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Combination of artificial neural network and particle swarm intelligence algorithm for diagnosing diabetes

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Highlights

- Data mining, particularly using neural networks, is effective for uncovering hidden patterns in medical records, aiding in disease diagnosis.
- Diabetes, influenced by factors like nutrition, obesity, and genetics, can be diagnosed early through data analysis techniques, reducing its impact.
- Traditional blood tests for diabetes diagnosis have limitations, prompting the exploration of alternative methods like data mining.
- Particle swarm intelligence algorithm, coupled with neural networks, enhances the accuracy of diabetes diagnosis by discovering hidden patterns.
- The proposed method achieves high accuracy, specificity, and sensitivity rates, making it a promising tool for diabetes diagnosis.

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Abstract

Data mining is an appropriate approach for uncovering information and hidden patterns within extensive datasets that are not readily detectable through conventional methodologies. This method has wide applications in various sciences, and one of its interesting applications is to identify diseases and disease patterns by examining patients' medical records. Diabetes is one of the challenges of today's society and is influenced by important factors such as nutrition, obesity, physical inactivity, and genetic background. Early diagnosis of diabetes reduces the effects of this destructive disease. The usual method for diagnosing this disease is to perform a blood test, which, despite its high accuracy, has disadvantages such as pain, cost, stress, and limited availability of laboratory facilities. The information of diabetic patients has hidden patterns that can be used to check the possibility of diabetes in people. As a powerful data mining tool, neural networks are a suitable method for discovering hidden patterns in the information of diabetic patients. In this study, in order to discover hidden patterns and diagnose diabetes, a particle swarm intelligence algorithm has been used along with a neural network to increase the accuracy of diabetes diagnosis. The general results of the research showed that the proposed method has accuracy, specificity, and sensitivity of about 94.15%, 92.89%, and 92.13%, respectively. Furthermore, in diabetic disease modeling, artificial neural networks have demonstrated outstanding accuracy compared to alternative methods such as machine learning, regression, artificial neural networks, and decision trees.

1. Introduction

The global prevalence of diabetes indicates that this disease is a global threat, and currently, diabetes is the fourth leading cause of death in developed countries[1]. Diabetes is characterized by increased blood sugar or glucose levels to a critical threshold, posing a significant

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risk to many bodily functions and potentially leading to deterioration or dysfunction[2], [3]. Two primary factors contribute to an abnormal increase in blood glucose levels. In the first case, the pancreas cannot generate insulin appropriately, resulting in type 2 diabetes. In the second case, type 2 diabetes arises when the pancreas adequately synthesizes insulin, yet the body's cells cannot effectively uptake insulin due to several factors[4].

Data mining is a valuable approach that can be employed to discover and diagnose diseases, categorize patients in disease management, and uncover patterns that facilitate expedited patient diagnosis and the prevention of consequences[5]. The data mining technique significantly improves the types of analytical tools accessible and is considered a valid, sensitive, and reliable method to discover patterns and correlations among various elements[6], [7]. Data mining methods are extensively utilized to get insights into marketing patterns and customer behavior, analyze patient data, and detect fraudulent activities[8].

Data mining is a prominent technique to uncover concealed medical insights from extensive datasets, particularly patient information [9]. A wide range of data mining techniques exist to detect and predict diseases [10]. These techniques include decision trees, Bayesian classification, neural networks, genetic algorithms, fuzzy systems, regression, and spline [11]. The decision tree has a structure very similar to that of a tree and possesses notable attributes, including simplicity and efficacy [12]. Neural networks are extensively employed as practical approaches for modeling complex systems and expansive situations characterized by numerous variables [13]. Neural networks can be employed in classification tasks, where the desired output corresponds to a certain class, and regression tasks, where the desired output is a numerical value [14]. In every neural network, there exists an input layer with nodes that correspond to the prediction variables [15]. A neural network comprises a variable and an indeterminate number of neurons [16]. The primary role of neurons is to make connections between input and output in problems, with each connection being facilitated by a weight assigned to the respective interface [17]. Han et al. (2006) compared the accuracy of three methods of logical regression, neural networks, and decision trees in diagnosing diabetes. The general results of their study showed that decision trees, logical regression, and neural network models have higher accuracy for diagnosing diabetes, respectively [18].

