Optimizing Multi-Layer Perceptron using Variable Step Size Firefly Optimization Algorithm for Diabetes Data Classification

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Abstract—According to a survey conducted by the International Diabetes Federation, the proportion of people living with diabetes is gradually rising. Diabetes mellitus is a chronic disorder caused by a combination of genetic or environmental factors. For the early diagnosis and treatment of diabetes patients, efficient machine-learning methods are needed. Data Classification is a significant subject in many areas of life, and it is also a very challenging job in data mining. Clinical data mining has recently gained attention in complicated healthcare challenges relying on healthcare datasets. The principal objective of classification is to classify all data in a given dataset to a certain class label. In the healthcare field, classification is commonly employed in many research articles. A hybrid method for diabetes data classification is suggested by integrating multilayer perceptron with a modified firefly optimization algorithm for diabetes data classification. The performance of the proposed hybrid multilayer perceptron variable step size firefly algorithm is compared with other hybrid models such as the hybrid multilayer perceptron particle swarm optimization algorithm, hybrid multilayer perceptron differential evolution algorithm, and hybrid multilayer perceptron firefly optimization algorithm. The performance of these models is calculated based on accuracy, precision, recall, F1 score, and mean square error. In comparison to other models, the proposed hybrid model produces superior outcomes for Pima Indian diabetes data classification.

Keywords—classification, multi-layer perceptron, particle swarm optimization algorithm, differential evolution algorithm, firefly optimization algorithm

1 Introduction

Diabetes is recognized as one of the topmost chronic disorders in the modern world. It causes disability and mortality, moreover, its prevalence is rising, especially in developing nations. Diabetes is a chronic disease that is rapidly spreading among humans. Diabetes Mellitus (DM), generally known as diabetes, is one of the deadliest

illnesses today [1]. A large number of people worldwide are presently dealing with the detrimental impacts of diabetes. Many patients get undiagnosed in the initial phase. This can cause serious health-related issues like blindness as well as kidney failure over time. Different machine learning (ML) algorithms can be used to recognize and classify the disease. We need carbohydrate-rich foods to maintain healthy physical and mental equilibrium in diabetics [2–4]. Diabetics have excessive levels of glucose in their blood in addition to urine, which can cause serious complications such as blindness and failure of kidneys over time. Diabetes must be detected early and accurately to be managed effectively. Machine learning algorithms are a prospective method for detecting diseases. The main objective is to enhance the early diagnosis of diabetes using different machine learning methods.

Type I diabetes (T1D), type II diabetes (T2D), and gestational diabetes (GD) are the three different forms of diabetes. T1D is most generally found in young persons below the age of 30. Polyuria, thirst, persistent hunger, weight loss, and visual problems are all due to T1D. T2D affects people above the age of 45 and is often linked to obesity, hypertension, dyslipidemia, and arteriosclerosis, in addition to other illnesses. Gestational diabetes is the third kind of diabetes, it is a condition that affects pregnant women. Because most medical data is nonlinear, abnormal, correlation organized, and complex studying diabetic data is a difficult task [5]. In the field of healthcare, machine learning-based methods have a great role. It also supports people in effectively diagnosing diabetes with the best classifier being one of the most critical issues for proper diabetes risk prediction. In this context, different machine learning methods have been used to classify and predict diabetes like K-nearest neighbors (KNN), Decision tree (DT), Support vector machine (SVM), Random Forest (RF), Logistic regression, Naïve Bayes (NB), Artificial neural network (ANN), and so on [6].

Thus, in this context, a hybrid machine learning algorithm for diabetes prediction has been proposed using a multilayer perceptron (MLP) and a modified firefly optimization algorithm (VSFA). The main objective of this work is to apply the proposed hybrid model for diabetes prediction. The main contribution of this study is listed below.

- A hybrid MLP-based VSFA has been projected, in which the VSFA has been used to improve the training efficiency of the MLP algorithm.
- The performance of the proposed hybrid multilayer perceptron variable step size firefly algorithm (HMLPVSFA) is compared with the hybrid multilayer perceptron particle swarm optimization algorithm (HMLPPSO), hybrid multilayer perceptron differential evolution algorithm (HMLPDE), and hybrid multilayer perceptron firefly optimization algorithm (HMLPFA) on basis of accuracy, precision, recall as well as F1 score.

This study has been organized as follows: Section 2 highlights interrelated research studies of machine learning applications on diabetes prediction. Section 3 explains the proposed algorithms used for this work. In Section 4 the simulation results have been discussed. Section 5 concludes the study with a conclusion followed by future work.

