Pattern Recognition Letters 125 (2019) 432–438

Contents lists available at ScienceDirect

Pattern Recognition Letters

journal homepage: www.elsevier.com/locate/patrec

Diagnosis of diabetes diseases using optimized fuzzy rule set by grey wolf optimization☆

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ARTICLE INFO

Article history:
Available online 5 June 2019

MSC:
41A05
41A10
65D05
65D17

Keywords:
Grey wolf optimization
Ant colony optimization
Fuzzy rules

ABSTRACT

Diabetes disease increased with a high rate due to unhealthy lifestyle, work culture, and lacking of physical activity. Diabetes is an incurable and chronic disease but early sugar monitoring and diagnosis prevent from the harmful effects. In this research work diabetes prediction model is presented which is based on the grey wolf optimization with fuzzy logics. This work has been done by using the concept of artificial intelligence in which model learns the fuzzy rule and then optimized according to the GWO algorithm.

1. Introduction

Diabetes is a disease which occurred in the human body when the level of blood sugar is increased. Blood sugar is the main source of energy in the human body which comes from the eaten food. When the level of this sugar is increased then it is harmful to the human body and creates many problems [16]. According to the age of peoples, diabetes is commonly three types that are type1, type2, and gestational diabetes. Diabetes leads to many problems in the human body that are like nerve damage, eye problem, heart disease, kidney, and dental disease. The common symptoms that are faced by the diabetes person are excessive hunger, thirst, urination, weight gain, and weight loss.

Type-2 diabetes is basically a chronic disease occurred when the production of insulin from the pancreas is not enough according to the need of the human body. The early detection method helps in proper diagnosis and treatment. During the diagnosis, process physician analyzes the different factors for diagnosis. Sometime due to lack of experience and their fatigue may lead erroneous diagnosis of the disease [23]. The early detection of disease helps to change the lifestyle which affects the disease and prevent from the high complications.

In this work the model based on the different factors that are pregnancy which considers the number of pregnancy, glucose level also helps to find diabetes because if the glucose level is high chances of disease is more. The same phenomena applied to the blood pressure its maximum limit is 120 if it is more than this limit it is also in the symptom of diabetes. The skin thickness, insulin level, Diabetes Pedigree Function (define the diabetes level on the basis of heredity), and age also helps to define the diabetes level and enhance the accuracy of the prediction.

2. Related study

Diabetes is a disease which affects the peoples badly when the amount of metabolites such as glucose is increased in the human body. A large number of peoples are affected by this disease and majorly of them women. Iyer et al. presented a classification approach using mining approaches for diabetes diagnosis. The prediction of the diseases is based on the decision trees and Naive Bayes model in the pregnant women. The results evaluation is done by using 10 fold cross-validations on decision trees and Naive Bayes [16]. It is possible to treat diabetes effectively if it diagnoses properly and this is based on the prediction models used for the prediction. Md. et al. worked on the Gaussian Process Classification approach for diagnosis and this approach is based on the machine learning framework. GPC approach basically used 3 types of kernels that are linear, polynomial and radial basis kernel. The performance evaluation of the GPC is done by comparing it with LDA, NB, and QDA approach. The accuracy, sensitivity, and specificity of the GPC approach are better than other approaches. This study shows the effectiveness of machine learning in diabetes data

☆ Editor: Prof. G. Sanniti di Baja.

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https://doi.org/10.1016/j.patrec.2019.06.005
0167-8655/

detection [23]. Santhnam et al. proposed the K-mean and Genetic Algorithm for the diabetes diagnosis. The K-mean algorithm is used for noise removal and optimal solutions are given by the genetic algorithm. The optimal features are classified by using SVM (Support Vector Machine classifier) and gives effective results on diagnosis accuracy [31]. Kumari and Singh presented a model for automatic diabetes detection by using the concept of a neural network. In this work firstly network designing and training is performed which neural network is initialized and then give this input to the next layer with associated bias. The back-propagation error is also calculated in this approach and the learning is performed. The outcomes of this approach provide the result with high accuracy [18].

Samant et al. proposed diabetes detection by using machine learning techniques from Iris images. The model used to diagnose type-2 diabetes which gives reliable and effective result in a diagnosis. The diagnosis based on the region of interest from the iris images. By using this region of extraction statistical, textural and discrete wavelength transformation feature. The classification based on random forest classifier and it provides effective specificity and sensitivity [30]. Swapna et al. proposed a diabetes detection model using CNN and CNN-LSTM and heart rate signals from the ECG. The identification based on the heart rate variation in the ECG signals. The CNN-LSTM used for the automatic detection of the abnormality in the heartbeat. The database in this model splitting for training and testing for providing the maximum accuracy using 5 fold cross-validation [33].

