An Adaptive Neuro-fuzzy Inference System to Evaluate Trustworthiness of Users in a Social Network

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Abstract–In recent years, the emergence of various social networks has led to the growth of s ocial network users. However, activity in such networks depends on the level of trust that users hav e in each other. Therefore, trust is essential and important issue in these networks, especially whe n users interact with each other. In this article, we examine this issue and provide a method to evaluate it.It is not easy to measure the accuracy of trust for users who interact with social networks. Here,interactions are virtual. In this article, we have used the adaptive neuro-fuzz inference system to evaluate trustworthiness by considering different personality attributes of users such as reli ability,availability, interest, patience and adaptability. Using these features as input and based on the adaptive neuro-fuzzy inference system,we evaluated the trustworthiness of users in socialnetwork.Thep roposed adaptive neuro-fuzzy inference system is expandable because in this system,trustcan be defin ed as a set of one or more personality attributes.Epinions social network dataset is also used to sim ulate and validate the proposed method. In the proposed method, the absolute mean value of error is less than 0.0095 and the value of F-score is more than 0.9884. Based on theobtainedresults and com pared to the previous methods,the proposed adaptive neuro-fuzzy inference systemshows an acceptable accuracy for evaluating the trustworthiness of users.

Keywords:Social Network,Trust, Adaptive neuro-fuzzy inference system

1. Introduction

Trust is a multifaceted concept, and can be defined differently according to the application that it has, so it is difficult to determine trust and it is possible to make a mistake. Different domains have brought about different definitions concerning the concept of trust some of which are referred to below. In [1] psychologists, in their studies, have concluded that trust focuses on the mind-set of an individual when he trusts or distrust someone. In [2] trust in computer science generally divides into two parts: 1- User, 2- System. The concept of user trust is obtained with a standard definition from psychology and sociology under the title "a person's mental expectation about the future behavior of others". The concept of system trust comes from the field of security. That is, it is the expectation that a device or system has to achieve the desired goals. In social networks, one of the topics where trust plays a vital role is the creation and maintenance of relationships, so that one can say that the basis of any relationship is trust.

In web-based social networks, a person's level of trust is obtained from his virtual personality, which is caused by his interactions in the virtual space, and it cannot be compared with everyday life, which is real.A person's virtual personality depends on the personality attributes they have observed in virtual. Some of the personality attributesthat lead to thetrustworthiness of users can be mentioned as reliability, availability, interest, patience and adaptability.The pointthat matters is that these attributes are internal and can be interpreted in a variety of ways, based on a definition thatwe provide about trust.In this research, we have proposed method in which the trustworthiness of users can be evaluated depending on one or more personality attributes. The rest of the article is organized as follows. In section 2, social networks and trust managementare expressed. In section 3, discusses related works about trust in social networks. In Section 4, explains the proposed adaptive neuro-fuzzy inference system for evaluating trustworthiness. In section 5, describes the evaluation of the the proposedadaptive neuro fuzzy inference system, andthe conclusionis discussed in section 6.

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Received: 2023.09.27; Accepted: 2024.01.20

2. SOCIAL NETWORKS and TRUST MANAGEMENT

Social networks Can be specified as a set of nodes and edges that are systematic., so that the nodes describe users, groups, and communities and the edges describe communications.Nowdays, with the advancement of technology and more people's access to social networks and the influence these networks have on people's daily lives, many people have turned to these networks to do many of their daily tasks in this way.Things like sharing information, communicating with each other, sending photos and videos, and many similar things that are increasing in development and diversity every day [3].Web-based social networks provides other way to communicate with others, affecting on social relationships in the real world. It can be said that many of the relationships created in these networks, despite being virtual, are stronger than real-world relationships [4].

2.1 Properties of Social Networks

In [5] They have discussed the phenomenon of hemophilia and the small world that are the properties of social networks. Hemophilia means the user is ready to create relationships with other users.In [5], the phenomenon of hemophilia was investigated in two cases. The first mode is the state of homophily, in which users tend to communicate with those who have similar social characteristics, such as race, age, occupation, etc. The second mode of homophily is a value based on values, attitudes and beliefs.This means that users tend to connect with like-minded users regardless of their location. The small world phenomenon visualizes the world as a "small world", where all users are connected by a small chain. For example, users with similar interests communicate with each other through social networks.

2.2 The Importance of Trust in Social Networks

The growth of web-based social networks in online communities has become a major source of communication, and can be seen from the popularity of social networks sites such as Facebook, You Tube, Instagram, and so on [4]. This popularity has led to the creation of many social networks with the purpose of users communication and interaction with each other[5]. In social networks, the concept of FOAF (Friend of a Friend) has many uses. This concept suggests that someone can interact with friend of friends and engage in friendship, and given the fact that the trust is the basis of each friendship, trustworthiness may not be true for a friend of friends. According to the concept expressed, it can be said that one of the possible risks in social networks is data security.

2.3 Trust Management in Social Network

In [6] trust management systems, into three categories are classified:

1- Credential and policy-based 2- reputation based 3- social networks based

The main purpose of the first category, which is based on credentials and policies, is to validate the entity to enable access control.The second category, which is based on reputation, creates reliable and secure communication by evaluating the reputation and popularity of users in the environment. The third category in trust management systems based on social networks, in addition to considering reputation, uses social relationships among users to establish trusted relationships [6].

