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DIABETES DETECTION BASED ON FAST LEARNING NETWORK MODEL

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ABSTRACT

In the last decades, machine learning algorithms have witnessed a high significance in healthcare applications in terms of detecting various diseases. For instance, diabetic disease is considered one of the major health problems around the world. However, there is a need to deeply study a machine learning algorithm in the detection of diabetic disease. Therefore, this study presents a Fast Learning Network (FLN) algorithm in the detection of diabetic disease based on different numbers of hidden nodes. In this work, the Pima Indians Diabetes Database (PIDD) is used for training and testing the proposed FLN algorithm. Furthermore, the performance of the proposed model has been assessed in terms of several evaluation measurements such as accuracy, precision, recall, F-Measure, G-Mean, MCC, and specificity. The experimental results show that the highest achieved accuracy, recall, F-Measure, G-Mean, and MCC were 82.17%, 80.95%, 71.33%, 71.84%, and 59.54%, respectively. Meanwhile, the highest obtained results for precision and specificity were 67.50% and 83.12%, respectively. In addition, the performance of the proposed model has outperformed its comparative in terms of detection accuracy.

Keywords: diabetic detection, fast learning network, Pima Indians diabetes database, and evaluation measurements.

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1. INTRODUCTION

Machine learning (ML) techniques are considered a subfield of the Artificial Intelligence (AI) domain, where such methods can solve real-world problems by providing the ability to learn to computers with no need for further programming [1]. In addition, ML has been improved over many decades by many different researchers to make computers have the ability to learn and collect the knowledge to imitate the human brain. In 1952, Arthur Samuel performed the first attempt at ML, where this attempt was conducted to develop a game-playing program for checkers. In other words, this attempt has been performed to achieve more skills for the machine and make it win versus the world checker champion. Thereafter, Frank Rosenblatt made an electronic device in 1957, where this electronic device can learn how to solve complicated issues through mimic the process in the human brain [2]. Besides, there are three main types of ML which are supervised learning, unsupervised learning, and reinforcement learning. Figure 1 shows types of ML. Supervised learning is the ML task for learning and training ML algorithms based on a labelled database [3]. Whereas in unsupervised learning, the algorithms in this type will be learned and trained by using an unlabeled database [4]. Reinforcement learning is the third type of ML, where the algorithms in this type will be learned and trained to rely on rewarding desired behaviours and punishing undesired behaviours [5]. In other words, it can analyses its environment, take action, and learn via trial and error.

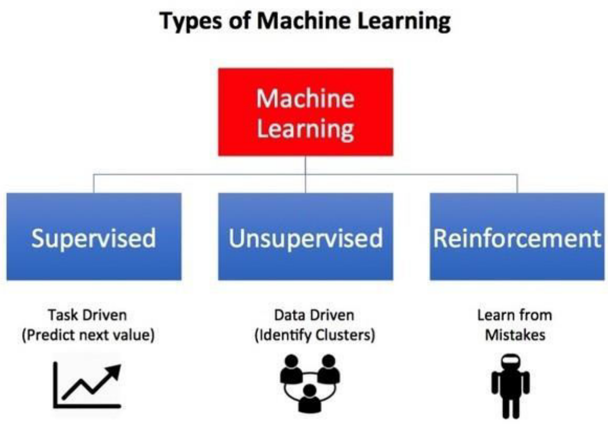

Figure-1. Types of machine learning.

Furthermore, due to the provided abilities of ML algorithms in the classification task, these algorithms have been used and proposed in many different applications. For example, ML algorithms have been applied in the identification of spam emails [6], vehicle detection [7], Wi-Fi Localization [8], image classification [9, 10], fog-cloud network [11], facial emotion recognition [12, 13], and voice pathology detection [14]. The essential purpose of utilizing ML algorithms is to learn, train, and build a system that is qualified to identify different subjects efficiently [15, 16]. The ML techniques can present assist tools in medical applications. ML techniques permit computer programs to learn from databases, which results in creating a model for identifying familiar patterns and being able to make decisions relying on collected data.