2 Related work

Scientists proposed research intends to develop a model that accurately predicts diabetes in humans. Classifiers regulated by ML such as SVM, KNN, LR, NB, Gradient Boosting (GB), and RF have been used. The investigation is based on the Pima Indian Diabetes Database (PIDD), a Kaggle data repository dataset. Experiments demonstrate that RF has the best performance compared to the other classifiers utilized in the suggested methodology, [7]. By using the R data manipulation tool, scientists utilized ML to generate trends and find patterns having risk factors in the Pima Indian diabetes dataset. Utilization of the R data manipulation tool to design and analyze five different predictive models categorizing patients as diabetic or non-diabetic. ML algorithms in the Supervision category such as the linear kernel SVM (SVM-linear), the radial basis function (RBF) kernel SVM, the KNN, the ANN, and multifactor dimensionality reduction (MDR) for this has been employed. Concerning all parameters, the SVM-linear and the KNN are the top two algorithms for calculating whether a person is diabetic or not [8]. Researchers attempt to demonstrate different strategies such as GB, LR, and NB, to detect diabetic conditions having 86 percent accuracy for GB, 79 percent for LR, and 77 percent for NB [9]. The Enhanced and Adaptive Genetic Approach (EAGA), a new hybrid attribute optimization algorithm has been used to obtain an optimal symptoms dataset. A likely occurrence of diabetes is predicted depending on readings of symptoms in the optimized obtained dataset. The EAGA model is then combined with MLP (EAGA-MLP) to evaluate diabetes based on the symptoms reported. It's furthermore been tested on seven other disease datasets to check the performance. The suggested model's performance was tested against several key performance measures. It is observed that the proposed (EAGA-MLP) model beat all other existing classification models in terms of classification accuracy [10].

A novel hybrid training approach in the stochastic domain for MLPs neural networks based on the newly announced grasshopper optimization algorithm (GOA) has been proposed. The suggested GOAMLP model is being tested on five different datasets: breast cancer, Parkinson's disease, diabetes, coronary heart disease, as well as orthopedic patients. Outcomes are qualitatively and quantitatively evaluated in contrast to eight well-known and recent algorithms. It is demonstrated as well as proof that the suggested stochastic training algorithm GOAMLP improves the classification rate of MLPs significantly [11]. A new training process in which the number of hidden neurons as well as connection weights in feedforward neural networks can be optimized simultaneously. A fresh training approach based on hybrid particle swarm optimization with multi-verse optimization based on Lévy battle (PLMVO) (FFNN) has been used. Nine biomedical datasets were used to benchmark and evaluate the comparison. PLMVO offers better results than other training algorithms in all datasets. It is proven as capable as an alternative to conventional methods of training [12].

A stacking-based integrated kernel extreme learning machine (KELM) technique for assessing the serious issues of type-II diabetic patients using the diabetes research center dataset's follow-up period has been created. The Hybrid Particle Swarm Optimization-Artificial Fish Swarm Optimization (HAFPSO) approach solves problems

in the multi-objective domain by enhancing Classification Accuracy (CA) as well as lowering the kernel complexity of the selected optimum learners (NBC). Finally, the method is combined by using the KELM as a meta-classifier. It integrates the detection of all twenty Base Learners. Different measurements such as accuracy, sensitivity, specificity, Mathews Correlation Coefficient, and Kappa Statistics are evaluated to test the suggested approach. The findings indicate that the KELM-HAFPSO method is a potential novel technique for the diagnosis of type 2 diabetes [13]. The general PSO is a well-known swarm-based algorithm. It was influenced by the communal behavior of birds, created to simulate their collective knowledge. The PSO's key feature is its easy method of sharing data amongst agents, which is dependent on certain equations [14]. The DE process is a type of evolutionary programming technique. For its simple structure, adaptability, efficiency, and reliability, DE provides a variety of applications. DE is among the good genetic algorithms for real-valued problem resolution [15]. The MLP is a type of neural network designed with three layers: an input layer, one or more hidden layers, and an output layer. Training MLPs in a supervised manner can be effectively used to address challenging and diverse tasks. The data is received by the input layer, then transmits to the hidden layer [16].

