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Feature engineering with gray wolf algorithm and fuzzy methods for friend recommender system in social networks

Aida Ghorbani[1], Ladan Riazi[2*], Amir Daneshvar[2], Reza Radfar[3]

[1] *Department of Information Technology Management, Science and Research Branch, Islamic Azad University, Tehran, Iran*
[2]*Department of Information Technology Management, Electronic Branch, Islamic Azad University, Tehran, Iran*
[3]*Department of Technology Management, Science and Research Branch, Islamic Azad University, Tehran, Iran*

aida.ghorbani@srbiau.ac.ir, l_riazi@iauec.ac.ir, a_daneshvar@iauec.ac.ir, r.radfar@srbiau.ac.ir

Abstract
Due to the expansion of the use of social networks, new areas of research in this field have been presented to researchers. One of these areas is using intelligent methods for friend recommender system. In this research, by using fuzzy methods and the gray wolf optimization algorithm, a solution for friend recommender system in social networks has been proposed. The use of fuzzy methods is considered to extend the extracted features in the network. The gray wolf algorithm has also been used to identify the appropriate subset of the feature set. Also, the process of learning the patterns in the extracted feature set has been done by the neural network method. The results of the implementation of this research and its comparison with other available methods showed that the artificial neural network was a good choice for choosing the learning model. The results showed that the feature selection mechanism using the gray wolf algorithm and the use of fuzzy information has a significant impact on improving system performance. In addition, the study of system performance on different data sets showed that the proposed method is highly accurate.
Keywords: Friend recommender system, neural network, gray wolf optimization, fuzzy methods

1-Introduction

With the growth of the Internet and the creation of social network, individuals and organizations can easily interact and create a large social network that allows them to communicate with each other and share knowledge in virtual environments. Social networks are expanding daily and adding to their popularity (Rahmaty et al. 2022). In these networks, the issue of making friends has become an important issue in the analysis of social networks and the need for a strong algorithm with a low error rate is felt in them. This refers to understanding the processes that create social interactions. The issue of friend recommender on social networks states that two nodes in a network will be connected or not in the near future (Pourghader et al. 2021). Many researchers have implemented several programs related to link prediction analysis in various areas of the network.

*Corresponding author
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However, the importance of this issue has led to a lot of research in this area every year. In this research, a new solution based on data mining techniques for the friend recommender system in social networks is presented, in which neural network methods, gray wolf optimization and fuzzy techniques are combined.

The proposed system of this research selects the appropriate features in the studied data set. In addition, it considers the fuzzy information extracted by the fuzzy inference system. Finally, it proposes the right relationship for the recommender system. In the continuation of this research, first, a review of related works in the field of research is made. A proposed system is then presented that describes the feature engineering, classification model, and techniques used in the research. The results obtained from the proposed system are then given. At the end of the work, the final conclusion is made.

2-Literature review

In recent years, many techniques, models and approaches have been proposed and implemented to recommend various cases in social networks in the literature. In many effective approaches, techniques based on artificial intelligence have been used (Chobar et al. 2022). This section refers to a number of recent cases. In paper (Fan et al, 2019), a neural network-based graph representation framework (GraphRec) for social recommendations was presented. In this research, a principled approach was presented to depict common interactions and opinions in the user-item graph. The results of several experiments on two real-world datasets demonstrate the effectiveness of the proposed GraphRec framework over basic methods.

In the article (Fu et al, 2018), a new deep learning method was proposed to overcome the limitations of collaborative filtering methods, which provides an effective intelligent advice by understanding users and item already. In the initial phase, the corresponding low-dimensional vectors are learned separately from users and items. In the prediction phase, feed-forward neural networks are used to simulate user-item interaction, and pre-trained vectors are used as neural network inputs. The results of experiments on two benchmark data sets (MovieLens 1M and MovieLens 10M) show that this model performs significantly better than previous methods that used feed-forward neural networks. In research (Tourinho et al, 2021), a method using fuzzy logic-based collaborative filtering (FACF) was proposed that uses users' activities to model their preferences and recommend subsequent visits to them. In this study, experiments were performed on two real LBSN datasets and the results showed that this technique works better in almost all experimental evaluations of the location collaborative filter. Thus, with fuzzy clustering of areas of interest, the FACF is more appropriate in improving the recommendations. In the research work (Katarya & Verma, 2017), a new web-based recommender system was developed that operates based on sequential user navigation information on web pages. C-mean fuzzy clustering (FCM) was used in this study. Similar users were identified for the target user and the weight of each webpage was also evaluated. MNSBC real-world datasets were used to test the results in experiments. A comparison between the existing model and the proposed model of this research showed that the accuracy of this system is three times better than the existing systems. The accuracy of the proposed model of this research is close to 33%.