There is a huge interest by researchers in medical applications, where different ML algorithms have been used in the detection and classification of various diseases. Diabetes is considered one of the main health problems in many different countries (i.e., developed and developing countries) [17]. According to the report of National Diabetes Statistics (NDS) in 2020, there are 34.2 million people in the population of U.S. have diabetes disease. In other words, there are 26.9 million people (U.S. population) who are diagnosed with diabetes. Whilst, there are 7.3 million people (U.S. population) who have diabetes are unaware [18]. Furthermore, about 77 million people in the population of India have been diagnosed with diabetes disease in 2019 [19]. In addition, India has been ranked as the second country with the largest number of diabetic patients in the whole world [19]. Diabetes disease is one of the most popular and quickly increasing illnesses with no cure. However, diabetic disease is a condition in which there is a high level of blood sugar in the human body for a long time. Moreover, it occurs because of the inability of the pancreas to secrete sufficient insulin or it occurs because of the ineptitude of the human body to respond to insulin [20]. Thus, the detection of diabetic disease using ML algorithms is much needed. Therefore, this paper presents a new method for detecting diabetic disease based on the FLN algorithm. Besides, the performance of the proposed method has been evaluated by using different evaluation measurements.

2. RELATED WORK

Recently, the detection of diabetes disease based on ML algorithms has obtained significant attention from many researchers due to the real dangers of diabetes disease which can lead to death. As well as the effectiveness of ML algorithms and techniques that can be used in the detection part of several medical applications. Here, we will review the state-of-the-art that has been proposed in the detection of diabetes disease based on ML algorithms. The researchers in [21], have presented a model using a fused ML method for the detection of diabetes disease. In this study, there are two types of algorithms which are the Artificial Neural Network (ANN) algorithm and Support Vector Machine (SVM). These algorithms have been trained based on database samples to identify whether the diabetes diagnosis is negative or positive. The total number of samples in the database is 520. The target feature of the database is labelled with two classes, where class 1 indicates the Negative case (i.e., the person has no diabetic symptoms). Whilst, class 0 refers to the Positive case (i.e., the person has diabetic symptoms). The database is split into 70% for the training stage and 30% for the testing stage. The presented fused methods are stored in the cloud storage for future usage. The experiment results showed that the presented method using ML models achieved 94.87% detection accuracy.

The authors in [22], have presented a method for the prediction of diabetes disease based on different ML algorithms. They have used three different ML algorithms that have been widely used in the prediction part which are SVM, Random Forest (RF), and Decision Tree (DT). Furthermore, they have proposed a new framework that is called the intelligent diabetes mellitus prediction framework (IDMPF). In the proposed framework, the parameters of the Logistic Regression (LR) algorithm have been tuned to improve the detection accuracy. In this study, all algorithms have been trained and tested based on a database that contains 268 persons who are suffering from diabetes and 500 healthy persons (i.e., they do not have diabetic symptoms). Consequently, the total number of samples in the database is 768. Based on the experiment results, the proposed framework using the LR algorithm obtained a detection accuracy of 83% with the lowest error rate. The result of the proposed LR algorithms has outperformed other ML algorithms in the detection of diabetes disease.

In addition, the study in [23] has presented many different algorithms of supervised learning of ML in the detection of diabetes disease. Further, the analysis of features has been performed to evaluate the importance of these features and investigate their association with diabetes disease. The features used in this study are considered the most familiar symptoms that usually develop slowly with diabetes disease. These important features have been used to train and test the presented ML algorithms. The presented ML algorithms have been evaluated based on different evaluation measurements and under 10-fold cross-validation and database dividing (i.e., 80% for the training stage and 20% for the testing stage). The total number of participants in the database is 520. Based on the experiments, the K-Nearest Neighbors (K-NN) algorithm and RF algorithm achieved the best performance in terms of detection accuracy as compared with other ML algorithms in the identification of diabetes disease.

Regarding the detection of diabetes disease, the study in [24] has presented a model for detecting diabetes disease based on many ML algorithms. These algorithms belong to the supervised learning type. These algorithms are used for the classification part and they are the LR algorithm, Linear Discriminant Analysis (LDA) algorithm, SVM algorithm, Polynomial Kernel with SVM, RF algorithm, and voting algorithm. These algorithms have been trained and tested by using the Pima Indians database which is taken from the National Institute of Diabetes and Digestive and Kidney Diseases. In this database, there are 768 instances for diabetes class and healthy class. The experimental results showed that the obtained accuracies for LR, LDA, SVM, and Polynomial kernel SVM are 80%, 79%, 79%, and 79%, respectively. In addition, the achieved detection accuracies for RF and Voting algorithms are 82%, and 80%, respectively. Thus, the highest accuracy has been achieved by the RF algorithm in the identification of diabetes disease.