An artificial neural network is an important approach for diagnosing and predicting diseases [19], [20]. The artificial neural network is a machine learning technique that utilizes neural architecture to develop a model capable of predicting and estimating complicated problems through learning and imitation [21]. Utilizing an artificial neural network for learning purposes is insensitive to minor training data errors [22]. The network under consideration comprises interconnected neural cells spanning multiple layers within an artificial network [13]. However, a limitation of this approach is its dependence on medical examinations. Purnami et al. (2009) employed an artificial neural network to diagnose diabetes without a medical examination at home [23]. Polat et al. (2008) could diagnose diabetes in patients accurately based on four data mining methods, including artificial neural networks, decision trees, logistic regression, dependency rules, and using 3D body images. Their technique was to create a dataset based on image processing techniques, where laser-type sensors extracted the important features of each patient [24]. In the study conducted by Sigurdardottir et al. (2007), the decision tree approach was employed for the purpose of diagnosing diabetes. The findings of this study indicated that age is the most significant variable in terms of blood sugar control [25]. Another study was conducted to examine the variables that impact blood sugar control, utilizing simple Bayesian and decision tree techniques. The findings of their study demonstrated that parameters such as age, duration of disease diagnosis, requirement for insulin treatment, blood glucose levels, and dietary habits exert significant influence on the control of blood sugar [26]. In Toussi et al.'s research (2009), the effect of bariatric surgery on the recovery of diabetic patients, which was performed by reducing the stomach volume of 88 patients, was investigated. The results showed that variables such as Alanine aminotransferase, cholesterol, and blood pressure are the most important factors that affect the recovery of diabetic patients after bariatric surgery [27].

Numerous evolutionary techniques have been utilized in the optimization of artificial neural networks to determine the most appropriate weights for the network. Particle Swarm Optimization (PSO) is a widely employed technique in the field of machine learning for solving optimization problems[28], [29], [30], [31], [32]. It is particularly effective in training artificial neural networks and classifying diverse datasets with varying characteristics [31]. This study aims to enhance the diagnosis of diabetes and its various kinds by employing a hybrid methodology that combines the artificial neural network model with the PSO algorithm. The authors in [33] proposed the use of PSO algorithm in the optimization of support vector machine and logistic regression algorithms using Indian PIMA diabetes dataset. In [34] convolutional neural networks (CNN) and particle swarm optimization (PSO) have been investigated for the classification of diabetic retinopathy. Therefore, by studying and reviewing past researches, the purpose of this paper is to discover hidden patterns and diagnose diabetes using particle swarm intelligence algorithm along with neural network to increase the accuracy of diabetes diagnosis.

The rest of this paper can be categorized as follows: In Section 2, the proposed method is presented. The results are expressed in Section 3, and the conclusion is also stated in Section 4.

2. Proposed method

Using learning data, multi-layer artificial neural networks can determine the optimal link weights between network nodes. This process allows the neural network to effectively represent the training data, which can be evaluated by quality and accuracy tests [33]. In a multi-layer neural network, the connections between network nodes are characterized by coefficients that modulate the influence of each input, and these coefficients are commonly referred to as weights [34]. The appropriate selection of weights facilitates the convergence of the artificial neural network towards a more precise model, enhancing the accuracy of predictions. An artificial neural network is a computational model representing a hyperplane to perform estimation and prediction tasks[35].