In research (Katarya & Verma, 2017), a recommendation system based on a hybrid collaborative filtering was proposed, which improved the accuracy of the recommendations. In this work, fuzzy c-mean (FCM) and artificial algae algorithm (AAA) were used. In addition, advanced multilevel pearson correlation coefficient (PCC) was used to find similarities between two users. The proposed system succeeded in providing recommendations with better quality and accuracy compared to other techniques and showed remarkable results in evaluation criteria such as mean absolute error (MAE), precision and recall. In study (Selvi & Sivasankar, 2019), a modified fuzzy c-means clustering approach was proposed to reduce the error in the recommendation. In this study, a new modified cuckoo search algorithm (MCS) was added to optimize data points in each cluster. The performance of the proposed recommender system was evaluated by performing experiments on the MovieLens benchmark data set. The effectiveness of the proposed MCS algorithm was compared with particle swarm optimization and cuckoo search algorithms. The experimental results showed the effectiveness of the proposed method in the benchmark optimization function. In the research of kini et al (2022), the performance of different machine learning algorithms was compared with the evaluation criteria, and the algorithm that has the highest accuracy and minimum execution time was selected as the friend recommendation algorithm. The study used a data set from the Kaggle site. The LightGBM method achieved the highest accuracy of 93.71% with meta-parameters.

Parveen et al in their research (Parveen et al, 2021) implemented various machine learning techniques such as Random Forest Classifier, XGBoost, Light GBM, and Cat Boost and compared the performance of each of them. Implementation results showed that Random Forest and Light GBM were less accurate than XGBoost and CatBoost algorithms. The XGBoost algorithm was more accurate than other algorithms. For the Facebook (Kaggle) dataset, 73% accuracy was obtained using the XGBoost method. In the paper of (Behera et al, 2021), a supervised learning model using XGBoost was proposed to solve the link prediction problem that called LPXGB. The performance of the LPXGB model was tested with three real-world datasets of Karate, Money Blog and Facebook. The LPXGB model was compared with various classifiers of machine learning. The results showed that the proposed model of this research achieved a relatively higher classification accuracy. The following are the numerical results of the last three articles in table 1.

Table 1. Results of recent reviewed articles

Research	Dataset	Accuracy	Method
kini et al, 2022	Facebook (Kaggle)	93.71%	LightGBM
Parveen et al, 2021	Facebook (Kaggle)	73%	XGBoost
Behera et al, 2021	Karate	0.9304	LPXGB
	Polblogs	0.9194	
	Facebook	0.7778	

3- The proposed system

The proposed system of this research uses a combination of artificial neural network, gray wolf algorithm and fuzzy system to build a friend recommendation system in social networks. The proposed system flowchart is given in figure 1. The details of this method are given below.

