

Original article

Hybrid Particle Swarm Optimization and Genetic Algorithm for Diabetes Prediction

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Abstract

Diabetes is a prevalent chronic illness across the world, and early detection has proven to be of great importance to enhance patient well-being. Machine learning algorithms have shown strong performance in forecasting diabetes, especially MLP neural networks. However, MLP prediction accuracy depends heavily on selecting optimal hyperparameters, which often presents an optimization challenge. To enhance the performance of MLPs in predicting diabetes, this study proposes an enhanced adaptive hybrid framework combining particle swarm optimization and a genetic algorithm (AHP SO-GA). The particle swarm optimization (PSO) algorithm is used to efficiently explore the search space and identify the best hyperparameter configurations for the MLP model. The genetic algorithm (GA) is applied to overcome the early convergence and diversity limitations associated with the PSO algorithm, periodically applying the best candidate solutions generated by the PSO algorithm. Furthermore, an adaptive strategy is introduced to dynamically adjust the mutation rate as the optimization process progresses. Specifically, when accuracy does not improve for a given number of iterations, the mutation rate is increased to encourage exploration; otherwise, it is decreased to promote the exploitation of high-quality solutions. The proposed AHP SO-GA-MLP framework was evaluated using a diabetes-specific dataset and compared to traditional MLP models. The experimental results showed that the proposed method achieved performance for accuracy was 84.0%, Precision 81.48%, Recall 88.0%, area under the curve (AUC) 87.60%, and F1-Score 84.62%.

Keywords: Diabetic Disease, genetic algorithm (GA), Disease Prediction, particle swarm optimization (PSO).

Introduction

Diabetes is a common disease around the world and presents itself as a major health problem [1]. Diabetes is a condition characterized by an insufficient amount of insulin produced in the body, which causes high levels of blood glucose. Machine learning algorithms have become quite popular nowadays in making diagnoses in medicine because of their capability to detect patterns linked to diseases [2]. Multilayer neural networks (MLNs) have demonstrated performance in prediction tasks, thanks to their ability to model complex nonlinear relationships between properties. However, the performance of MLPs depends heavily on the optimal selection of hyperparameters, including the number of hidden layers, the number of neurons, the learning rate, and the training parameters. Inappropriate hyperparameter settings can lead to poor convergence or reduced prediction accuracy.

To address this limitation, meta-heuristic optimization algorithms have been used to automatically search for the best hyperparameters. One of the most well-known optimization methods that enjoy fast convergence in the search process is the particle swarm optimization (PSO). Nevertheless, the PSO technique tends to converge prematurely and fall into local optimal solutions. In contrast to that, the GA technique demonstrates good exploration properties due to the mating and mutation mechanisms that enable population diversification and help enhance the search process.

The current study suggests applying an adaptive hybrid algorithm for particle swarm optimization and the genetic algorithm (AHP SO-GA) to optimize the hyperparameters of the multi-layered neural network (MLP) models. The PSO is used in the AHP SO-GA to explore the solution space, whereas the GA properties are implemented to prevent premature convergence and increase population diversity. Besides, an adaptive mutation strategy is employed in order to control the mutation probability depending on the progress of the optimization procedure. In particular, the mutation probability is raised when the quality of the solutions stabilizes after several iterations.

This research aims to improve the prediction performance of an MLP network in diabetes diagnosis by combining the rapid search capability of the algorithm, the diversity mechanism of the algorithm, and an adaptive optimization strategy. The proposed framework will be evaluated by comparing it to traditional optimization methods in terms of classification accuracy and other performance metrics. [3] based on ensemble learning for diabetes prediction combined with a hybrid Particle Swarm Optimization–Grey Wolf Optimization (PSO-GWO) algorithm for hyperparameter tuning. The objective of the study was to increase the accuracy by optimizing the parameters of classifiers prior to the creation of an ensemble classifier. As a result of the proposed strategy for the framework, an accuracy of 98.39% was achieved. [4] introduced the use of the Synthetic Minority Over-sampling Technique (SMOTE) for tackling the problem of class imbalances in datasets related to diabetes. This was done through the combination of various classifiers and data balancing approaches that helped achieve an accuracy of about 97.8%.