In this study, we employed an artificial neural network with a singular output that identifies an individual's health status, distinguishing between wellness and illness. The first step in order to present the proposed algorithm is to define a multi-layer artificial neural network where the variable n_f represents the number of inputs, which in this study shows the number of features of the Pima dataset. n_L and n_i show the number of layers and the number of nodes in layer i, respectively. In the hypothetical neural network, every individual node possesses a bias, which is subsequently incorporated into the input weights of the node. The parameter b_{ij} shows the bias node i in the layer j. The number of variables changed by neural network training in the proposed method is calculated by (1).

$$v = \sum_{i \in nodes} \sum_{j \in nodes} b_{ij} + n_f \times n_L + \sum_{i=2}^{n} n_i \times n_{i+1} \quad (1)$$

In the second step, in order to optimize the weights of the artificial neural network, an objective function, which is the average modeling error, is used according to (2):

$$\hat{e} = \frac{1}{n} \sum_{i=1}^{n} (f(x) - \hat{f}(x))^2 \quad (2)$$

where $f(x)$, $\hat{f}(x)$ and n are the actual value, the estimated value and the number of training data, respectively in the form that $x \in Dataset$.

In the third step, the formulation of the variables of the problem is crucial for the particle swarm intelligence algorithm to determine the minimum of the objective function effectively. The neural network depicted in Fig. 1 comprises an input layer, a hidden layer, and an output layer. In the desired neural network architecture, the nodes within the hidden layer can be either active or inactive. When a node is deemed inactive, no computations are executed for that particular node. The network edge can be active or inactive, similar to the nodes inside the network. In the inactive state, the intended weight is considered zero.

As shown in Fig. 1, a neural network and its variables can be modeled in the form of matrixes and linear arrays. In the first layer, the weights utilized are supplemented by bias values as follows:

$$W_1 = \sum_{i \in layer\ 1} \sum_{j \in layer2} w_{ij} + B_1 \quad (3)$$

where W_1 is the matrix of weights along with the corresponding bias matrix, and B_1 is the bias matrix of the first layer, which is calculated as follows:

$$B_1 = [b_1 \dots b_n] \quad (4)$$

furthermore, the number of biases is equal to the number of nodes of the first layer or layer n.

In the second layer, the identification of active and inactive nodes can be expressed by defining the node matrix, which is computed as (5):

$$node = \begin{bmatrix} 0\ or\ 1 \\ \cdots \\ 0\ or\ 1 \end{bmatrix}_{m \times 1} \quad (5)$$

in the matrix $node$, the number of rows represents the nodes of the second layer. When a node is active, its corresponding array value is 1, whereas an inactive node has a corresponding array value of 0.

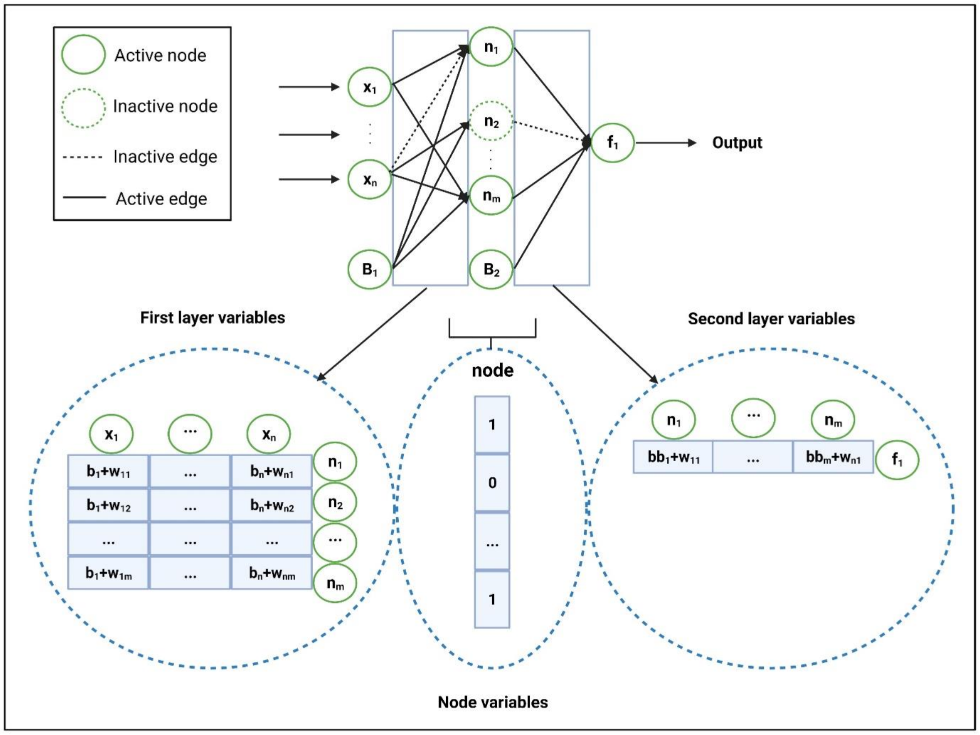

Fig. 1. Formulation of a neural network based on the weights and biases associated with its layers