The FA is a population-based algorithm that investigates the hunting activities of fireflies to identify the global optima of objective functions relying on swarm intelligence. In FA, agents commonly known as fireflies, are arbitrarily scattered throughout the search area [17–18]. By using MLP and PSO, a new hybrid predictive model has been developed. The PSO evolutionary algorithm is used to improve the efficiency of the MLP classifier by using its basic principles and problem-solving method [19]. In HMLPDE the MLP is integrated with DE for data classification. In this piece of research, the DE algorithm is utilized to train MLP The MLP and DE have been hybridized to get better classification accuracy [20]. This is a hybrid approach based on MLP and FA algorithms. Compared to other algorithms like popular PSO and GA-based approaches, the FA algorithm has been proven to be quite efficient. If we employ a single strategy, we may not be capable of achieving good classification accuracy. So, a hybrid mechanism using DE and MLP has been used to make classification accuracy better [21].

3　The proposed HMLPVSFA model

In the proposed HMLPVSFA model the MLP is hybridized with a modified FA optimization process named variable step size firefly optimization algorithm to perform better than the standard FA algorithm. The performance of the standard firefly algorithm can be improved by increasing the convergence speed [22]. To overcome the drawbacks of the standard FA algorithm, global exploration and local exploitation should be maintained properly. For this purpose, the step size α should be adjusted dynamically. In a standard FA algorithm, the step size α is constant; it will not perfectly follow the searching process. In VSFA, the step size α is considered a variable [23].

To maintain the balance between the identification and development capacity of the firefly algorithm, initially the step size α should be a larger value. Subsequently, decreases over iterations. Based on various search spaces of optimization issues, a large search step size is needed if the definition space of the optimization target is high. Otherwise, a small search step size is required, which will aid the algorithm's ability to acquire a variety of optimization issues [24].

The MLP is a feed-forward neural network (FFNN) that is extensively employed for several modeling applications. The MLP framework consists of three main levels (one input layer, one output layer, and one or more hidden layers), and each one contains certain neurons. The number of neurons in the input along with output layers is equivalent to the total of input and output variables in the structure. However, the optimum size of neurons in the hidden layer has been calculated using a trial-and-error method based on the lowest RMSE criterion [25]. The VSFA can optimize the weights as well as biases of neurons in the MLP model, resulting in the network output having the smallest mean square error. The initial selection of weights and biases for the MLP model between zero and one has a considerable impact on the generating of local optima, training, and system convergence speed. To train the MLP model, the VSFA first establishes the initial weights and biases of the neurons, and it is critical to have fitness functions of the VSFA as well as assess them for improving the MLP network. The HMLPFA approach can generate a more exact output from the local optimum and if appropriate termination conditions are satisfied, the network iterations stop. It proved to be a more effective model than the other existing hybrid models. In Figure 1 the architecture of the work is presented. Initially, input data is normalized. Then the normalized dataset is divided into training as well as testing subsets and the transfer function of neurons is defined. The MLP structure is trained with a training dataset. Then the weight and bias of the MLP structure are extracted to optimize for VSFA. The simulation results obtained from the optimized model are tested.

The proposed HMLPVSFA is summarized as follows:

1. Start
2. Read the dataset.
3. Normalization of the input dataset.
4. 80% of data is taken for training whereas 20% of data is taken for testing and the transfer function of neurons is defined.
5. The MLP model is constructed.
6. Train the model with the training data structure.
7. Weight and bias are extracted and introduced for VSFA inputs.
8. Weight and bias are optimized by using VSFA.
9. Model constructed by using the optimized weight and bias.
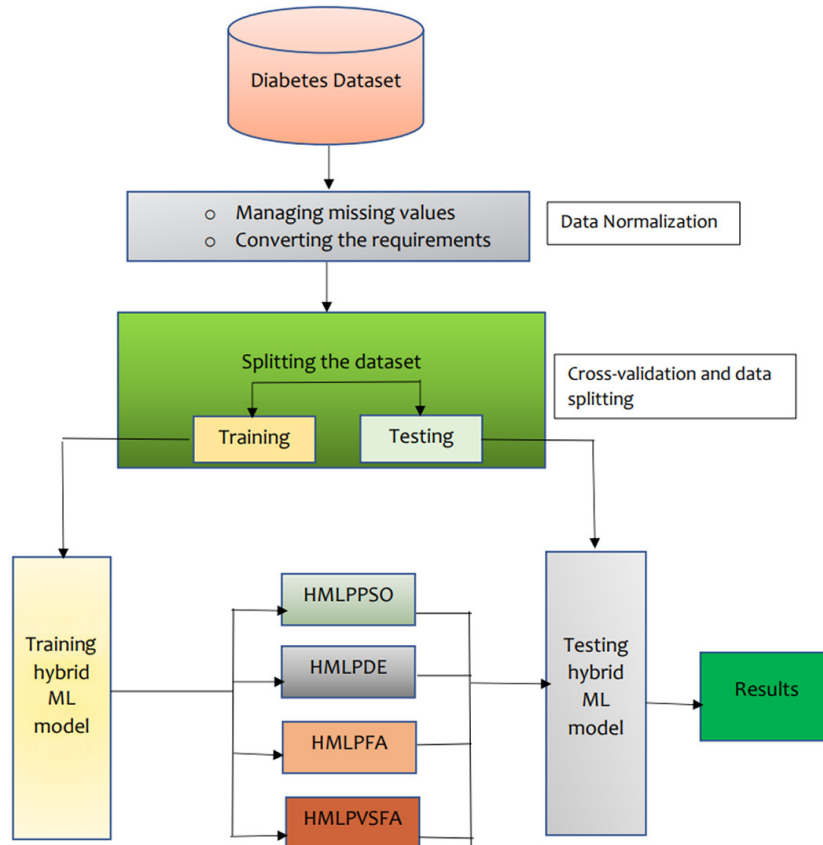10. Simulate and test the optimized model.
11. End