[5] developed a crowd classifier that combined CatBoost, logistic regression, random forest, gradient enhancement, and linear discriminant analysis algorithms. Before training the model, they applied preprocessing and outlier removal techniques. The proposed framework achieved an accuracy of 90.62%.

[6] proposed using an improved XGBoost genetic algorithm, combined with a stacked clustering framework. The genetic algorithm was used to improve feature selection, while the clustering framework incorporated several core learners to enhance performance. The results demonstrated that the proposed approach achieved higher accuracy than traditional machine learning methods. [7] presented an interpretable aggregate of data using feature segmentation transforms for prediction. The proposed custom framework not only optimizes classification performance but also includes an interpretable model. The experimental results are notable for being established using feature segmentation transforms with an accuracy of up to 96%, providing interpretive insights into the most important feature characteristics.

[8] used a particle swarm optimization (PSO) algorithm and a genetic algorithm-based feature selection (GA) algorithm to predict diabetes with random forest classifiers and XGBoost. Optimization techniques were used to identify the most relevant features. The proposed framework revealed that the XGBoost model achieved 98% accuracy, outperforming the unoptimized classifiers. [9] proposed improving diabetes prediction using a multilayer neural network (MLPNN), the meme algorithm (MA), and the computational optimization algorithm (AOA). The optimization process relied on precise and simultaneous feature selection and parameter optimization. The results demonstrated the effectiveness of the optimization algorithms in enhancing the learning capabilities of neural networks.

Methods

This study used Adaptive Hybrid Particle Swarm Optimization and Genetic Algorithm (AHP SO-GA) to optimize the hyperparameters of a Multilayer Perceptron (MLP) model. The methodology consists of the following stages:

Dataset Collection

The diabetes dataset utilized in this study was found in the UCI Machine Learning Repository [10]; it consists of 768 cases of patients divided into 500 non-diabetic cases and 268 diabetic cases. It contains several clinical attributes, including features such as glucose level, blood pressure, body mass index (BMI), insulin level, age, and other relevant medical indicators. The target variable represents the absence of diabetes.

Data Preprocessing

Data preprocessing is performed to improve data quality. The preprocessing stage includes:

1. Handling missing values.
2. Removing duplicate records.
3. Feature normalization using Standardization.
4. Splitting the data set into the training set and testing set.
5. Performing k-fold cross-validation.

Multilayer Perceptron (MLP) Model

The Multilayer Perceptron serves as a classifier. The MLP consists of an input layer, one or more hidden layers, and an output layer. Several hyperparameters significantly influence the performance of the MLP, including: Number of hidden layers, Number of neurons in each hidden layer, Learning rate, Batch size, Activation function, Number of training epochs, Optimizer type.

Selecting appropriate values for hyperparameters is a challenging optimization problem.

● Proposed AHP SO-GA Optimization Framework

The Adaptive Hybrid Particle Swarm Optimization and Genetic Algorithm (AHP SO-GA) framework is proposed to optimize the MLP hyperparameters.

● Particle Swarm Optimization Phase

Initially, a population is generated randomly. Each particle represents a candidate set of MLP hyperparameters. The PSO algorithm updates particle positions according to both individual and global best solutions. The fitness value is evaluated using the classification accuracy.

● Genetic Algorithm Enhancement

Genetic Algorithm is incorporated to enhance population diversity.

The GA operations include: Selection of high-quality candidate solutions, Crossover to generate new offspring solutions, and Mutation to avoid local optima.

● Adaptive Mutation Strategy

An adaptive mutation mechanism is introduced to dynamically adjust the mutation rate during optimization. If the fitness value remains unchanged for a number of iterations, the mutation rate is increased to encourage exploration, and if continuous improvement is observed, the mutation rate is decreased to strengthen exploitation around promising regions. This method combines the concepts of exploration and exploitation during the entire optimization process.