The relationship between the second and third layers with the matrix W_2 is expressed as (6):

$$W_2 = \sum_{i \in layer\ 2} \sum_{j \in layer3} w_{ij} + B_2 \quad (6)$$

in (6), the weights between the second and third layers are added with the bias of the second layer, which is represented as (7):

$$B_2 = [bb_1 \dots bb_n] \quad (7)$$

The desired matrixes can be shown in the form of a linear array in Fig. 2 and used as the initial population of the particle algorithm. The arrays that are used in Fig. 2 as the initial population used by the particle swarm intelligence algorithm have different variables according to (1).

In the fourth step, a number of vectors shown in Fig. 2 are considered the initial population of the particle algorithm. The artificial neural network is trained using diabetic data and initial populations, and the steps of the particle-on-particle algorithm are followed. During each iteration, the optimal particle is selected, and in the last iteration, the network is modeled based on the global best particle. In the initial steps of the collective intelligence algorithm of particles, particles are created with random positions and velocities. During the execution of the algorithm, the position and velocity of each particle in the t+1st step of the particle algorithm are made from the information of the previous step. If x_j is the jth component of the vector x, then the relationships that change the velocity and position of the particles are calculated as follows:

$$v_j^i(t+1) = wv_j^i(t) + c_1 r_1 \left(x_j^{ibest}(t) - x_j^i(t)\right) + c_2 r_2 (x_j^{gbest}(t) - x_j^i(t)) \quad (8)$$

$$x_j^i(t+1) = x_j^i(t) + v_j^i(t+1) \quad (9)$$

where the coefficient of inertia r_1 and r_2 are random numbers in the interval [0, 1] with a uniform distribution and c_1 and c_2 are the learning coefficients of the collective intelligence algorithm of particles.

