35	76.01	66.00	78.30	81.59	82.28
42	80.04	69.35	82.96	85.42	86.47
49	83.37	73.01	86.88	88.79	89.81
56	86.05	75.43	90.63	92.04	92.94
63	89.21	77.98	93.25	95.12	95.80
70	91.54	80.36	96	97.54	98.45

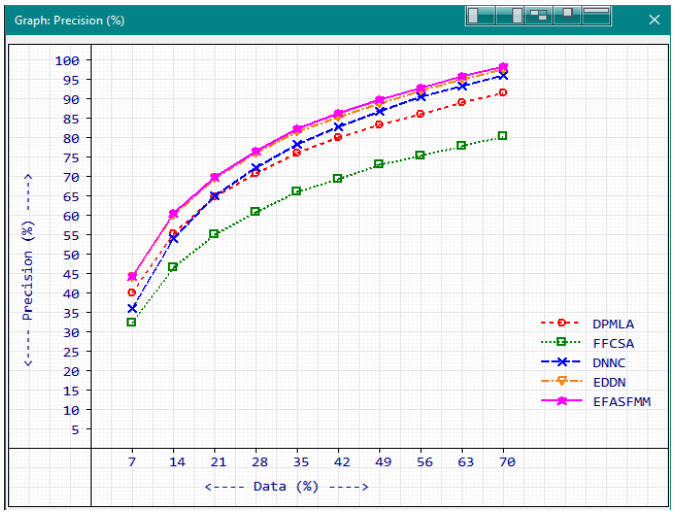

Fig. 5. Precision graph obtained during training.

TABLE V. PRECISION OBTAINED DURING TESTING

Data (%)	DPMLA	FFCSA	DNNC	EDDN	EFASFMM
7	90.45	80.04	95.39	96.58	98.17
14	90.01	79.21	95.85	96.97	98.17
21	91.11	79.38	95.71	96.67	98.22
28	90.89	79.1	95.57	97.22	97.43
35	90.49	80.01	95.12	96.52	98.04
42	91.05	79.5	95.04	96.66	97.12
49	90.42	79.45	95.51	97.08	98.11
56	90.72	80.12	95.53	96.08	97.48
63	91.18	79.92	95.3	96.75	97.49
70	90.54	79.58	95.49	96.94	97.98

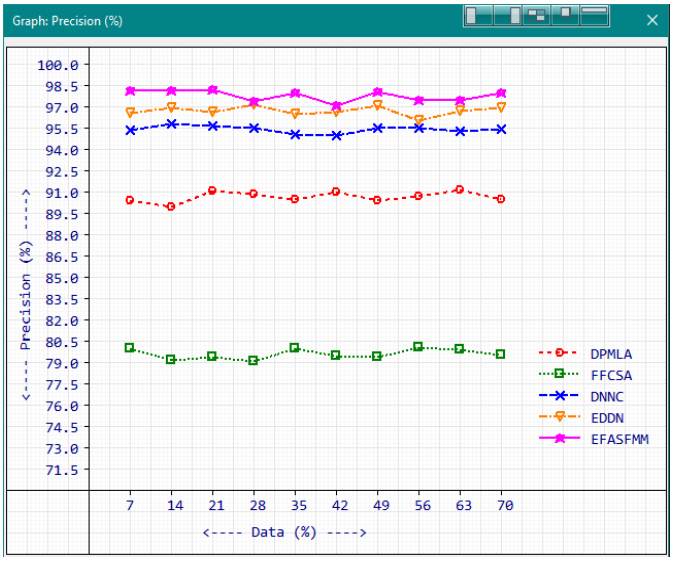

Fig. 6. Precision graph obtained during testing.

C. Sensitivity

Sensitivity values are referred in the Table VI for training and Table VII for testing. The corresponsing graphs for precision during training and testing are shown in Fig. 7 and 8, correspondingly.

During training the average values of sensitivty for the existing and proposed approaches such as DPMLA, FFCSA, DNNC, EDDN and EFASFMM observed are 71.53%, 64.07%, 76.99%, 78.80% and 80.20%. During testing the average values of sensitivity for the existing and proposed approaches are given as 88.09%, 79.68%,97.69%, 96.53% and 98.10%.