Fig. 1. The architecture of the work

4 Simulation results

4.1 Preliminaries

The system utilized to simulate this study has a 4 GHz processor and 8 GB of RAM. Microsoft Windows 10 is used as the operating system. MATLAB R2015a has been used to perform the tests. To check the efficiency of the multiple models, the Pima Indian diabetes classification dataset from the UCI machine learning repository is employed. This research focuses on factors such as accuracy, precision, and recall, along with the F1 score to examine the efficiency of the utilized models for diabetes datasets. The Pima Indian diabetes datasets from the UCI machine learning repository have been divided into two groups. 80% of the datasets are utilized for training, while the rest 20% are used to test the suggested models. Table 1 has a thorough overview of the diabetes dataset that is used.

The following algorithms are computed using the above-discussed diabetes dataset.

- The proposed HMLPVSFA.
- HMLPFA.
- HMLPDE.
- HMLPPSO.
- KNN, RF, VM, DT, and MLP.

The network's parameters including the number of nodes in the input, weight values for linking nodes, and biases were put at random. The diabetes data is used to generate the input and output. A tan-sigmoid activation function is employed for the method. Each algorithm was trained and tested on biases, as well as updated weights, meta-heuristically. The number of iterations allowed in each attempt is set to 100. Each dataset has been tested a total of 10 times since the commencement of selected algorithm validation. The number of epochs, accuracy, precision, recall, F1 score, and mean square error (MSE) are documented in separate files for each trial. A detailed description of the parameters used is mentioned in Table 2. The algorithms employed are HMLPVSFA, HMLPFA, HMLPDE, and HMLPPSO. The population size for HMLPVSFA, HMLPFA, HMLPDE, and HMLPPSO is 50. The upper bound and lower bound for all four discussed hybrid algorithms is set to [5, −5].

4.2 Diabetes dataset

The Pima Indian diabetes dataset collected from the ML repository of California University (UCI) has included 768 adult female samples with multivariate features. In this dataset 9 attributes are divided into 8 medical predictors (independent) variables and one target (dependent) variable, Outcome. This dataset consists of 768 patients; 268 patients are diabetic and 500 patients are nondiabetic. This displays the chemical changes that occur in the female body from the beginning to the final stage which converts to diabetes disease.

Independent variables include:

- Pregnancies: The number of pregnancies the patient has had.
- 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)
- Outcome: Class variable (0 or 1) 268 of 768 is 1, and the others are 0.

Table 1. Diabetes dataset description

Data Sets	Total Instance	Training Sample	Testing Sample	Attributes
Diabetes	768	80%	20%	9

Table 2. Parameter setting

Algorithms	Population Size	Iterations	Upper Bound	Lower Bound
HMLPVSFA	50	100	5	−5
HMLPFA	50	100	5	−5
HMLPDE	50	100	5	−5
HMLPPSO	50	100	5	−5

4.3 Results analysis

The dataset consists of eight medical predictor variables and one target variable. The number of instances is 768. The performance of other machine learning classifiers like LR, SVM, NB, DT, RF, and MLP based on accuracy for the diabetes dataset is mentioned in Table 3. The efficiency of discussed hybrid algorithms is clearly explained in Table 4.