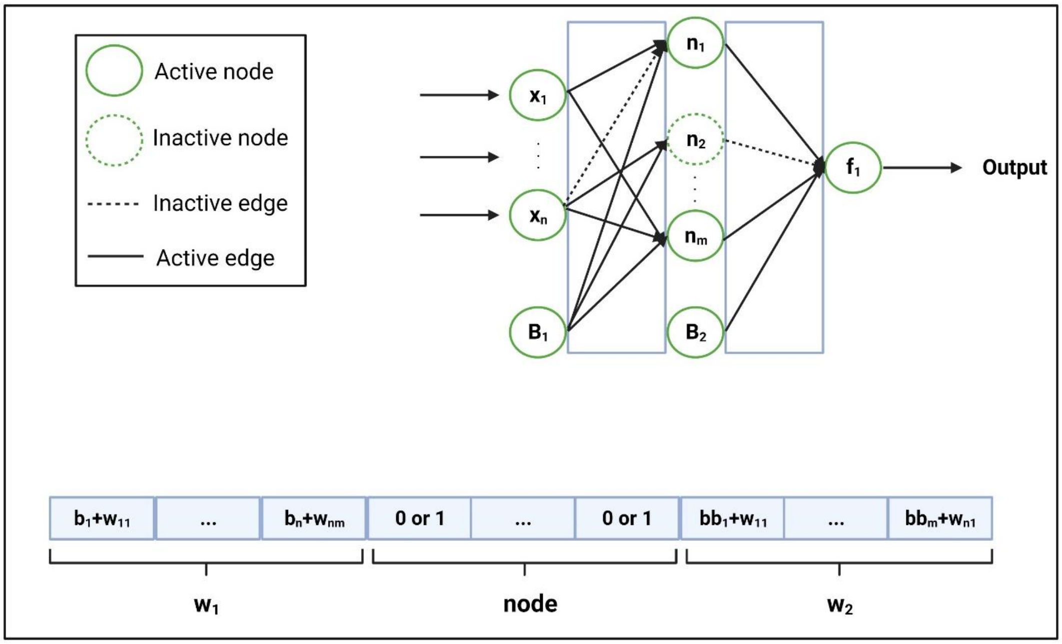

Fig. 2. Initial population formulation in particle swarm intelligence algorithm

2.1. Diagram of the proposed method

The proposed method presented in this research actually improves the outputs of the artificial neural network in each iteration. In the proposed method, which is simulated in the diagram of Fig. 3, there is sequential feedback from the output of the neural network to its input, which repeatedly optimizes the weights of the neural network with the particle optimization algorithm. In this diagram $k(y)$, $\hat{k}(y)$, and $k(e)$ are the actual output value in the kth iteration, the estimated output value in the kth iteration and the average amount of error in the kth iteration, respectively. The average error in the k iteration is expressed by (4), which is the objective function of the particle algorithm.

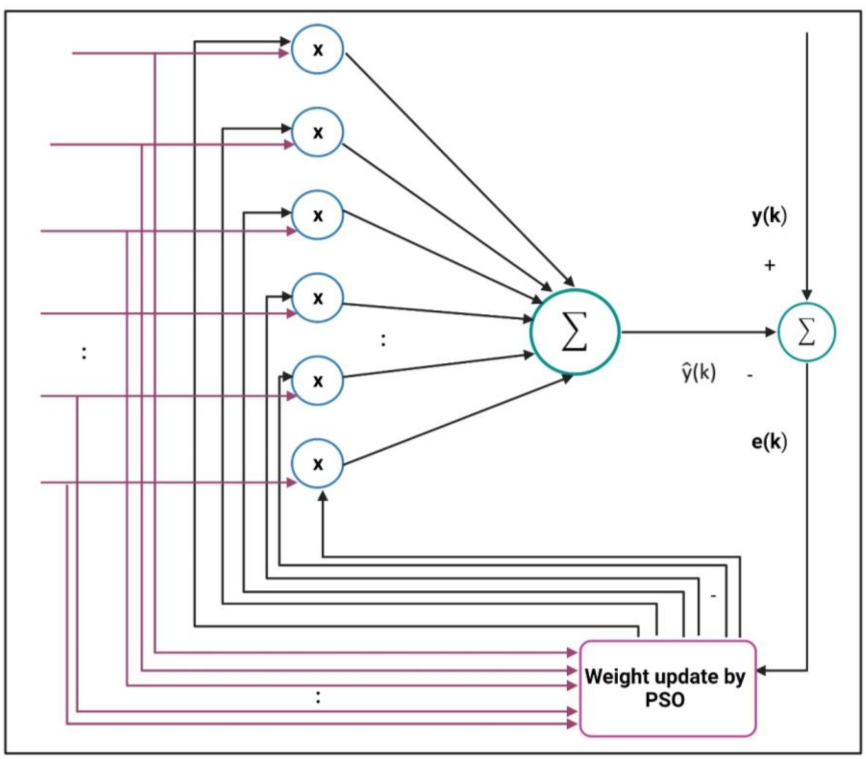

Fig. 3. Diagram of the proposed method

2.2. *Analysis of the proposed method*

In order to evaluate the proposed method and compare it with diabetes diagnosis methods, five criteria of accuracy, sensitivity characteristic, positive predictive value, and negative predictive value have been used as follows:

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \quad (10)$$

$$Specificity = \frac{TN}{FP + TN} \quad (11)$$

$$Sensitivity = \frac{TP}{TP + FN} \quad (12)$$

$$PPV = \frac{TP}{TP + FP} \quad (13)$$

$$NPV = \frac{TN}{TN + FN} \quad (14)$$

where TP is diabetic people who are correctly diagnosed, TN is healthy people who are correctly diagnosed as healthy, FP is people who are wrongly diagnosed as diabetic, and FN is people who are wrongly diagnosed as healthy[36], [37].