TABLE VI. SENSITIVITY OBTAINED DURING TRAINING

Data (%)	DPMLA	FFCSA	DNNC	EDDN	EFASFMM
7	38.86	33.08	36.39	43.76	44.94
14	53.78	47.25	55.00	59.61	61.23
21	62.65	55.75	65.78	69.35	70.36
28	68.82	61.47	73.80	75.99	77.26
35	73.79	66.40	79.50	81.27	82.37
42	77.85	69.78	84.69	85.54	86.76
49	80.94	72.97	88.85	88.65	90.17
56	83.62	75.51	92.22	92.04	93.37
63	86.30	78.19	95.20	94.81	96.48
70	88.64	80.29	98.50	97.01	99.03

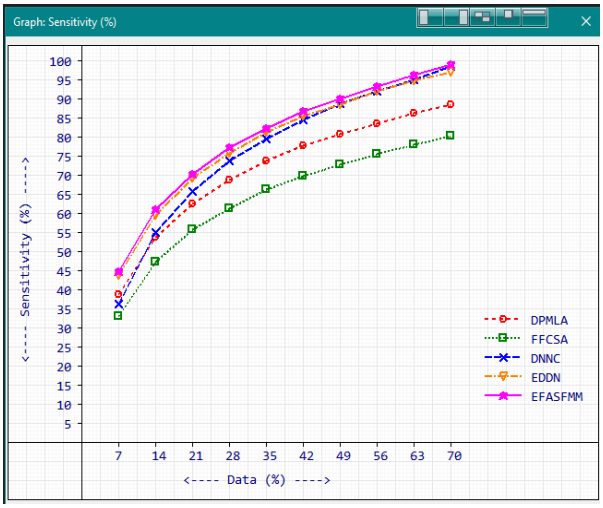

Fig. 7. Sensitivity graph obtained during training.

TABLE VII. SENSITIVITY OBTAINED DURING TESTING

Data (%)	DPMLA	FFCSA	DNNC	EDDN	EFASFMM
7	88.30	79.93	98.21	97.12	98.52
14	87.87	80.04	97.69	96.64	97.53
21	87.92	79.32	97.33	96.24	97.56
28	88.48	79.06	97.49	97.17	97.55
35	87.44	79.88	97.27	96.36	98.69
42	88.16	79.42	98.08	96.03	98.39
49	87.82	79.88	97.53	96.06	98.04
56	88.49	79.74	98.21	97.15	98.10
63	88.40	79.57	97.71	96.18	98.37
70	87.97	79.93	97.41	96.34	98.205

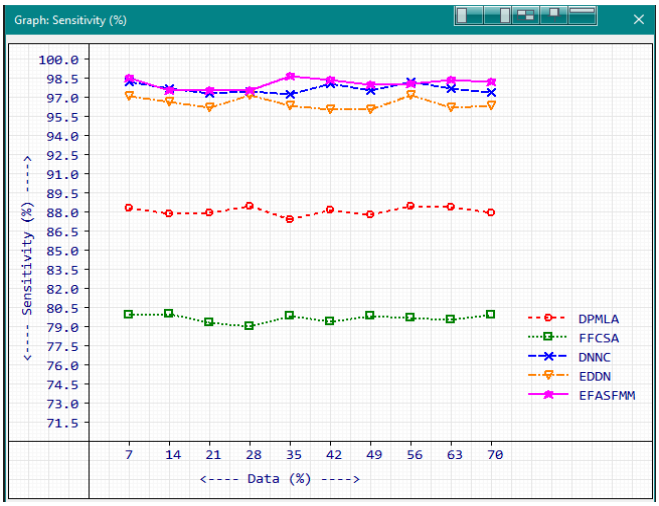

Fig. 8. Sensitivity graph obtained during testing.

D. Specificity

Specificity values are referred in the Table VIII for training and Table IX for testing. The corresponsing graphs for precision during training and testing are shown in Fig. 9 and 10 correspondingly.

TABLE VIII. SPECIFICITY OBTAINED DURING TRAINING

Data (%)	DPMLA	FFCSA	DNNC	EDDN	EFASFMM
7	38.20	33.71	36.69	43.69	45.05
14	54.01	47.31	54.87	59.78	61.04
21	63.58	55.63	65.49	69.51	70.02
28	69.98	61.29	72.96	76.06	76.73
35	75.26	66.20	78.62	81.51	82.30
42	79.47	69.54	83.30	85.44	86.52
49	82.85	73.00	87.17	88.77	89.85
56	85.63	75.46	90.79	92.04	92.98
63	88.83	78.04	93.38	95.10	95.83
70	91.25	80.34	96.09	97.53	98.46

During training the average values of specificity for the existing and proposed approaches such as DPMLA, FFCSA, DNNC, EDDN and EFASFMM observed are 72.91%, 64.05%, 75.94%, 78.94% and 79.88%. During testing the average values of specificity for the existing and proposed approaches are given as 90.40%, 79.64%, 95.55%, 96.74% and 97.82%.