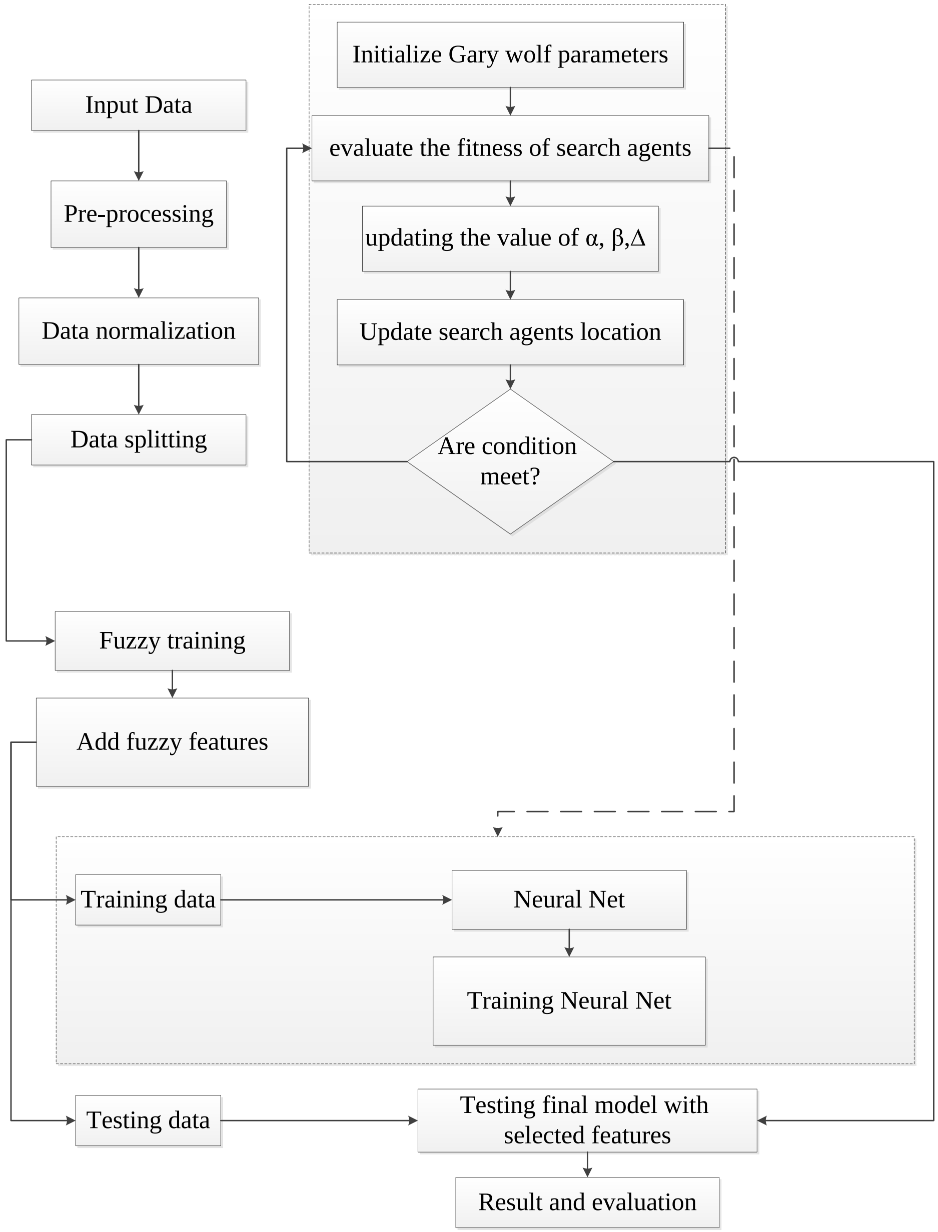

Fig 1. The proposed system

In the features engineering section of the proposed system, a Mamdani and Sugeno fuzzy inference system has been used to improve the features. In this section, the studied data set is first given to the fuzzy inference system. Fuzzy inference system prediction will be added as a new feature to the features in the data set.

In the next step, the gray wolf optimization algorithm is used to select effective features. The result that is obtained from this algorithm as the best result during iterations actually determines the best features that are in the current data set. The technique used to learn the objective function of the gray wolf optimization algorithm is the artificial neural network. In fact, the position of each gray wolf reflects a number of features. According to these features, the corresponding neural network is created. The result obtained from the neural network corresponding to the position of each gray wolf is used as the wolf fitness in the objective function of the gray wolf optimization algorithm. After running the gray wolf optimization algorithm, the optimal answer will actually determine the best features to solve the problem of the friend recommender system. Finally, the evaluation of the proposed system will be done using the specified features.

3-1- Feature engineering

In this research, the link prediction collection has been used. This collection can be found at https://noesis.ikor.org/datasets/link-prediction. This collection of information has collected 22 networks from different sources and fields. The proposed system is implemented on the BUP dataset and some other datasets. The BUP dataset represents the network information of political blogs. This data set includes 105 nodes, 441 links and 8.4 degrees (Martínez Gómez, 2018, Maadanpour et al. 2021).

3-1-1-Feature Extraction

Nod2vec package is used for feature extarction in this research. Node2vec is a flexible neighborhood sampling strategy that allows us to gently interpolate between BFS (Breadth First Search) and DFS (Depth First Search). This method is implemented by developing a biased flexible random walking method that can explore neighbors in both BFS and DFS methods (Grover & Leskovec, 2016).