Mercaldo et al. proposed machine learning approach for diagnosis and classification of diabetes. The model proposed to determine diabetes affected people and non-effected peoples by using machine learning methods. The test performed on the PIMA dataset of the female patient. This dataset obtained from the UCI machine learning repository. This dataset contains the values from the medical reports [22]. Ijaz et al. proposed a hybrid prediction model for type-2 diabetes disease. The proposed model based on the density-based clustering and over-sampling methods which balance the distribution of classes. The disease classification is done by using random forest classifier. The proposed model gives effective outcomes by predicting diabetes and hypertension with high accuracy [15]. Zhu et al. introduced the concept of multiple classifier systems for the early detection of diabetes [37]. Marateb et al. also proposed a hybrid predictor of diabetes without using data related to urinary albumin. These hybrid approaches give effective results in form of sensitivity, specificity, and accuracy [21].

Maniruzzaman et al.worked on machine learning by using the concept of Gaussian model for classification for diabetes. The classification done by using three different kernels that are the linear, polynomial and radial basis. The model gives higher accuracy than traditional and performs efficiently [11]. Beloufa et al. proposed a hybrid diabetes detection model by using fuzzy classifier and artificial bee colony optimization. The performance of the model improved by adding the mutation operator. The diversity of ACO was enhanced but without compromising the solution quality. The ACO automatically optimized the membership function and rules from data [4]. Kumar et al. proposed the optimized neural network which helps to diagnose diabetes in support system in clinics. The diagnosis has done after filling the details of the report in the support system. The performance is effective due to ant colony optimization [17].

Chikh et al. presented a method of diabetes diagnosis by using the fuzzy and k-nearest neighbor. This model is a part of the artificial immune recognition system which classified the medical data. The model provides high classification accuracy and validated by 10-fold cross-validation method [6]. Ijaz et al. proposed a hybrid prediction model for diabetes by using parameter hypertension. The outlier data was removed by using the DBSCAN algorithm and distribution of class balanced by using SMOTE (Synthetic Minority Over-Sampling Technique) and classification is done by using Random Forest. The experiment performed on the benchmark datasets and utilized to predict the risk of diabetes and hypertension [27].

2.1. Neural network based approaches

A huge amount of data is available related to the medical field and disease symptoms. This data is used for the prognosis of the disease early and it is done by using the medical applications of the neural networks. The neural networks mainly used to integrate the data and classified the results accordingly [2]. A sequential model for diabetes prediction was presented by Jin et al. using a neural network. This model based on the multi-layered perceptron and back-propagation learning. The prediction probability based on the multivariate logistic functions in consecutive layers [25]. The prediction also based on supervised learning using an artificial neural network. The model based on the Bayesian algorithm and performed effectively as compared to other classical algorithms. The prediction accuracy of this model is also enhanced from the base model and provides better prediction [32].

2.2. Support vector machine based prediction approaches

The issue related to the features classification in the field of medical data resolved by using the support vector machine which is a supervised learning approach. This approach classifies by generating a hyperplane and classifies the features effectively. The SVM transform the data mathematically into high-dimensional space and then classify. The classification in this work based on different factors like race, age, BMI, hypertension, and weight. Wei et al. [36] presented this model and classify diabetes and pre-diabetes disease.

Barakat et al. proposed the intelligent model based on SVM for the diagnosis of diabetes. The additional explanation module makes the SVM model intelligible for diagnostic decision. This provides effective accuracy, sensitivity, and specificity for diabetes prediction [3]. Kumari et al. presented a diabetes classification model using a support vector machine. The SVM algorithm has the ability to make maximum margin between the hyperplane. This model also performed the classification of non-linear features by using the Radial basis kernel functions (RBF). This function mainly used for the analysis of high dimensional data. This model can be enhanced by improving the feature subset selection process [19].

Çalişir et al. proposed an LDA (Linear Discriminant Analysis) and Morlet SVM based classifier model which automatically diagnose diabetes. In this model Linear Discriminant Analysis (LDA) used for the extraction and reduction of the features. This method also classifies the features related to patients and healthy peoples. This classification performed by using Morelet wavelet SVM classifier. The performance evaluation of the proposed model done by analysis of sensitivity, specificity, classification accuracy, and confusion matrix. The classification accuracy of the LDASVM model is better than the existing model and this can be enhanced by using the different classifier or feature extraction method [5].

2.3. Ant colony optimization based approaches

Ant colony optimization algorithm plays an important role in the diabetes detection because it provides the effective results of optimization. Christmas et al.proposed a model based on genetic approach and optimization with the help of ant colony optimization algorithm. In this model ACO used for the identification of common gene variant which are associated with diabetes. The ACO algorithm in this model mainly used for the SNP data analysis and extraction of data associated with the large database. The performance analysis of the model shows good result to the different levels of the noise present in the dataset [7].