The present work employed the Pima Indians Diabetes Database to assess the proposed methodology. This database is a rich resource containing comprehensive information on diabetes obtained from the medical records of individuals diagnosed with diabetes. The dataset consists of 768 records, with each record representing a patient. For each patient, there are eight attributes defined. The data set was obtained from a specific population in India that exhibits a much higher genetic susceptibility to diabetes compared to other racial groups. Within this dataset, the initial eight attributes pertain to input type, whereas the ninth attribute corresponds to output type, specifically indicated by values of 0 or 1. The information contained in this set includes pregnancies, oral glucose tolerance (OGTT) tests, low blood pressure, thickness of the skin fold, insulin tests, body mass index, functional outcome, and age [38], [39], [40], [41]. In order to simulate and test the proposed method, the Matlab/Simulink model was used.

3. Results

In order to implement the proposed method, about 90% of the data in the PIMA dataset was used as training data, and the remaining data was used for evaluation and testing. Random selection was employed to choose the test and learning data for each execution of the program. In Figs. 4, 5, 6, and 7, the initial population in the particle swarm intelligence algorithm is considered constant at a value of 200. However, the iterations of the particle algorithm were chosen as 50, 100, 150, and 200, respectively. According to the depicted graphs, elevating the number of iterations in the particle algorithm within the suggested method leads to enhancements in the NPV, PPV, specificity, sensitivity, and accuracy measures. In Table 1, the fixed number of iterations in the particle swarm intelligence method is set at 50, and on the other hand, the initial population is a variable factor with values of 50, 100, and 150. Based on the analysis conducted, it can be generally concluded that augmenting the initial population results in improved accuracy of the proposed approach.

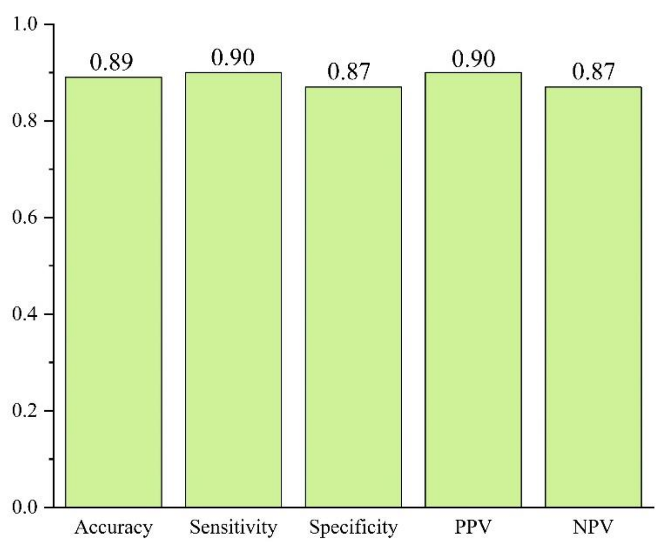

Fig. 4. Values of accuracy, sensitivity, specificity, PPV, and NPV criteria with an initial population of 200 and 50 iterations

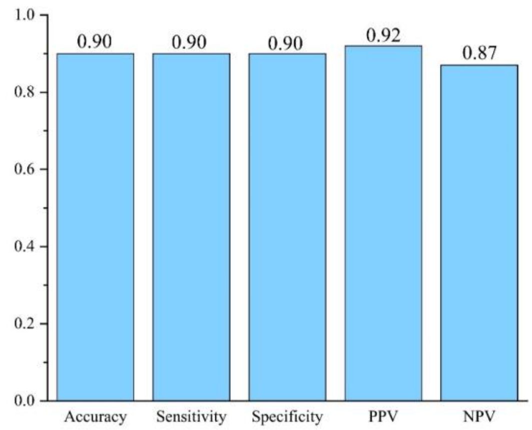

Fig. 5. Values of accuracy, sensitivity, specificity, PPV, and NPV criteria with an initial population of 200 and 100 iterations