4.4 Confusion matrix

To evaluate and compare the models to determine the most effective diabetes prediction algorithm, we employed Confusion Matrix (CM), Accuracy, MSE, Precision, Recall, and F1 Score, as result indicators. When there are two or more types of output, a confusion matrix is utilized to classify them. A confusion matrix is a two-dimensional table: "Actual" and "Predicted," as also "True Positives (TP)," "True Negatives (TN)," "False Positives (FP)," and "False Negatives (FN)" both dimensionally.

Table 3. Performance of machine learning classifiers

Algorithms	Accuracy (%)
LR	77.27
SVM	77.25
NB	75.32
DT	68.83
RF	75.93
MLP	78.0

Table 4. Performance of HMLPPSO, HMLPDE, HMLPFA, and HMLPVSFA algorithms

		Algorithms			
	Parameters	**HMLPPSO**	**HMLPDE**	**HMLPFA**	**HMLPVSFA**
Training	Accuracy(%)	78.0	77.2	79.5	86.8
	MSE	0.44565	0.43065	0.23455	0.12456
	Precision(%)	52.7	48.6	60.8	90.23
	Recall (%)	80.4	81.8	78.3	89.18
	F1 Score (%)	63.66	60.97	68.44	94.7
Testing	Accuracy (%)	64.4	74.0	83.8	84.9
	MSE	0.40564	0.42777	0.22587	0.11348
	Precision(%)	59.4	70.3	87.5	96.9
	Recall (%)	100	100	94.9	87.3
	F1 Score (%)	74.52	82.56	91.04	91.84

From Table 3, the MLP algorithm performs better with 78% of classification accuracy on diabetes dataset classification than other machine learning classifiers. This motivates further study on MLP. Hence in this study, the suggested hybrid model MLP is applied with a VSFA for diabetes prediction.

Table 4 shows the accuracy, MSE, Precision, Recall, and F1 Score of the suggested and all other discussed hybrid algorithms over the 100 epochs that each algorithm was run. It can be observed that the proposed HMLPVSFA algorithm is the most effective hybrid algorithm with the highest accuracy rate of 86.8%, a precision of 90.23%, recall of 89.18%, F1 score of 94.7% lowest MSE of 0.12456 for the 80% of training datasets, whereas for the 20% of a testing dataset having 84.9% accuracy rate, the precision of 96.9%, recall of 87.3%, F1 score of 91.84% with 0.11348 MSE. Additionally, HMLPFA lags below the HMLPVSFA concerning accuracy, precision, recall, F1 score, and MSE. For the training dataset, HMLPFA achieves 79.5% accuracy, 60.8% precision, 78.3% recall, and a 68.44% F1 score with 0.23455 MSE. This method achieved an 83.8% accuracy rate, 87.5 for precision, 94.9% for recall, and 91.04% for F1 score with 0.22587 MSE for the testing dataset. Furthermore, the HMLPDE falls behind the proposed HMLPVSFA algorithm based on accuracy, precision, recall, F1 score, and MSE with 77.2% of accuracy, 48.6% precision, 81.8% recall, 60.97% F1 score, and 0.43065 MSE for the training dataset. In addition to this, the testing dataset gets a 74.0% accuracy rate, 70.3% precision, 100% recall, 82.56% F1score, and 0.42777 MSE. Finally in terms of accuracy, precision, recall, F1 score, and MSE. HMLPPSO also lags behind the proposed HMLPVSFA algorithm with 78.0% accuracy, 52.7% precision, 80.4% recall, 63.66% F1 score, and 0.44565 MSE for the training dataset. Whereas, this algorithm achieves 64.4% accuracy, 59.4% precision, 100% recall, and 74.52% F1 score with 0.40564 MSE for the testing dataset. The performance of all the discussed hybrid algorithms is shown in the confusion matrix in Figures 2–9. The proposed HMLPVSFA algorithm is also compared with other discussed hybrid algorithms in terms of convergence graph which is shown in Figure 10. The performance of all the discussed hybrid algorithms concerning the accuracy, precision, recall, and F1 score