A random walk is defined by two parameters p and q. Assume that the current random walking position is node v. The position of the previous step is node t. In order to determine the next position, the probabilities of π_{vx} transfer at the edges (v, x) leading to v must be evaluated. We set the probability of anomalous transfer to $\pi_{vx} = \alpha_{pq}(t, x)\cdot w_{vx}$. In particular, α_{pq} is defined as follows.

$$\alpha_{pq} = \begin{cases} \frac{1}{p} & d_{tx} = 0 \\ 1 & d_{tx} = 1 \\ \frac{1}{q} & d_{tx} = 2 \end{cases} \tag{1}$$

Where d_{tx} defines the shortest distance between node t and node x and the value of d_{tx} must be 0, 1 or 2. The p parameter controls the possibility of re-visiting a node during a random walk. When the p value is high, the visited nodes are rarely sampled. This strategy encourages moderate exploration and prevents 2-hop redundancy in sampling. On the other hand, if the value of p is low, it leads the walk one step backwards (figure 2) and this keeps the walk "local" close to the starting node u.

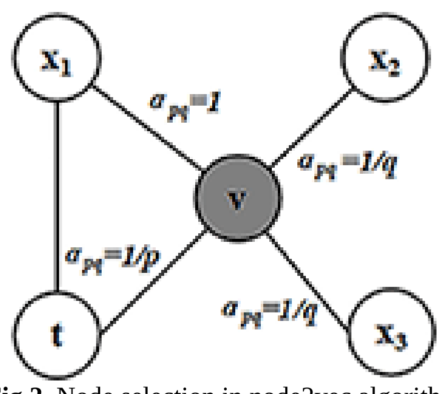

Fig 2. Node selection in node2vec algorithm

The current position in a random walk is at node v and the previous step is at node t. In this example x_1, x_2 and x_3 are neighbors. The values of a_{pq} are calculated based on the distance between v and t (Peng et al, 2019). The q parameter allows the search to distinguish between "local" and "global" nodes. As shown in figure (2), if q> 1, a random walk is more likely to be sampled from nodes around the node. The BFS samples the nodes in a small location. Conversely, if q <1, the random walk is farther away from v, which can receive more general information about the features. Therefore, the distance between the sampling node and the given source node does not increase strictly (Peng et al, 2019).

3-1-2- Fuzzy inference system

By introducing the theory of fuzzy sets, Professor Lotfizadeh provided the basis for inaccurate information modeling and approximate reasoning with mathematical equations. One of the features of fuzzy logic is the use of the basic rule structure of fuzzy logic, in which control problems become a series of IF x And y THEN z rules that respond to the desired output of the system for the input conditions given to the system. Building a fuzzy inference system involves three steps: data fuzzification, rule building and defuzzification. In the fuzzification stage, the definite variables are converted to linguistic variables. In the second step, the system behavior is defined using a set of if-then rules. The degree of correctness of each hypothesis is performed according to the available examples and the combination of the antecedent using the specified operator. In the third stage, linguistic values are converted into definite numbers to make decisions (Wang, 1999).

In general, the most important types of fuzzy systems in terms of input and output data types are Sugeno and Mamdani. In Mamdani system, both the first part of the rules and the part of the result are fuzzy. In the Sugeno system, the first part is the fuzzy rules, but the result part is non-fuzzy and is a linear combination of input variables. In this research, Mamdani and Sugeno fuzzy inference system are used for create new features. Result of Mamdani and Sugeno prediction on dataset, added as a new column to dataset to extent feature set.

3-1-3- Normalization

The Z-score Normalization method is used for normalization. In this method, the criteria of mean and standard deviation are used to re-scale the data so that the resulting features have a zero mean and a unit variance.

Each instance, xi,n of the data is transformed into x ′ i,n as follows:

$$X'_{\mathrm{i,n}} = \frac{X_{\mathrm{i,n}} - \mu_i}{\sigma_i} \quad (2)$$

Where μ and σ denote the mean and standard deviation of ith feature respectively (Singh & Singh, 2020).