Fitness Function

The objective function used is the classification accuracy of the MLP model:

Fitness = Accuracy

The optimizer searches for the hyperparameter combination that maximizes classification accuracy.

Performance Evaluation

The proposed AHP SO-GA-MLP framework is evaluated using several performance metrics: Accuracy, Precision, Recall, Specificity, F1-Score, Area Under the ROC Curve (AUC). The results are compared against:

1. Traditional MLP.
2. PSO-MLP.
3. GA-MLP

Results

Experimental results have been provided to measure the comparative performance of four MLP-based models used for predicting diabetes: Traditional MLP, PSO-MLP, GA-MLP, and the novel model called AHP SO-GA-MLP. The measures that have been adopted to assess the comparative performance of the models include accuracy, precision, recall, F1-score, and area under the curve (AUC).

GA-MLP gave 84.00% accuracy and 90.00% recall, in addition to 84.91% F1-Score. This shows that the GA-MLP method performed very well in detecting positive diabetic patients in the conducted test. The precision of the GA-MLP method was 80.36%, and its AUC was 85.49%.

The proposed AHP SO-GA-MLP showed an accuracy of 84.00%, a precision of 81.48%, a recall of 88.00%, and an F1-score of 84.62%. The accuracy of the proposed AHP SO-GA-MLP model was the same as that of the GA-MLP model, but the precision was higher than that of the other models. Nevertheless, its recall and F1-score were slightly lower than those of GA-MLP. Assuming that the reported AUC value is 87.60%, the proposed model also did not outperform the Traditional MLP in terms of AUC as in Table 1.

Overall, the proposed hybrid framework demonstrated improvements over the Traditional MLP and PSO-MLP in several evaluation metrics. It failed to prove superior to GA-MLP in all aspects, though. This is why the results allow drawing a conditional conclusion about the competitiveness of the hybrid algorithm, but not its absolute supremacy. Additional verification by means of cross-validation, confidence intervals and tests for statistical significance is required to confirm the reliability of the obtained results.

Table 1. Comparison of Traditional MLP, PSO-MLP, GA-MLP, and the Proposed AHP SO-GA-MLP.

	Accuracy	Precision	Recall	F1-Score	AUC
Traditional MLP	81.0	80.39	82	81.19	88.38
PSO-MLP	82.5	80.95	85	82.93	87.94
GA-MLP	84	80.36	90	84.91	85.49
Proposed AHP SO-GA-MLP	84	81.48	88	84.62	87.60

Conclusion

In this research, an adaptive Hybrid PSO-GA approach for tuning the hyperparameters of the MLP model was examined. In this method, the PSO algorithm's ability to explore and the GA algorithm's ability to generate diversity and mutate were exploited. An adaptive mutation approach was also employed in order to maintain the balance between exploration and exploitation phases of the tuning process.

Based on the experiment results, it was noted that the new AHP SO-GA-MLP framework was capable of giving accuracy of 84.00%, precision of 81.48%, recall of 88.00%, and F1 score of 84.62%. When compared to the conventional MLP, there was an improvement of 3 percent in accuracy and 3.43 percent in F1 score. Furthermore, it achieved the highest precision among the four evaluated models, indicating improved precision in its positive predictions. Nevertheless, the GA-MLP model produced a better recall rate of 90.00% and an F1 score of 84.91%, whereas the GA-MLP and the suggested models had the same accuracy rate of 84.00%. If we consider the AUC value for the suggested model to be 87.60%, then it is seen that the traditional MLP had a slightly better AUC value of 88.38%.

These findings indicate that the proposed hybrid optimization framework offers competitive performance for diabetes prediction and improves several evaluation metrics compared with the traditional MLP and PSO-MLP models. Future work will investigate larger optimization populations, alternative fitness functions, and additional machine learning classifiers. Further experiments using repeated stratified cross-validation and appropriate statistical significance tests will also be conducted to evaluate the consistency and reliability of the observed improvements. Additionally, evaluation of the algorithm on independent data sets with diabetes patients would provide an understanding of its generalizability and possible clinical applications.

Conflict of interest. Nil

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