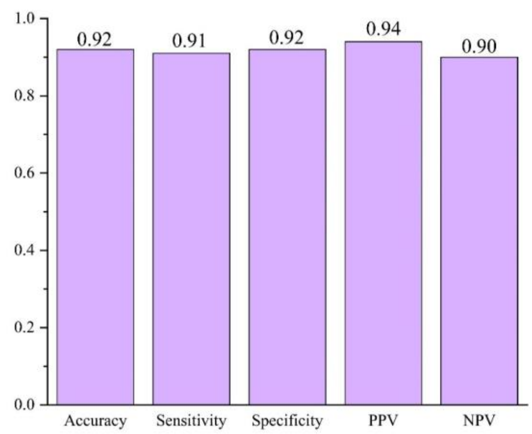

Fig. 6. Values of accuracy, sensitivity, specificity, PPV, and NPV criteria with an initial population of 200 and 150 iterations

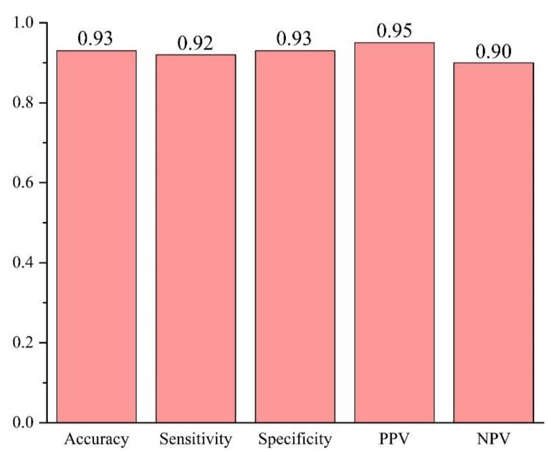

Fig. 7. Values of accuracy, sensitivity, specificity, PPV, and NPV criteria with an initial population of 200 and 200 iterations

Table 1. Performance results of the proposed method with different population and number of iterations

Criteria	The number of iterations	50	100	150	200	50	50	50
	Initial population	200	200	200	200	50	100	150
	Accuracy	0.89	0.90	0.92	0.93	0.88	0.90	0.94
	Sensitivity	0.90	0.90	0.91	0.92	0.90	0.88	095
	Specificity	0.87	0.90	0.92	0.93	0.84	0.93	0.92
	PPV	0.90	0.92	0.94	0.95	0.88	0.95	0.95
	NPV	0.87	0.87	0.90	0.90	0.87	0.84	0.92

In order to analyze and compare the accuracy of the proposed method with other methods of diagnosing diabetes, the initial population and the number of iterations were considered to be 200 To ensure a more accurate . ,assessment 50 separate experiments were conducted, and the results were calculated by considering c_1 and c_2 to a value of2,200 repetitions 200 initial populations and 50 .experiments

In Table 2, the proposed methods of artificial neural network-particle swarm optimization (ANNPSO) are compared and evaluated with methods based on machine learning, three common data mining techniques regression, artificial neural network and decision tree)[42], [43], [44] based on the criteria of accuracy, sensitivity and specificity.. The findings indicated that the suggested approach outperformed other methods concerning accuracy and specificity. However, it exhibited inferior performance compared to the FWSVM-IM-MCS method solely in terms of sensitivity. Fig. 8 displays a comparison chart between the proposed method and the methodologies mentioned above. In Fig. 9 the proposed method is , evaluated against three data mining techniques in terms of sensitivity, accuracy, and specificity. The results of the comparative analysis suggest that the proposed methodology outperforms regression, artificial neural networks, and decision tree approaches across all three evaluation criteria.