3-2- Classification model

3-2-1- Neural networks

Inspired by the complex capabilities of the human brain, artificial neural networks simulate a certain level of intelligence. Artificial neural networks consist of a number of very simple and highly interconnected processors called neurons that act similarly to biological nerve cells in the brain. An artificial neural network consists of an input layer of neurons, one or more hidden layers of neurons and one output layer of neurons (Negnevitsky, 2005).

Similar to human learning using samples, a neural network is trained with the help of a set of data and input samples called a training set. The output of the neural network is obtained from training data, and during the training process, the goal is to minimize neural network error by adjusting the weight between the neurons. During training and testing of neural network architecture, an independent data set called validation set is given to the neural network and it is used to evaluate the system performance and select the best architecture and weights for the network. After the validation step, a data set called the test data set is used independently to determine the level of neural network performance.

3-3- Feature selection with GWO

One of the most important parts of a data mining is feature selection. Unlike academic problem, where the features of the problem are usually specific, in practical topics, the required features must be extracted from a large amount of data. In some cases, even new datasets need to be created.

Feature selection refers to the process of identifying related features and removing unrelated and duplicate features with the goal of selecting a subset of features that describe the problem well. Advantages of feature selection include increasing the efficiency of machine learning algorithms, reducing the memory required, increasing the speed and simplicity of the models.

In the proposed method of this research, Grey wolf optimization algorithm is used to feature selection. In this section, more relevant features are selected so that the performance of the friend recommender system is improved.

3-3-1-Grey wolf optimization algorithm

The gray wolf algorithm is inspired by the social life and hunting of gray wolves and uses four types of wolves to simulate the hierarchy of leadership. Gray wolves have a very strict social hierarchy. The leaders of the group are a male and a female called alpha. Alpha is mainly responsible for deciding on hunting, sleeping place, waking time and so on. Alpha decisions are dictated to the group. However, a kind of democratic behavior has been observed in which Alpha follows the other wolves in the group. In group aggregation, the whole group recognizes the alpha by holding its tail down. Alpha commands must be followed by the group. Alpha wolves are only allowed to choose a mate in the group. Interestingly, Alpha is not necessarily the strongest member of the group, but it is the best member in terms of group management. This shows that the organization of a group is much more important than its power (Mirjalili et al, 2014).

The second level in the gray wolf hierarchy is beta. Beta is the alpha consultant and organizer of the group. Beta executes alpha commands throughout the group and refers its feedback to alpha. Omega has the lowest rank among gray wolves. Omega plays the role of victim. They are the last group of wolves allowed to eat. If the wolf is not alpha, beta, or omega, it is called a subordinate (or delta in some sources). Delta has to report alpha and beta, but dominates omega. In addition to social hierarchy, hunting gray wolves has three stages: tracking, chasing, and approaching prey. To model the social hierarchy of wolves, we consider the best answer as alpha and among the best solutions, the second and third as beta and delta. The rest of Candida's solutions are considered omega. The optimization is driven by alpha, beta and delta, and the fourth group follows these three groups. Modeling wolf siege behavior uses - and - equations.

$$\vec{D} = \left|\vec{C} \,.\vec{X}_P(t) - \vec{X}(t)\right| \tag{3}$$

$$\vec{X}(\mathrm{t}+1) = \vec{X}_P(t) - \vec{A}.\vec{D} \tag{4}$$

In them, t is the number of current iterations, A and C are the coefficient vectors, $\vec{X}_P$ is the hunting position vector, and X is the position vector of a wolf. Equations (5) and (6) are used to calculate vectors A and C.

$$\vec{A} = 2\vec{a}.\vec{r_1} - \vec{a} \tag{5}$$

$$\vec{C} = 2\vec{r_2}. \tag{6}$$

The vector $\vec{a}$ decreases linearly from 2 to 0 over the course of iterations. $\vec{r}$ is The random vector between 0 and 1. Due to the randomness of the vectors r1 and r2, wolves can change their position randomly in the space around the prey using equations (7) and (8). Gray wolf hunting is often led by alpha. Beta and delta wolves also occasionally hunt. In order to model this behavior, save three of the best ways to solve and other search agents are forced to update their position according to the position of the best search agents according to equation (9).