2.4. Fuzzy based approach

Varma et al.proposed a diabetes prediction model by using decision tree to predict the occurrence. This model resolved the issue of crisp boundaries and also predicts the better decision rule by using fuzzy logic on the datasets. The decision tree constructed on the basis of split points and these points are identified by using Gini Index. The gini indices reduced by using the Gaussian fuzzy function which identify the split points. The proposed model tested on the Pima dataset and it performs better than other decision tree algorithm models[34].

2.5. Machine learning based approach

There are so many methods and techniques are developed for the diabetes recognition, classification, and prediction. This thing helps in early prediction of disease and timely treatment to tackle it. Sajida et al. presented a model for diabetes prediction using AdaBoost and bagging. The diabetes patient's classification done by using diabetes risk factors. The results show that the overall performance of AdaBoost is effective than bagging [28]. Huang et el. proposed classification and selection model for diabetes patients. This model identifies the diabetes factor by using feature selection and classification to classify diabetes factors. The input data were collected from the hospital and then data mining approaches are applied to discover the predictors and latent knowledge. The computation efficiency of the model is good because feature selection is done by using supervised model construction. After selecting the effective features Naive Bayes Classifier is used for classification and prediction. The model gives effective accuracy and sensitivity result in diabetic patient prediction [14].

Hybrid method also proposed for the better prediction accuracy and efficient results. Patil et al. presented a model based on K-mean clustering for the prediction of type-2 diabetic patients. The final model for classification builds by using the C4.5 algorithm using k-fold cross-validation approach. The performance evaluation of this model based on the sensitivity and specificity of the prediction results. The overall accuracy of the model is better than existing approaches [26].

A new algorithm based on machine learning proposed by the Guang et al. which is a single hidden layer based feed - forward network. This algorithm also based on the radial basis function and uses 30 neurons for the functioning. The training time of ELM_RBF is low as compared to SVM and its success rate if more efficient than SVM [13].

Different types of data mining algorithms have been used for diabetes data screening and artificial neural network provides better accuracy among all the approaches. Another model proposed by Abdullah et al. based on the regression model and Oracle software data mining tool. It divides the feature into two types one for young age patient and other for old age patient and recommends accordingly. This study concluded that young age patient can be delayed drug treatment to avoid side effects but old age cannot delay the drugs [1,12].

2.6. Grey wolf optimization

Grey wolf optimization algorithm used in the various medical application for prediction and classification. Sahoo et al. proposed a cervix lesion classification method by using multi-objective grey wolf optimization. The feature selection is done by using the wrapper based method which selects the optimal features and improves the classification results of cervix lesion [29]. Li et al. presented an extended GWO algorithm for feature selection wrapped kernel and used discrete searching space. The performance evaluation of the work was done by using precision, accuracy, specificity, g-mean and f-measure [20].

Faris et al. presented a review based on the grey wolf optimization and gives a detail introduction to the working of GWO by using different operations in it. The different version of GWO that are hybrid, modified and paralleled discussed in detail and describes the property of global optimization [10].

Wei et al. worked on finding the student's final decision by using the improve grey wolf optimization. In this study, current positions updated by using GWO in discrete search space. The classification of features done by using support vector machine classifier. The classification accuracy in this work measured by using the ROC curve, sensitivity, specificity, and accuracy [35]. El Bakrawy et al. used the grey wolf optimization with Naive Bayes classifier for heart disease detection. Grey wolf optimizer used to determine the weights of the Naive Bayes and maximize the accuracy by providing effective optimal weighted features [9].

Attributes	Attributes description
Pregnancies	Defines the number of pregnancies
Glucose	Defines glucose level
Blood Pressure	Defines blood pressure
Skin Thickness	Defines the triceps skin fold in thickness
Insulin	Defines the level of insulin in 2 h
BMI	Defines body mass index
Diabetes Pedigree Function	Define the diabetes according to heredity factor
Age	Defines age in years

Grey wolf optimization used by Pal et al. for the breast cancer classification with the help of the trained neural network. This study helps to provide better and efficient accuracy in the prediction of breast cancer from the biopsy test reports. The results given by GWO were robust and effective due to global optimization [24].

3. Proposed work

The input in the model given in the form of PIMA data set it is basically contains the data related to the diabetes prediction. This dataset obtained from the UCI machine learning repository [8]. This dataset contains the values from the medical reports. All the data related to the female patients. The dataset contains the 8 feature and two classes.

Create Fuzzy Rules by using the above defined features. This model creates 17 fuzzy rules by using the 8 features and two classes. After this these rules are given as input in grey wolf optimization algorithm where it provides the optimal rules as output. This section of the paper presents the proposed methodology framework with flow chart and its step by step working in the form of algorithm. This work is based on the grey wolf optimization algorithm which provides the optimal fuzzy rules as their outcome (Fig. 1).