The work in [25] has proposed an intelligent system for constant monitoring of the physiological cases of those who are suffering from diabetic disease. Besides, the proposed system allows medical doctors the possibility of monitoring the health condition of these patients with diabetic disease remotely, by integrating sensors in various portable devices such as smartwatches, iPads,

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smartphones, etc. The proposed method can predict blood glucose levels, identify the riskiness of different conditions, as well as it can classify blood glucose events. There are different ML algorithms used in this study which are the Random Tree (RT) algorithm, Naive Bayes (NB) algorithm, OneR algorithm, Sequential Minimal Optimization (SMO) algorithm, ZeroR algorithm, and J48 algorithm. The experimental results showed that the J48 algorithm has achieved the highest results as compared with other algorithms, where the highest achieved results of the J48 algorithm were 99.17% accuracy, 99.47% sensitivity, and 99.32% precision.

3. PROPOSED METHOD

In this work, the proposed diabetes detection system contains three major phases which are database, feature extraction, and classification. In the first phase, the PIDD database is used for the assessment of the proposed FLN model. In the second phase, eight different features are extracted to be used as input into the FLN model. Lastly, the third phase uses the FLN model to detect whether the input is positive or negative diabetes. Figure-2 presents the proposed diabetes detection system.

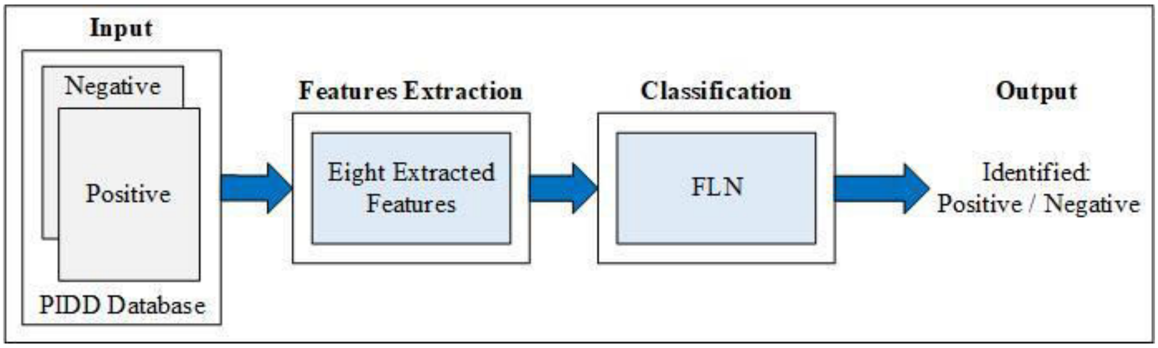

Figure-2. The proposed diabetes detection system diagram.

3.1 Database

The current study has used the Pima Indian Diabetes Dataset (PIDD) database for the evaluation purpose of the proposed FLN model. The PIDD database was taken from [26], where it has been collected by the National Institute of Diabetes and Digestive and Kidney Diseases. The PIDD database has two main categories which are positive diabetes and negative diabetes with a total number of samples equal to 768. The PIDD is an unbalanced database where the category of positive diabetes contains 268 samples while the category of negative diabetes contains 500 samples. All the samples have been collected from Pima-Indian-heritage females with age at least twenty-one years old. In the present study, all the experiments were conducted based on the ratio of 70% of the database for training purposes and 30% of the database for testing purposes. Table-1 provides a deep description of the PIDD database that has been used in this study.

Table-1. The PIDD database description.

Class Name	Total Samples Number	Training Samples Number	Testing Samples Number	Label
Positive Diabetes	268	188	80	1
Negative Diabetes	500	350	150	2

3.2 Features Extraction

The PIDD database was provided in the form of eight different extracted features. These extracted features include pregnancies, glucose, blood pressure, skin thickness, insulin, BMI, diabetes pedigree function, and age. More description and details of the PIDD database features can be found in [26]. Figure-3 shows the eight different features of the PIDD database and its meaning.