$$\overrightarrow{D_\alpha} = \left|\overrightarrow{C_1}\,.\vec{X}_\alpha - \vec{X}\right| \tag{7}$$

$$\overrightarrow{D_\beta} = \left|\overrightarrow{C_2}\,.\vec{X}_\beta - \vec{X}\right|$$

$$\overrightarrow{D_\delta} = \left|\overrightarrow{C_3}\,.\vec{X}_\delta - \vec{X}\right|$$

$$\overrightarrow{X_1} = \overrightarrow{X_\alpha} - \overrightarrow{A_1}.\overrightarrow{D_\alpha} \tag{8}$$

$$\overrightarrow{X_2} = \overrightarrow{X_\beta} - \overrightarrow{A_2}.\overrightarrow{D_\beta}$$
$$\overrightarrow{X_3} = \overrightarrow{X_\delta} - \overrightarrow{A_3}.\overrightarrow{D_\delta}$$

$$\overrightarrow{X(t+1)} = \frac{\overrightarrow{X_1}+\overrightarrow{X_2}+\overrightarrow{X_3}}{3} \quad (9)$$

In this algorithm, the implementation of the exploitation or attack phase is done by reducing the value of the variable from 2 to 1. The value of $\vec{A}$ is also dependent on $\vec{a}$, so it decreases. As the value of $\vec{A}$ decreases, wolves are forced to attack prey. An identification phase is also provided to prevent getting in the local minimum. Wolves distance themselves from each other in search of prey, and approach and cooperate to attack each other. To simulate this divergence, vector $\vec{A}$ is used with random values greater than 1 or less than -1.

Another influential component is the process of identifying the value of C. The value of this random numeric vector is in the range [0, 2]. This random value affects the position of the prey in determining the distance, intensity (1 <C) or weakness (1> C). This vector can also be considered as the effect of barriers that prevent prey from approaching in nature (Mohammadzadeh et al, 2019).

4- Results

In this section, the result of proposed method is presented. For compare with other methods, we used AdaBoost Classifier, Decision Tree with max depth of 4, decision tree with max depth of 8 and Neural network. The confusion matrices obtained from the proposed method for the train and test data is given in figures 3.

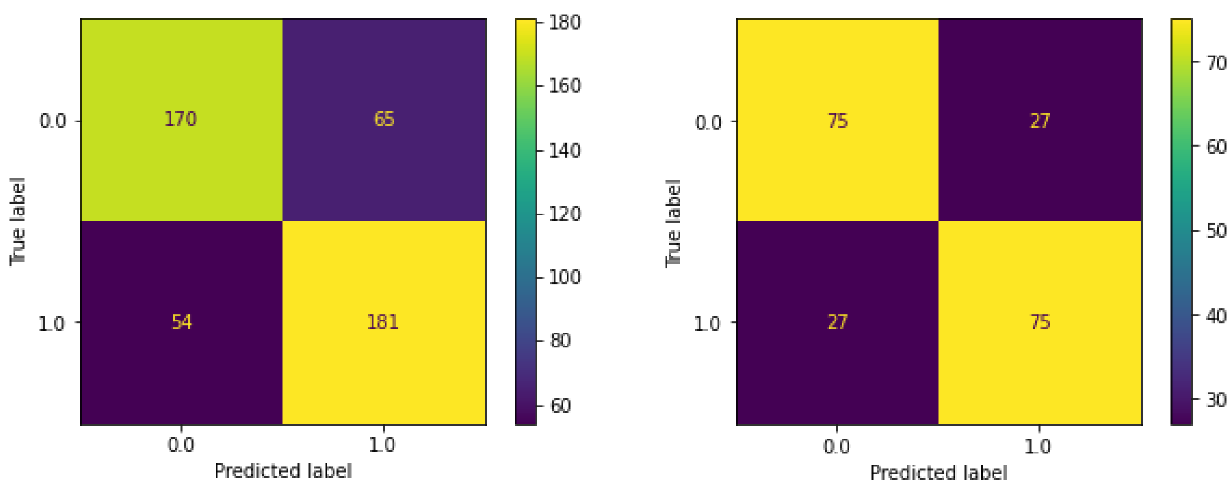

Fig 3. Confusion matrix for proposed method for BULP dataset. Left figure is for training and right figure is for testing dataset

Results are showed in table 2. According to this table, the proposed method for BUP dataset has best result for different measures. The results of this table show that among the AdaBoost methods, two versions of Decision Tree and Neural network, the neural network method have the best results. So that it has performed better in three criteria than the others and only in the recall criterion the first version of the decision tree is better.