for both pieces of training, as well as a testing dataset in the bar graph, is shown in Figures 11 and 12 respectively.
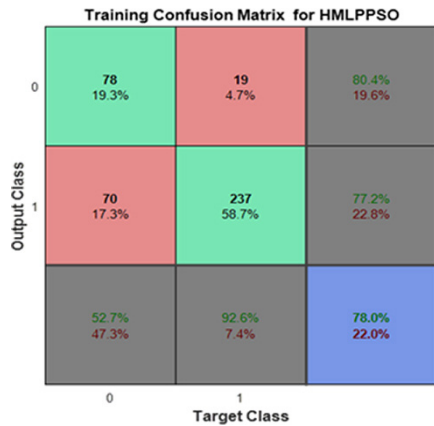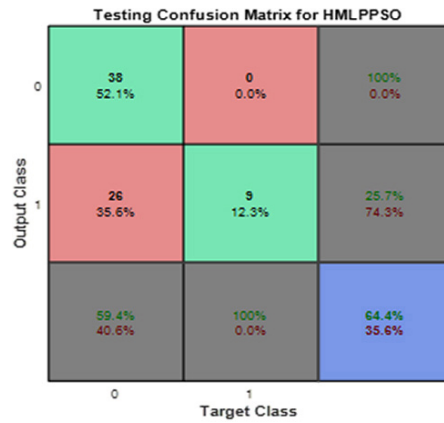

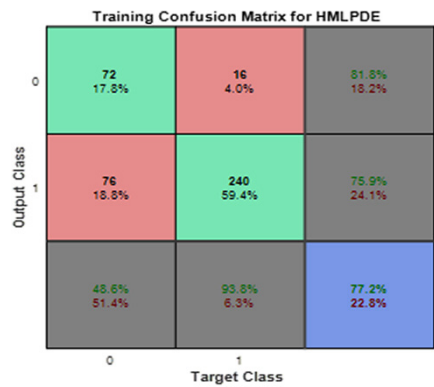**Fig. 2.** Training CM for HMLPPSO

Fig. 3. Testing CM for HMLPPSO
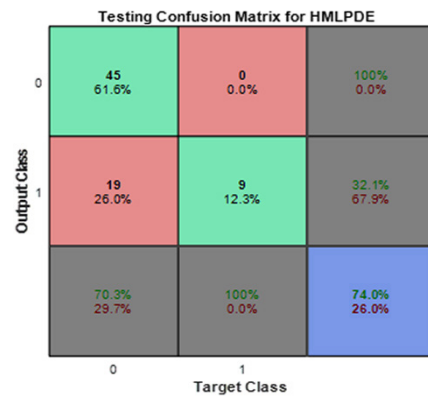

Fig. 4. Training CM for HMLPDE

Fig. 5. Testing CM for HMLPDE
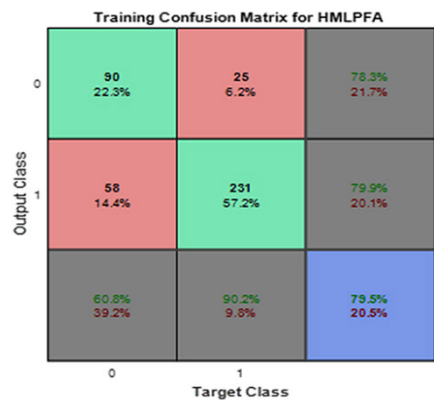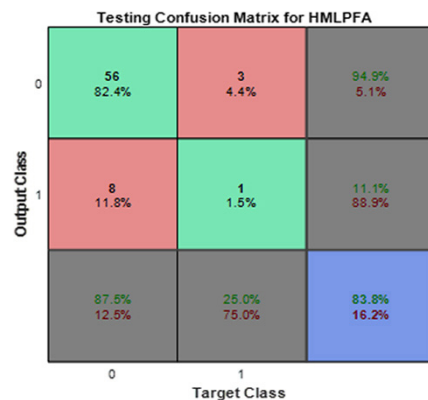

Fig. 6. Training CM for HMLPFA

Fig. 7. Testing CM for HMLPFA
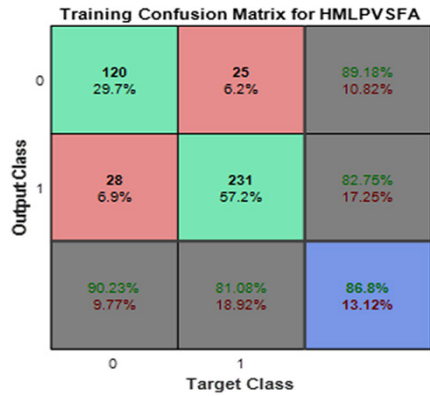
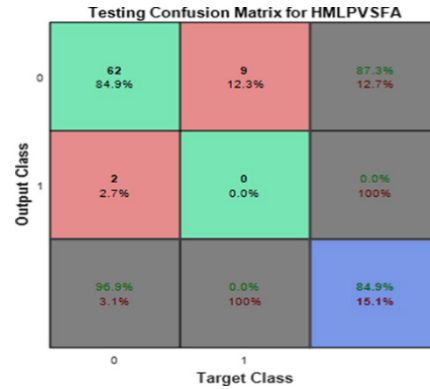**Fig. 8.** Training CM for HMLPVSFA