3.1. Grey wolf optimization

- The wolves on the first level are called alpha wolves (α) and they are leaders in the hierarchy. Wolves at this level are the guides to the hunting process in which other wolves seek, follow and hunt and work as a team. Decision making is the main task that is performed by the alpha wolves and the order by the alpha wolves is followed by all members of the pack.
- Second level wolves are called beta (β). These wolves are called subordinates and advisors of alpha nodes. The beta wolf council helps in decision making. Beta wolves transmit alpha control to the entire packet and transmit the return to alpha.
- The wolves of the third level are called Delta wolves (δ) and called scouts. Scout wolves at this level are responsible for

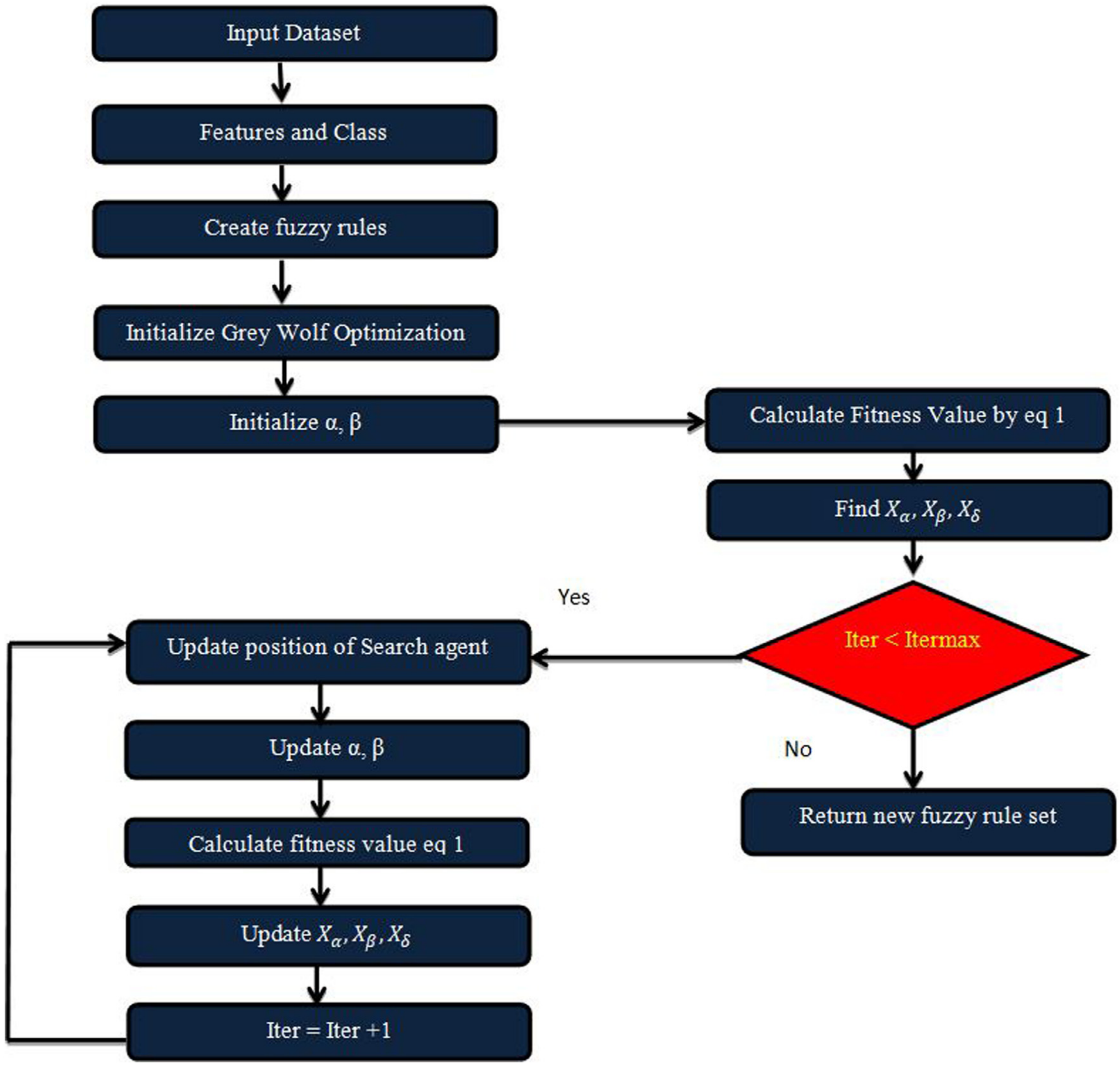

Fig. 1. Flowchart for GWO.

monitoring boundaries and territory. The sentinel wolves are responsible for protecting the pack and the guards are responsible for the care of the wounded and injured.