Attribute	Meaning
Pregnancies	Number of times pregnant
Glucose	Plasma glucose concentration 2 hours in an oral glucose tolerance test
Blood Pressure	Diastolic blood pressure (mm Hg)
Skin Thickness	Triceps skin fold thickness (mm)
Insulin	2-Hour serum insulin (mu U/ml)
BMI	Body mass index (weight in kg/(height in m)^2)
Diabetes Pedigree Function	Diabetes pedigree function
Age	Age (years)

Figure-3. Depiction of the eight different features of the PIDD database [26].

3.3 Fast Learning Network (FLN)

The FLN algorithm is considered a new dual parallel forward Neural Network (NN) that has been presented in [27]. In addition, the FLN algorithm has three types of layers which are the input layer, hidden layer, and output layer. In the FLN algorithm, there is a direct link between the input layer and the output layer. Besides, the FLN integrates the nonlinear association from the hidden layer to the output layer and the linear association from the input layer to the output layer. Figure-4 shows the general structure of the FLN algorithm.

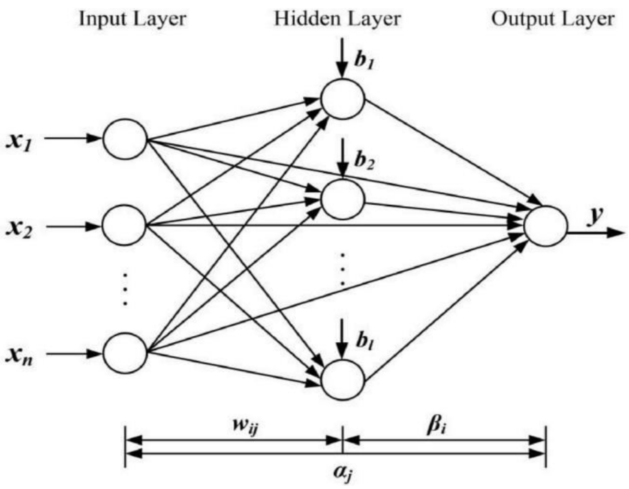

Figure-4. The general structure of the FLN algorithm.

Let's assume that there are q distinguished samples $\{(X_i, T_i), (i = 1,2, \ldots, q)\}$, where, $X_i = [x_{i1}, x_{i2}, \cdots, x_{in}]^T \in R^n$ refers to the n-dimensional input vector of i-th sample and $T = \left[T_1, T_2, \cdots, T_q\right]^T$ denotes to the output vector. In the proposed work, there are two nodes in the output layer for predicting diabetic disease. In other words, the outputs are labelled with two values, 1 refers to positive diabetes and 2 refers to negative diabetes. Furthermore, the activation function of the hidden layer has been represented as $g(x)$, and $B = [b_1, b_2, \ldots, b_m]^T$ refers to thresholds of the hidden layer. Also, the matrix of the input weight is represented as $W^{l\times n} = [W_1, W_2, \ldots W_l]^T$, the matrix of the weight for the association between the output layer and the hidden layer is represented as $\beta = [\beta_1, \beta_2, \ldots, \beta_l]$. Whilst, the weight matrix for the association between the output layer and the input layer is represented as $\alpha = [\alpha_1, \alpha_2, \ldots, \alpha_n]$. Consequently, the mathematical model of FLN can be calculated as shown in equation (1).

$$T_i = \alpha X_i + \sum_{j=1}^{l} g\left(W_j X_i + b_j\right)\beta_j i = 1,2, \cdots, q \quad (1)$$

Where: X_i denotes the input vector of the i-th, and T_i indicates the output vector. Further, equation (1) can be rewritten in a matrix as shown in equation (2).

$$T_{q\times 1} = X_{q\times n}^T \alpha_{n\times 1}^T + H_{q\times l}\beta_{l\times 1}^T = \left[X_{q\times n}^T, H_{q\times l}\right]\begin{bmatrix}\alpha_{n\times 1}^T \\ \beta_{l\times 1}^T\end{bmatrix} = \left[X_{q\times n}^T, H_{q\times l}\right] M_{(n+l)\times 1} \quad (2)$$