Fig. 9. Testing CM for HMLPVSFA

A confusion matrix is used for classification because accuracy is insufficient when the class is unbalanced and various kinds of the error have distinct cost effects. Higher TP and TN values and lower FP and FN values will improve the model's performance. The model should be developed to maximize TP and TN values while minimizing FP and FN values. Depending on the requirements of the classification problem, one or both FP and FN must be minimized. In Figures 2–9 the TP and TN values are higher than the FP and FN values. It implies that the proposed model is efficient enough to perform well for Pima Indian diabetes dataset classification.

To predict diabetes for the Pima Indian diabetes dataset, the performance of all four hybrid models is analyzed based on parameters like precision, recall, F1 Score, accuracy, and MSE. Accuracy is used to know how often the model is accurate to predict whether the patient is suffering from diabetes or not. Precision has been used to assess a classifier's capacity to make accurate positive diabetes predictions. In our work, recall is utilized to determine the percentage of actual positive instances of diabetes that the classifier properly detected. Since the weighted average of recall and precision yields the F1 score, this score considers for both. The best classifiers for F1 are those with scores close to 1. MSE evaluates the average squared difference between the values that were anticipated and those that were observed. The MSE is equal to 0 when a model is error-free. Therefore, based on the aforementioned studies, it can be concluded that HMLPVSFA is the best model having the highest accuracy and lowest MSE to predict whether a patient is suffering from diabetes or not. Further, it can be seen that recall of both HMLPPSO, HMLPDE and HMLPFA are greater in comparison to the HMLPVSFA model. If we closely study our Pima Indian diabetes dataset, we find that it is an example of a class that is unbalanced, with 500 negative cases and 268 positive examples, for such an imbalance ratio of 1.87. In the case of an unbalanced class, the recall may not be a very accurate indicator of how well a binary classifier performs. As it strikes a balance between precision and recall, the F1 score offers a better understanding of classifier performance in cases of unequal class distribution. Therefore, in this instance, F1 score should also be considered. In addition, it is obvious that the HMLPVSFA performs better having the highest accuracy and lowest error

value (Table 4) for diabetes prediction. As FA is more advance than PSO and DE for optimization tasks, HMLPFA is giving the second-highest classification result. In terms of solution accuracy and robustness, HMLPDE performs better than HMLPSO.
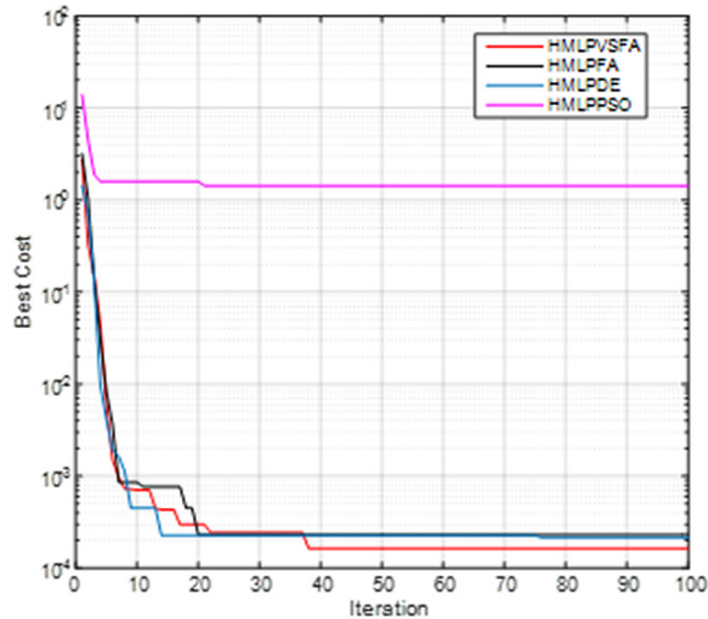