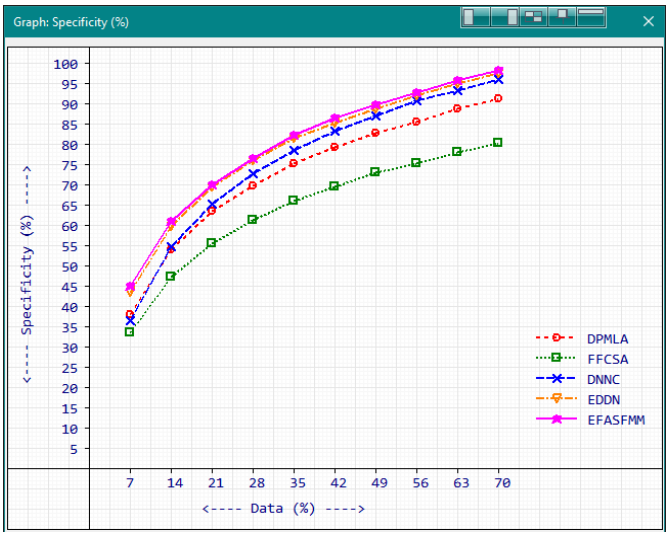

Fig. 9. Specificity graph obtained during training.

TABLE IX. SPECIFICITY OBTAINED DURING TESTING

Data (%)	DPMLA	FFCSA	DNNC	EDDN	EFASFMM
7	90.21	80.01	95.51	96.59	98.17
14	89.76	79.42	95.92	96.95	98.15
21	90.77	79.36	95.78	96.65	98.20
28	90.63	79.08	95.65	97.21	97.43
35	90.14	79.97	95.22	96.51	98.05
42	90.74	79.48	95.18	96.63	97.15
49	90.12	79.56	95.60	97.04	98.10
56	90.48	80.02	95.64	96.12	97.49
63	90.89	79.83	95.41	96.73	97.51
70	90.25	79.66	95.57	96.92	97.98

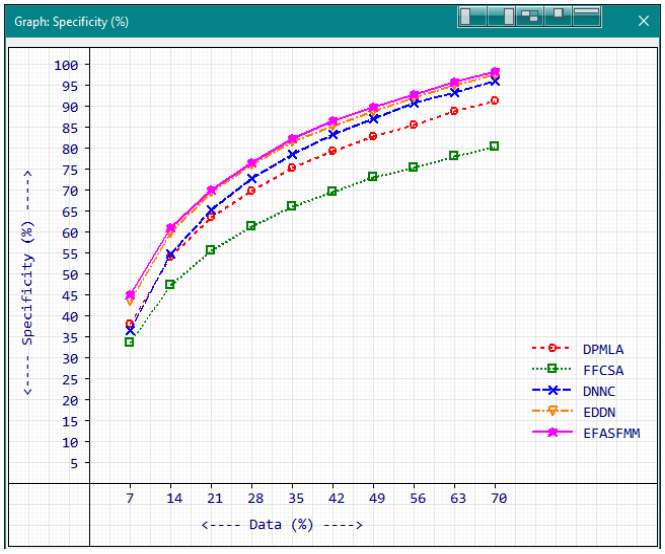

Fig. 10. Specificity graph obtained during testing.

E. F-Score

F-Score values are referred in the Table X for training and Table XI for testing. The corresponsing graphs for precision during training and testing are shown in Fig. 11 and 12 correspondingly.

TABLE X. F-SCORE OBTAINED DURING TRAINING

Data (%)	DPMLA	FFCSA	DNNC	EDDN	EFASFMM
7	39.42	32.76	36.19	43.88	44.69
14	54.55	46.98	54.62	59.87	60.96
21	63.74	55.46	65.47	69.50	70.06
28	69.83	61.23	73.13	76.04	76.88
35	74.88	66.20	78.90	81.43	82.33
42	78.93	69.56	83.82	85.48	86.62
49	82.14	72.99	87.85	88.72	89.99
56	84.82	75.47	91.42	92.04	93.16
63	87.73	78.09	94.21	94.96	96.14
70	90.07	80.32	97.23	97.28	98.74