Where: $T_{q\times 1}$ refers to the predicted output, $H_{q\times l}$ denotes the output matrix of the hidden layer, and $M_{(n+l)\times 1}$ is indicated the output weight matrix. The feed-forward NN model aims to reduce the output error, which is the minimum of $\sum_{i=1}^{q} ||Y_i - T_i||$, where Y_i and T_i are referred to the expected value and actual value, respectively. The training stage of the FLN algorithm is equivalent to finding the least square solution $M_{(n+l)\times 1}$ of the linear model $G_{q\times(n+l)} \cdot M_{(n+l)\times 1} = T$, where $G_{q\times(n+l)} = [X^T, H]$.

$$\widehat{\mathrm{M}} = G^{+}T \quad (3)$$

Where: G^{+} indicated the Moore Penrose generalized inverse of G. In general, the computation stages of the FLN algorithm can be summarized as follows:

- Generate the input weights and hidden layer thresholds randomly.
- Compute the matrix of the hidden layer output.
- Compute the matrix of the output weight M.
- Split M into a^T and β^T.

4. EXPERIMENTS AND RESULTS

In this work, the proposed FLN model was assessed based on several experiments with varying the number of hidden neurons in the [25-200] range and 25 an increment step. The total number of conducted experiments is eight. All the experiments were implemented in MATLAB R2022a programming language on a PC with Windows 10 Pro, RAM of 12 GB, and Intel Core-i7, 3.60 GHz CPU. Further, numerous assessment measurements have been used to assess the performance of the proposed FLN model in diabetes detection such as accuracy, precision, recall, F-Measure, G-Mean, MCC, and specificity. Table-2 presents all the results of the conducted experiments. While figures (5 and 6) show the confusion matrix and ROC of the best-achieved result. The mathematical calculations of the assessment measurements are depicted in equations (4-10).

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (4)$$

$$\text{Precision} = \frac{TP}{TP + FP} \quad (5)$$

$$\text{Recall} = \frac{TP}{TP + FN} \quad (6)$$

$$\text{F} - \text{measure} = \frac{2 \times Precision \times Recall}{Recall + Precision} \quad (7)$$

$$\text{G} - \text{Mean} = \sqrt[2]{\text{Specificity} \times \text{Recall}} \quad (8)$$

$$\text{Specificity} = \frac{TN}{TN + FP} \quad (9)$$

$$\text{MCC} = \frac{(\text{TP} \times \text{TN} - \text{FP} \times \text{FN})}{\sqrt{(TP+FP)(TP+FN)(TN+FP)(TN+FN)}} \quad (10)$$

Where: TP refers to true positive, TN refers to true negative, FP and FN denote false positive and false negative, respectively. According to the experiment outcomes in Table-2 and Figures (5 and 6), the proposed FLN model has achieved the highest results with an accuracy reached up to 82.17% when the number of hidden nodes is 75. At the same number of hidden nodes (i.e., 75), the highest achieved results of recall, F-Measure, G-Mean, and MCC were 80.95%, 71.33%, 71.84%, and 59.54%, respectively. Besides, the proposed method using the FLN algorithm has achieved the highest results for precision and specificity when the number of hidden nodes is 175, where the obtained results for precision and specificity were 67.50% and 83.12%, respectively. Based on the achieved experimental results, the proposed FLN model is effective in the detection of diabetes disease.

Table-2. All experiments results of the proposed FLN model.

Number of hidden Nodes	Accuracy	Precision	Recall	F-Measure	G-Mean	MCC	Specificity
25	79.57%	57.50%	77.97%	66.19%	66.96%	53.26%	80.12%
50	80.87%	61.25%	79.03%	69.01%	69.58%	56.44%	81.55%
75	82.17%	63.75%	80.95%	71.33%	71.84%	59.54%	82.64%
100	80.44%	66.25%	74.65%	70.20	70.32%	55.93%	83.02%
125	80.87%	63.75%	77.27%	69.86%	70.19%	56.60%	82.32%
150	80.00%	63.75%	75.00%	68.92%	69.15%	54.71%	82.10%
175	79.13%	67.50%	71.05%	69.23%	69.25%	53.50%	83.12%
200	78.70%	61.25%	73.13%	66.67%	66.93%	51.63%	80.98%