Fig. 10. Convergence graph for all discussed hybrid algorithms

Figure 10 shows the convergence graph for HMLPPSO, HMLPDE, HMLPFA, and the proposed HMLPVSFA based on iteration and best cost. The pink line represents the HMLPPSO the black line is used for HMLPFA the blue line is for HMLPDE and the red line is used for the proposed HMLPVSFA algorithm. From Figure 10 it can be observed that the proposed HMLPVSFA converges smoother and faster than other algorithms and gives superior results than other algorithms.
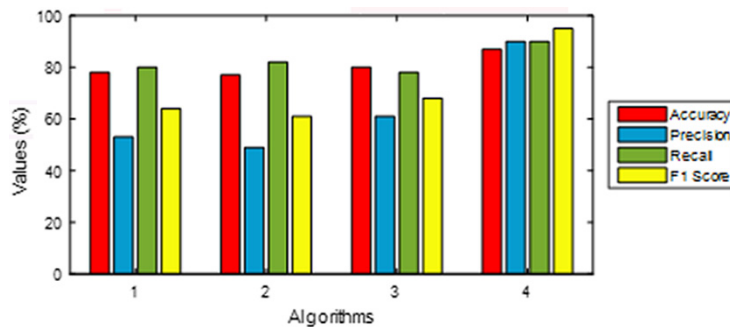

Fig. 11. Bar plot for training performance of HMLPPSO, HMLPDE, HMLPDE and HMLPVSFA
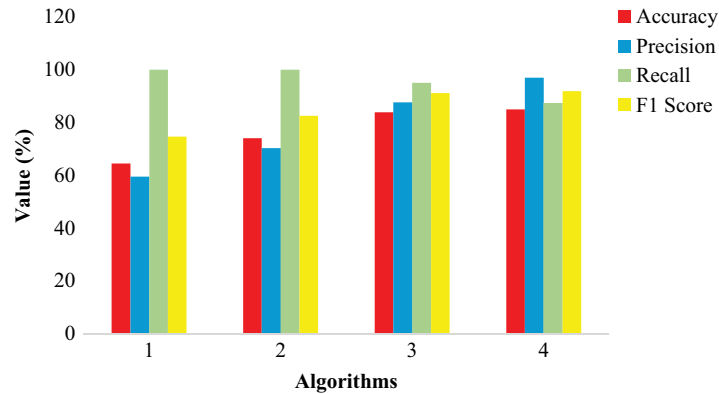
Fig. 12. Bar plot for testing performance of HMLPPSO, HMLPDE, HMLPDE and HMLPVSFA

In Figures 11 and 12, the training and testing performance of all discussed hybrid algorithms are represented in bar graphs respectively. In the X-axis of both graphs 1 refers to HMLPPSO, 2 represents HMLPDE, 3 is used for HMLPFA whereas 4 refers to the proposed HMLPVSFA algorithm. The Y-axis of both graphs is showing values(%). The red bar in graphs is used for accuracy, and the blue bar is applied for precision, similarly, the green bar is used for recall and the yellow bar represents to F1 score. From both the training and testing bar graph, it can be observed that the proposed HMLPVSFA gives superior results to all other algorithms with reference to accuracy, precision, recall, and F1 score.

5   Conclusion

Several studies have been conducted to classify diabetes data using ML classifiers. Various research has been also performed by using hybrid metaheuristic optimization algorithms. In this paper, a modified firefly optimization algorithm is hybridized with MLP. The main objective of the proposed HMLPVSFA model is to solve classification issues in diabetes datasets. As the complexity of data increased over time, MLP encountered challenges with wide applications. In the proposed HMLPVSFA algorithm, the variable step size firefly algorithm has been used to improve the training efficiency of the MLP algorithm. Hence, in this research, an MLP was suggested that was combined with a metaheuristic-based search algorithm termed variable step size firefly algorithm (VSFA). This work is significant because it presents a new strategy for MLP that differs from typical machine learning classifiers. In terms of accuracy, precision, recall, F1 score, and MSE the suggested HMLPVSFA model is compared to other hybrid algorithms such as HMLPPSO, HMLPDE, and HMLPFA algorithm both for training and testing on diabetes dataset. The simulation outcomes demonstrated that in comparison to other hybrid methodologies, the proposed HMLPVSFA algorithm for diabetes classification offers excellent improvements. The selected dataset only considers data from women, these results are expected to be valid also for men. In the future, the

proposed HMLPVSFA algorithm can be applied efficiently in various disease classifications. Additionally, HMLPVSFA can be applied in different areas for better performance. Furthermore, this research can be expanded to determine the likelihood that non-diabetics will develop diabetes in the coming years.

6   References

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