- The last and fourth level of the hierarchy is called Omega (ω). They are also called scapegoats and they must submit to all the other dominant wolves. These wolves follow the other three wolves (Algorithm 1).

$$\text{fitness} = \alpha * \text{Accuracy} + \beta \frac{\text{Total number of fuzzy rules} - \text{Select f rules}}{\text{Total number of rules}} \quad (1)$$

3.2. GWO algorithm implementation

Initialize GWO parameters such as (G_P),variable size (G_A)vector a are linearly decreased 1to 0 and maximum number of iteration $iter_{max}$

3.3. Fitness function

Here encircling the behavior of prey during hunt in which t represents the current iteration A and C are coefficient vectors of the prey. $\vec{G}$ is the position vector of the grey wolf

$$\vec{A} = 2a.rand - a \quad (2)$$

Algorithm 1 Grey wolf optimization.

Initialize grey wolf optimizer population
Initialize α, β
Calculate the fitness value by using Eq. (1)
α=[0,1]
β=1-α
Find the value of $X_\alpha, X_\beta, X_\delta$
if *iter <$iter_{max}$* **then**
    update the position of search agent
else
    return the new fuzzy rule
Update the value of α, β
Calculate the fitness value by given function Eq. (1)
IF = obtain topic distribution from iterative TWC (Algorithm 1)
Update the value of $X_\alpha, X_\beta, X_\delta$ and now Iter = Iter+1
Return the updated rules
Classification by updated fuzzy rules G_α
Analysis the classification results

$$\vec{C} = 2.rand \quad (3)$$

Here generate the value of vector $\vec{A}$ and $\vec{C}$ by using random function

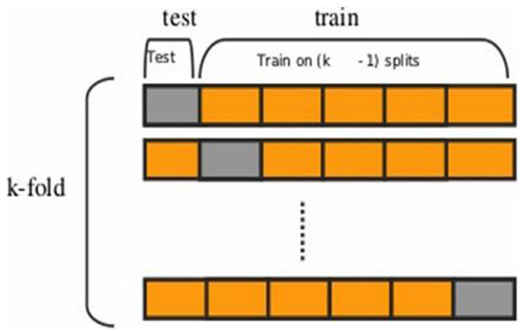

Fig. 2. K-fold validation process.

3.4. Random number of wolves

Random number of wolves expressed by 2-D array G_j^i is the initial value of ith pack of the jth wolves

$$G = \begin{bmatrix} G_1^i & G_2^i & G_3^i & \dots & \dots & G_{A-1}^i & G_A^i \\ G_1^{i+1} & G_2^{i+2} & G_3^{i+3} & \dots & \dots & G_{A-1}^{i+1} & G_A^i \\ \dots & \dots & \dots & \dots & \dots & \dots & \dots \\ \dots & \dots & \dots & \dots & \dots & \dots & \dots \\ G_p & G_p & G_p & G_p & G_p & G_p & G_p \\ G_1 & G_2 & G_3 & \dots & \dots & G_{A-1} & G_p \end{bmatrix} \tag{4}$$

$$\vec{F} = |C.G_P(t) - G(t)| \tag{5}$$

$$\vec{G}(t-1) = G_1(t) - \vec{A}.\vec{D} \tag{6}$$

$$\vec{D}_\alpha = |\vec{C}.\vec{G}_\alpha - \vec{G}| \tag{7}$$

$$\vec{D}_\beta = |\vec{C}.\vec{G}_\beta - \vec{G}| \tag{8}$$

$$\vec{D}_\delta = |\vec{C}.\vec{G}_\delta - \vec{G}| \tag{9}$$

$$\vec{G}_1 = G_\alpha - \vec{A}.(\vec{D}_\alpha) \tag{10}$$

$$\vec{G}_2 = G_\beta - \vec{A}.(\vec{D}_\beta) \tag{11}$$

Algorithm	Accuracy	Precision	Recall
Ant colony optimization (ACO)	71.4285	72.91	72.85
Grey wolf optimization (GWO)	81.1585	76.24	80.48

$$\vec{G}_3 = G_\delta - \vec{A}.(\vec{D}_\delta) \tag{12}$$

Identify the best hunt among all in this process hunts are guided by alpha and other beta and delta participate occasionally.

3.5. Updated value

Here is the updated value of alpha (Algorithm 2).