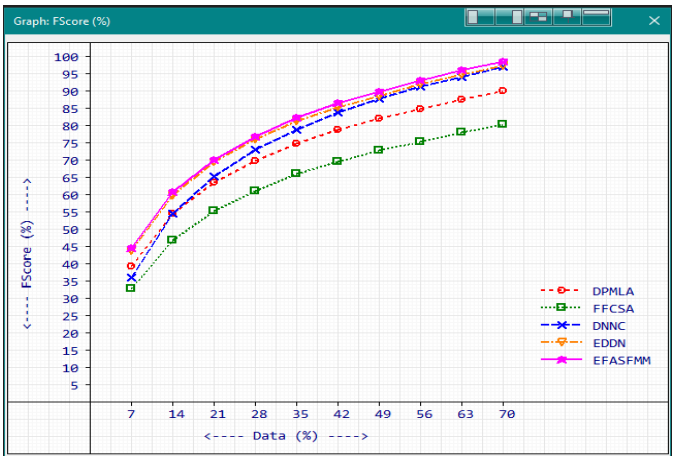

Fig. 11. F-score graph obtained during training.

TABLE XI. F-SCORE OBTAINED DURING TESTING

Data (%)	DPMLA	FFCSA	DNNC	EDDN	EFASFMM
7	89.36	79.98	96.78	96.85	98.34
14	88.92	79.62	96.76	96.80	97.85
21	89.49	79.35	96.51	96.45	97.89
28	89.67	79.08	96.52	97.19	97.49
35	88.94	79.94	96.18	96.44	98.36
42	89.58	79.46	96.53	96.34	97.75
49	89.10	79.66	96.51	96.56	98.07
56	89.59	79.93	96.85	96.61	97.79
63	89.77	79.74	96.49	96.46	97.93
70	89.23	79.75	96.44	96.64	98.09

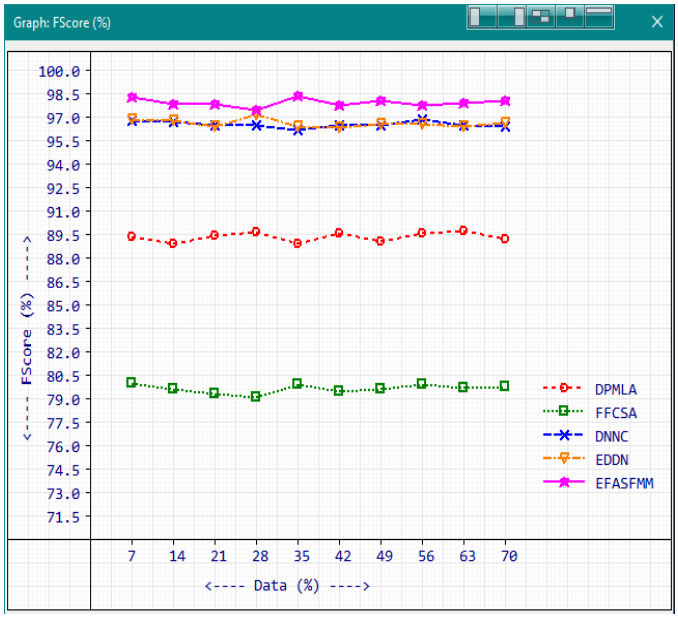

Fig. 12. F-score graph obtained during testing.

During training the average values of specificity for the existing and proposed approaches such as DPMLA, FFCSA, DNNC, EDDN and EFASFMM observed are 72.61%, 63.91%, 76.29%, 78.92% and 79.96%. During testing the average values of specificity for the existing and proposed approaches are given as 89.36%, 79.65%,96.56%, 96.63% and 97.95%.

V. CONCLUSION

Finding the best diabetes treatment primarily depends on early illness detection. One of the most common diseases in the world is diabetes. Whatever the sort of sickness, it is a frequent problem for doctors, medical professionals, and scientists to forecast the disease in its early stages. The main cause of this is a lack of awareness in developing and underdeveloped nations. A person's life can be saved by ignoring paradoxical events, diagnosing the sickness early, and taking the right medication. The upgraded firefly technique and the semi-supervised min-max approach algorithm are combined in an original way in the current paper. Where the min-max strategy is employed for the early diagnosis of type 2 diabetes and the firefly algorithm is used for optimization. The proposed approach is unique in that

it achieves the best results in terms of the metrics taken into account, including accuracy, precision, sensitivity, specificity, and F-Score. The type 2 diabetes dataset is used in the sense of a 60-40%. The results for the factors that were taken into consideration during training and testing are presented as follows: 80.00%, 79.72%, 80.20%, 79.88%, 79.96%, and 97.96%, 97.82%, 98.10%, 97.82%, 97.95%. The suggested method is beneficial for both training and testing purposes, as well as for the early diagnosis of type 2 diabetics while taking into account minimal computational time and highly accurate findings. The primary problem facing researchers in the current situation is identifying the causes of retinopathy in type 2 diabetes.

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