The learning mechanism of the proposed system is based on the neural network. Therefore, the comparison of these methods with the proposed system shows that the information extracted by the fuzzy inference system and the feature selection mechanism by the gray wolf algorithm had a significant effect on all evaluation criteria.

Table 2. Result for class 1 in BUP dataset

	Precision	Recall	Fmeasure	Accuracy
AdaBoostClassifier	0.59	0.57	0.58	0.59
DecisionTree(max_depth=4)	0.61	0.70	0.65	0.63
DecisionTree(max_depth=8)	0.62	0.63	0.62	0.62
Neural network	0.67	0.67	0.67	0.67
Proposed Method	**0.74**	**0.74**	**0.74**	**0.74**

4-1- Results for other datasets

In this section, the proposed method on other datasets was also examined. These datasets are INF, CEG and UAL, respectively. The results of applying different methods to INF dataset are listed in table 3. The results of implementing the methods on the INF database also show the superiority of the proposed system in all criteria.

Table 3. Result for class 1 in INF dataset

	Precision	Recall	F-measure	Accuracy
AdaBoostClassifier	0.57	0.53	0.55	0.57
DecisionTree(max_depth=4)	0.59	0.51	0.54	0.58
DecisionTree(max_depth=8)	0.63	0.52	0.57	0.61
Neural network	0.62	0.61	0.61	0.62
Proposed Method	**0.67**	**0.67**	**0.67**	**0.67**

The results of applying different methods to CEG dataset are listed in table 4. The results from this table show that the proposed system performed better than other methods except for the recall criterion which is higher in the second decision tree. The results show that the second decision tree has the lowest precision despite having the highest recall. The high recall and low precision results in the second decision tree indicate that this returns many results, but most of the predicted labels are incorrect compared to the training labels. This advantage is not worth it.

Table 4. Result for class 1 in CEG dataset

	Precision	Recall	F-measure	Accuracy
AdaBoostClassifier	0.56	0.56	0.56	0.56
DecisionTree(max_depth=4)	0.58	0.51	0.54	0.57
DecisionTree(max_depth=8)	0.56	0.65	0.60	0.56
Neural network	0.60	0.59	0.59	0.59
Proposed Method	**0.64**	**0.63**	**0.63**	**0.64**

The results of applying different methods to UAL dataset are listed in table 5. The results of this table also show the superiority of the proposed method in all criteria.

Table 5. Result for class 1 in UAL dataset

		Precision	Recall	F-measure	Accuracy
AdaBoostClassifier		0.68	0.68	0.66	0.65
DecisionTree(max_depth=4)		0.68	0.59	0.63	0.65
DecisionTree(max_depth=8)		0.68	0.65	0.66	0.67
Neural network		0.69	0.71	0.70	0.70
Proposed Method		**0.71**	**0.71**	**0.71**	**0.71**

As can be seen, the proposed solution offers a good performance on the datasets under study.

5- Conclusion

In this research, a friend recommender system based on a combination of Gray wolf optimization algorithm and neural network is proposed. In this method, Gray wolf optimization algorithm is used for feature selection, and neural network is used for classification. Also we used fuzzy techniques to extend extracted features of graph. Implementation results showed that this system has been able to make good diagnoses in both existing classes and achieve good results.

Comparison of the proposed system with the neural network method showed that the feature selection mechanism based on the gray wolf algorithm and extracted fuzzy information could have a significant improvement in the performance of the proposed system. In addition, comparison of the proposed system with other methods (AdaBoost Classifier, Decision Tree with max depth of 4, Decision Tree with max depth of 8) in different datasets showed that the proposed method of this research can work well on different data sets.

Due to the good effect that the feature selection mechanism has had on the result obtained from the proposed system, in the continuation of this research, other available methods can be used to select the feature and evaluate the system improvement process.

In this research, Python programming language and its scientific libraries have been used to analyze the data. Python is a free, open source and object-oriented programming language that is widely used for a variety of purposes. Python runs on multiple platforms. Simple syntax, ease of learning, multiple online resources and many libraries are some of the advantages of this language that have led to the increasing use of this tool (Lafuente et al, 2021). Due to the existence of many libraries in the field of machine learning techniques and artificial intelligence in this research, this language has been used to implement the proposed method.

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