Algorithm 2 Checks the stopping condition by $iter_{max}$ if yes then stop.

```
I ← 1, Learned Rules ← t
for GWO Initialization do
    Initialize a, A and C by Eqs. (1) and (2)
    Size of wolves = Number of subset of fuzzy rules by Eq. (3) in GP
    Estimate the Gα, Gβ, Gδ
    iter = 1
    repeat
    for I to GP (Subset of fuzzy rules) do
        Update optimize location by Eq. (2)
    fitness value for Gα, Gβ, Gδ by Eqs. (4) and (5)
    update vector a, A, and C
    iter = iter 1
    iter > maximum number of iteration (stopping Criteria)
    output Gα
Classification by updated fuzzy rules Gα
Analysis the classification results
```

$$G(t+1) = \frac{\vec{G}_1 + \vec{G}_2 + \vec{G}_3}{3} \tag{13}$$

3.6. Results and discussion

This section describes the results of the proposed work and their comparison on the basis of accuracy of ant colony optimization algorithm and grey wolf optimization. The performance evaluation done on the basis of accuracy, precision and recall metrics. The results validation performed by using k-fold validation approach. K-fold cross validation is basically a way to estimate the skills of the model. In this validation firstly divide the data by k

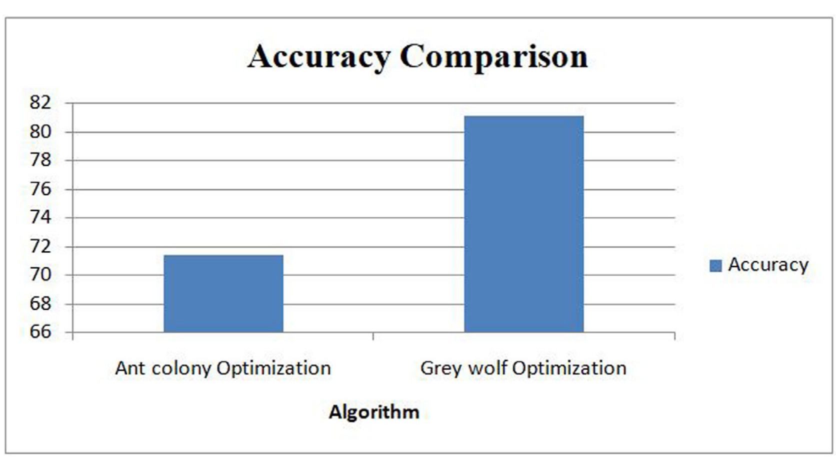

Fig. 3. K-fold validation process.

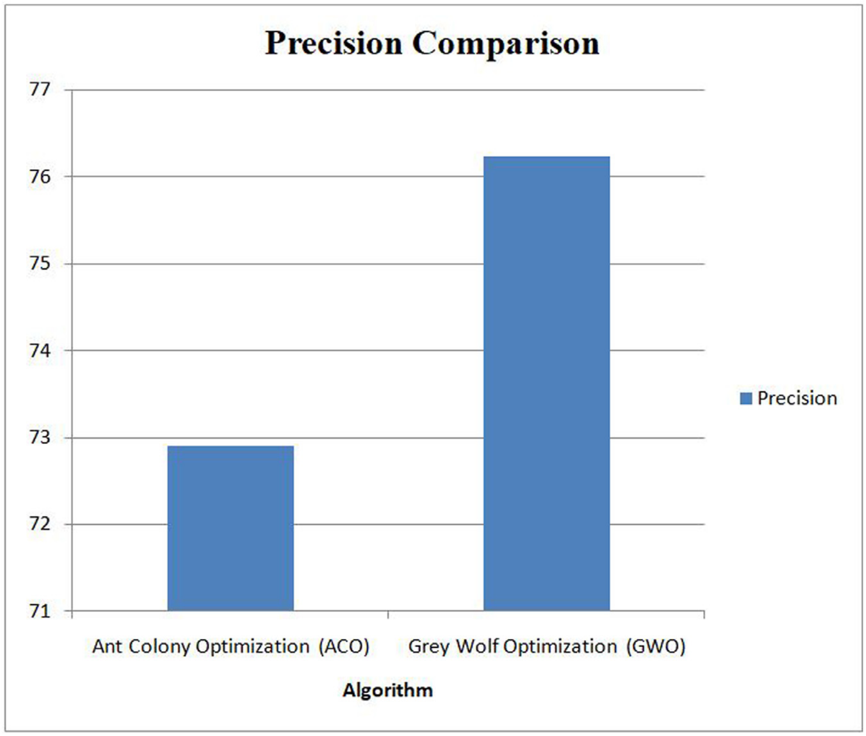

Fig. 4. Precision of algorithm in diabetes prediction.