Table 2. Comparing the performance of the proposed method with other methods

Method		(%) Accuracy	(%) Sensitivity	(%) Specificity
Methods based on machine learning	LS-SVM	78.21	80	73.91
	PCA-LS-SVM	82.05	83.33	79.16
	PCA-MI-LS-SVM	87.17	91.66	80
	PCA-PSO-LS-SVM	88.46	91.83	82.75
	MI-MCS-FWSVM	93.58	94.11	92.59
Three data mining techniques	Logisticregression	76.13	79.59	72.74
	Neural network	73.23	82.18	64.49
	Decision tree	77.87	80.68	75.13
Proposed method	ANNPSO	94.15	92.13	92.89

LS-SVM: Least-squares support-vector machines; **PCA-LS-SVM:** Principle component analysis-Least square support vector machine; **PCA-MI-LS-SVM:** Principle component ;analysis-Machine intelligence-Least-squares support-vector machines; **PCA-PSO-LS-SVM:** Principle component analysis-Particle swarm optimization- Least-squares support-vector machines **MI-MCS-FWSVM:** Machine intelligence-Modified cuckoo search_Feature weighted support vector machines

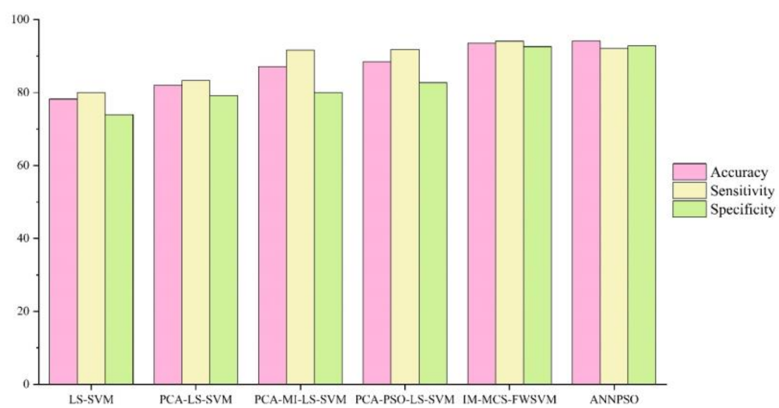

Fig. 8. Comparing the performance of the proposed method with methods based on machine learning

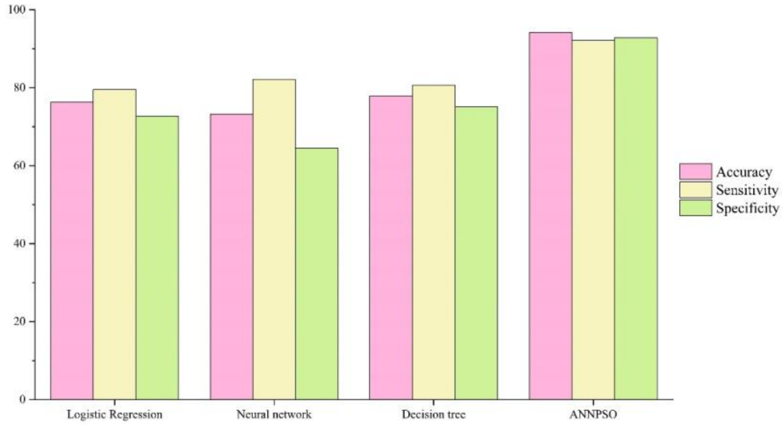

Fig. 9. Comparing the performance of the proposed method with the Three data mining techniques

4. Conclusion

This study employed a diagnostic approach for diabetes utilizing artificial neural networks and the particle swarm intelligence algorithm. The findings of the study indicate that the utilization of the particle swarm intelligence algorithm enhances the accuracy of selecting neural network weights. Diabetes disease modeling is performed more accurately with the utilization of artificial neural networks compared to other methodologies such as machine learning, regression, artificial neural networks, and decision trees. The accuracy of the proposed method is dependent on the appropriate selection of weights for the artificial neural network. By carefully selecting problem weights, the average modeling error was decreased and optimized through the utilization of the particle swarm intelligence algorithm. Furthermore, the employment of a particle swarm intelligence algorithm resulted in enhanced training of the artificial neural network through the augmentation of the iteration number in the proposed approach and the provision of more appropriate weights, as opposed to a lower number of iterations. Likewise, it was observed that the accuracy of the proposed approach exhibited a positive correlation with both the initial population size and the number of iterations.

For future work, a hybrid of particle swarm optimization algorithm and fuzzy system for diabetes diagnosis can be investigated and its performance compared with existing methods.

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