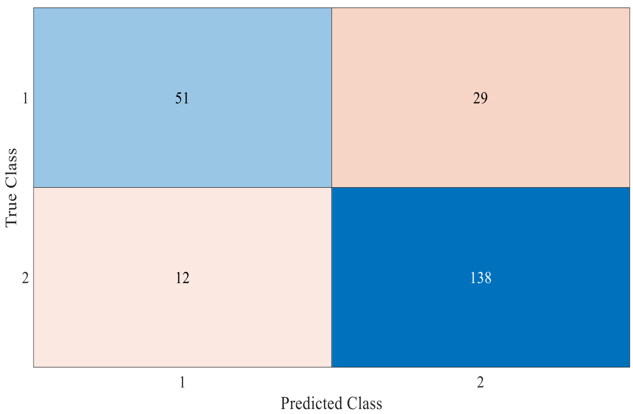

Figure-5. Confusion matrix for the best-achieved results.

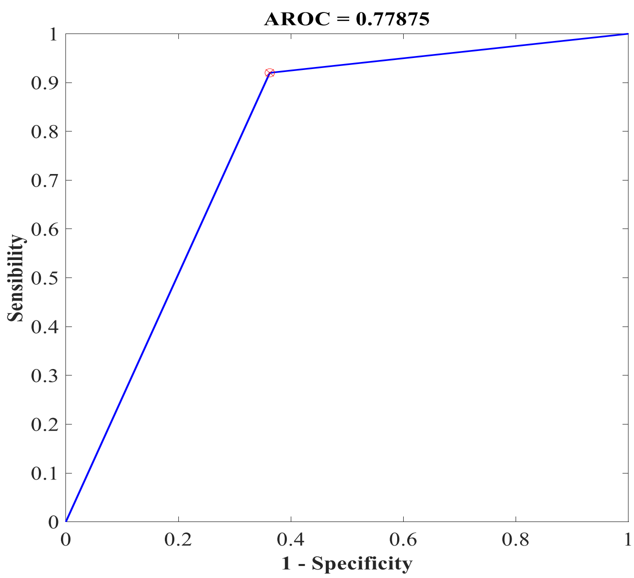

Figure-6. ROC for the best-achieved results.

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ARPN Journal of Engineering and Applied Sciences

Note: in Figure-5, 1 refers to the class of positive diabetes while 2 refers to the class of negative diabetes.

Moreover, the performance of the proposed FLN model was compared against some recent works [28-32] that have utilised the same PIDD database. Table-3 illustrates the comparison between the proposed FLN model and these recent works in terms of accuracy. The results showed that the proposed model using the FLN algorithm has outperformed its comparatives in terms of accuracy in the detection of diabetes disease.

Table-3. Comparison results between the proposed FLN model with other methods.

Methods	Accuracy
The proposed FLN model	82.17
Decision Tree [28]	73%
REPTree [29]	74%
Gaussian process [30]	81%
Naive Bayes [31]	76%
Probabilistic neural network [32]	81%

5. CONCLUSIONS

Diabetic disease is considered a real health issue in different countries. Thus, the detection of this disease using a machine learning algorithm is imperative. Therefore, this paper proposes an effective machine learning algorithm called the FLN algorithm in the detection of diabetic disease. This algorithm has been conducted by performing several experiments with varying the number of the hidden neurons in the [25-200] range and 25 an increment step. The proposed FLN algorithm has been trained and tested by using the Pima Indians Diabetes Database (PIDD). This database has been divided into 70% for training purposes and 30% for testing purposes. In addition, the performance of the proposed FLN model has been assessed in terms of many evaluation measurements such as accuracy, precision, recall, F-Measure, G-Mean, MCC, and specificity. Based on the experimental results, the highest achieved accuracy, recall, F-Measure, G-Mean, and MCC were 82.17%, 80.95%, 71.33%, 71.84%, and 59.54%, respectively. These results have been obtained when the number of hidden nodes was 75. Besides, the highest achieved results for precision and specificity were 67.50% and 83.12%, respectively. These results of precision and specificity were obtained when the number of hidden nodes was 175. In addition, the performance of the proposed model has achieved a higher accuracy compared with other methods in the detection of diabetic disease. Future work can include using the FLN algorithm in the detection of other health problems such as voice pathology and COVID-19.

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