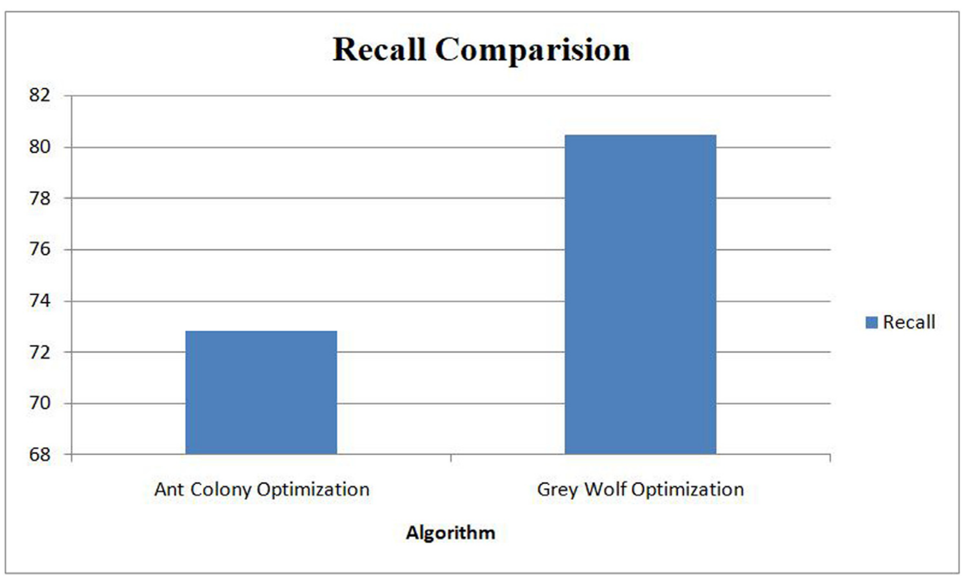

Fig. 5. Recall of algorithm in diabetes prediction.

and then make layers after dividing it. This model does not matters more how data gets divided After this select one random value for each layer and then test the model.

4. Conclusion

In this paper, diabetes prediction model is presented by using the concept of fuzzy rule and grey wolf optimization. The base model worked on the concept of ant colony optimization and fuzzy rule which does not provides the effective accuracy because this algorithm optimizes the local features only and gives 71% accuracy. The proposed model based on the grey wolf optimization algorithm and it is able to optimize features globally and give higher accuracy than ACO (Figs. 2–5).

Declaration of interest

None.

References

[1] A.A. Aljumah, M.G. Ahamad, M.K. Siddiqui, Application of data mining: diabetes health care in young and old patients, J. King Saud Univ.-Comput. Inf. Sci. 25 (2013) 127–136.
[2] F. Amato, A. López, E.M. Peña-Méndez, P. Vaňhara, A. Hampl, J. Havel, Artificial neural networks in medical diagnosis, 2013.

[3] N. Barakat, A.P. Bradley, M.N.H. Barakat, Intelligible support vector machines for diagnosis of diabetes mellitus, IEEE Trans. Inf. Technol. Biomed. 14 (2010) 1114–1120.
[4] F. Beloufa, M.A. Chikh, Design of fuzzy classifier for diabetes disease using modified artificial bee colony algorithm, Comput. Methods Programs Biomed. 112 (2013) 92–103.
[5] D. Çalişir, E. Doğantekin, An automatic diabetes diagnosis system based on LDA-wavelet support vector machine classifier, Expert Syst. Appl. 38 (2011) 8311–8315.
[6] M.A. Chikh, M. Saidi, N. Settouti, Diagnosis of diabetes diseases using an artificial immune recognition system2 (airs2) with fuzzy k-nearest neighbor, J. Med. Syst. 36 (2012) 2721–2729.
[7] J. Christmas, E. Keedwell, T.M. Frayling, J.R. Perry, Ant colony optimisation to identify genetic variant association with type 2 diabetes, Inf. Sci. 181 (2011) 1609–1622.
[8] J. Davis, M. Goadrich, The relationship between precision-recall and ROC curves, in: Proceedings of the 23rd international conference on Machine learning, ACM, 2006, pp. 233–240.
[9] L.M. El Bakrawy, Grey wolf optimization and Naive Bayes classifier incorporation for heart disease diagnosis, Aust. J. Basic Appl. Sci. 11 (2017) 64–70.
[10] H. Faris, I. Aljarah, M.A. Al-Betar, S. Mirjalili, Grey wolf optimizer: a review of recent variants and applications, Neural Comput. Appl. (2018) 1–23.
[11] M.F. Ganji, M.S. Abadeh, A fuzzy classification system based on ant colony optimization for diabetes disease diagnosis, Expert Syst. Appl. 38 (2011) 14650–14659.
[12] M. Heydari, M. Teimouri, Z. Heshmati, S.M. Alavinia, Comparison of various classification algorithms in the diagnosis of type 2 diabetes in iran, Int. J. Diabetes Dev. Ctries 36 (2016) 167–173.
[13] G.-B. Huang, C.-K. Siew, Extreme learning machine with randomly assigned RBF kernels, Int. J. Inf. Technol. 11 (2005) 16–24.
[14] Y. Huang, P. McCullagh, N. Black, R. Harper, Feature selection and classification model construction on type 2 diabetic patients data, Artif. Intell. Med. 41 (2007) 251–262.
[15] M. Ijaz, G. Alfian, M. Syafrudin, J. Rhee, Hybrid prediction model for type 2 diabetes and hypertension using dbscan-based outlier detection, synthetic minority over sampling technique (smote), and random forest, Appl. Sci. 8 (2018) 1325.
[16] A. Iyer, S. Jeyalatha, R. Sumbaly, Diagnosis of diabetes using classification mining techniques, (2015) arXiv:1502.03774.
[17] M. Kumar, A. Sharma, S. Agarwal, Clinical decision support system for diabetes disease diagnosis using optimized neural network, in: Engineering and Systems (SCES), 2014 Students Conference on, IEEE, 2014, pp. 1–6.
[18] S. Kumari, A. Singh, A data mining approach for the diagnosis of diabetes mellitus, in: Intelligent Systems and Control (ISCO), 2013 7th International Conference on, IEEE, 2013, pp. 373–375.
[19] V.A. Kumari, R. Chitra, Classification of diabetes disease using support vector machine, Int. J. Eng. Res. Appl. 3 (2013) 1797–1801.
[20] Q. Li, H. Chen, H. Huang, X. Zhao, Z. Cai, C. Tong, W. Liu, X. Tian, An enhanced grey wolf optimization based feature selection wrapped kernel extreme learning machine for medical diagnosis, Comput. Math. Methods Med. 2017 (2017).
[21] H.R. Marateb, M. Mansourian, E. Faghihimani, M. Amini, D. Farina, A hybrid intelligent system for diagnosing microalbuminuria in type 2 diabetes patients without having to measure urinary albumin, Comput. Biol. Med. 45 (2014) 34–42.
[22] F. Mercaldo, V. Nardone, A. Santone, Diabetes mellitus affected patients classification and diagnosis through machine learning techniques, Procedia Comput. Sci. 112 (2017) 2519–2528.
[23] M. Opper, O. Winther, Gaussian processes for classification: mean-field algorithms, Neural Comput. 12 (2000) 2655–2684.
[24] S.S. Pal, Grey wolf optimization trained feed foreword neural network for breast cancer classification, Int. J. Appl. Ind. Eng. 5 (2018) 21–29.
[25] J. Park, D.W. Edington, A sequential neural network model for diabetes prediction, Artif. Intell. Med. 23 (2001) 277–293.
[26] B.M. Patil, R.C. Joshi, D. Toshniwal, Hybrid prediction model for type-2 diabetic patients, Expert Syst. Appl. 37 (2010) 8102–8108.
[27] C. Pérez-Gandía, A. Facchinetti, G. Sparacino, C. Cobelli, E. Gómez, M. Rigla, A. de Leiva, M. Hernando, Artificial neural network algorithm for online glucose prediction from continuous glucose monitoring, Diabetes Technol. Ther. 12 (2010) 81–88.
[28] S. Perveen, M. Shahbaz, A. Guergachi, K. Keshavjee, Performance analysis of data mining classification techniques to predict diabetes, Procedia Comput. Sci. 82 (2016) 115–121.
[29] A. Sahoo, S. Chandra, Multi-objective grey wolf optimizer for improved cervix lesion classification, Appl. Soft Comput. 52 (2017) 64–80.
[30] P. Samant, R. Agarwal, Machine learning techniques for medical diagnosis of diabetes using iris images, Comput. Methods Programs Biomed. 157 (2018) 121–128.
[31] T. Santhanam, M. Padmavathi, Application of k-means and genetic algorithms for dimension reduction by integrating SVM for diabetes diagnosis, Procedia Comput. Sci. 47 (2015) 76–83.
[32] M.A. Sapon, K. Ismail, S. Zainudin, Prediction of diabetes by using artificial neural network, in: Proceedings of the 2011 International Conference on Circuits, System and Simulation, Singapore, 2829, 2011, p. 299303.
[33] G. Swapna, S. Kp, R. Vinayakumar, Automated detection of diabetes using CNN and CNN-LSTM network and heart rate signals, Procedia Comput. Sci. 132 (2018) 1253–1262.
[34] K.V. Varma, A.A. Rao, T.S.M. Lakshmi, P.N. Rao, A computational intelligence approach for a better diagnosis of diabetic patients, Comput. Electr. Eng. 40 (2014) 1758–1765.
[35] Y. Wei, N. Ni, D. Liu, H. Chen, M. Wang, Q. Li, X. Cui, H. Ye, An improved grey wolf optimization strategy enhanced SVM and its application in predicting the second major, Math. Probl. Eng. 2017 (2017).
[36] W. Yu, T. Liu, R. Valdez, M. Gwinn, M.J. Khoury, Application of support vector machine modeling for prediction of common diseases: the case of diabetes and pre-diabetes, BMC Med. Inform. Decis. Making 10 (2010) 16.
[37] J. Zhu, Q. Xie, K. Zheng, An improved early detection method of type-2 diabetes mellitus using multiple classifier system, Inf. Sci. 292 (2015) 1–14.