3. RELATED WORKS

In [7], an approach to determine the quantitative content of the shared content in terms of its reliability is proposed. Of course, the focus of the authors is mostly in the field of health. In [8], Algorithms for inferring trust among people who are not familiar with each other or do not interact with each other are presented. Also, a method for extracting information and integrating it into programs was examined. The proposed algorithms for trust inference depend on reputation information. In [9], an algorithm named TidalTrust is proposed for trust inference. The algorithm described in [9] cannot be properly implemented to determine the trustworthiness of users based on the provided personality traits. In [10], a system called PowerTrust was used to calculate peer-to-peer trust. The scalable system has a useful function but cannot be used to build trust in a social network.In [11], a model for trust evaluation based on gravity is presented. The proposed model has a two-step process. In the first stage, friendships and strengths are calculated, and in the second stage, social neighbors are used to calculate trust. This model cannot evaluate users trustworthiness based-ontheir personality characteristics. In [7], Algorithms for calculating behavioral trust are presented. In [12], social trust was discussed and two algorithms were presented to access implicit and explicit social trust.The proposed approach in [12] is more robust against tampering attacks and is applicable in areas such as DTN secure routingbut it is not suitable for our research work. In [13], A model has been designed so that users can share their information, which is called Strust.Shafiei et al. in [14] presented a Mamdani fuzzy system to evaluate the trustworthiness of users in social networks. In this article[14], some personality characteristics of the users were used as input to the fuzzy system.In [15], trust management in connection with Internet applications is investigated. In their research[15], a notation to specify the concepts of trust and recommendation is presented along with a set of tools to determine, analyze and monitor trust relationships.In [16], Shirgahi et al. have used the parameters of social network authority, page link credibility value, and semantic credibility to evaluate trust. In [17], the importance of the trust model based on users' beliefs and credibility is discussed.The goal pursued in [18] was to design a fuzzy system. This trust model was used in distributed systems, but it cannot predict users' trust in social networks. In [19], a genetic algorithm-based approach for trust inference is presented, which uses heterogeneous relationships to infer trust. Their algorithm [19] has achieved higher accuracy for trust values and is also scalable and expandable, but it does not have the ability to evaluate users' trust in a social network.The focus of [20] is on graphical representation for modeling trust relationships in multiagent e-commerce environments. In [21] suggests a subjective logic to express distrust and to evaluate the trust probability distribution.In [22] Danesh and Shirgahipredicted trust in social networks using structural similarity through neural network.According to the research background stated in this research, we have adopted an approach in which users' trust can be evaluated based on a set of their personality characteristics. This approach supports an unlimited number of personality attributes.

4. The proposed approach for evaluating trustworthiness

A web-based social network can be implemented as a directed graph G (V, E) so that V is a set of nodes that denote users and E is the set of edges that describe the interactions between these users. The number assigned to each edge from vi to vj (user i to user j), indicates the number of times the user i interacts with the user j. As an example, Fig. 1 illustrates a simple example of this network. In this figure, a directional graph shows their interactions with each other.

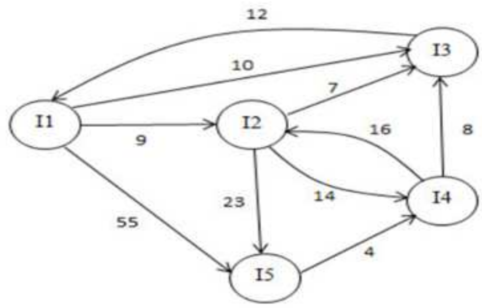

Fig. 1. Trust network as a directed graph

The values on each edge represent the total number of interactions performed by the user with the other users. It should be noted that in this figure, for example I1 is the sameas Individual1. Interactions have different natures and are based on rate. The rating of user's interactions is based on different characteristics. The ratings depend on the experience and feeling received by the users. Rating values are processed using fuzzy logic to evaluate trustworthiness.The two most important criteria of graph that used to evaluate trustworthiness of users are called In-degree and Out-degree. The In-degreeof a node indicates the number of users interacting with the selected user, and the Out-degreeof a node indicates the number of users with whom the selected user interacts.In other words, it can be said that In-degree node states that the selected user receives information about the other users, and Out-degree node points to the fact that the selected user disseminates information on his personality attributes on the social network to the other users.Low In-degree and Out-degree nodes denote less interactivity, in other words receiving or disseminating less information; and High In-degree and Out-degree nodes denote more interaction, that is receiving or disseminating more information.

Clearly, it is difficult for a user at Low In-degree to directly determine the trustworthiness of others. The proposed approach requires that each participant (for example, a user) receives ratings of each entity's different attributes with which he is interacting. A rating reflects experiences perceived by each entity about another one based on the attribute selected. Each scale can be used to rate the attributes from -S to +S. That means, if S=2, then the scale is from -2 to +2. Table 1 shows the rating scale for five personality attributes and their meanings.In this paper, we chose these five personality attributes based on our own mental perceptions and our studies.

Table 1. Five characteristics and their concepts

Rate	Reliability	Availability	Interest	Patience	Adaptability
-2	Ever unreliable	Ever unavailable	Ever dissimilar interests	Ever impatience	Ever unadaptable
-1	Often unreliable	Often unavailable	Often dissimilar interests	Often impatience	Often unadaptable
0	No comment	No comment	No comment	No comment	No comment
1	Often reliable	Often available	Often similar interests	Often patience	Often adaptable
2	Ever reliable	Ever available	Ever similar interests	Ever patience	Ever adaptable

Reliability expresses user ability to do something without failure. Availability indicates that users are always available to interact and support with each other. Interests include factors that make user attractive. In fact, the more users' interests are similar, the more they can trust each other. Patience means that patient user is able to tolerate setbacks, delays or unexpected challenges with-out becoming anxious or angry. Patient user has a better mental health. Adaptability is the emotional and current stability of social relationships. Adaptable user can quickly adapt to changes in plans. A user that is adaptable is associated with his various traits and characteristics.It is important to note that the proposed method is general and does not depend on the number of attributes. That is, trustworthiness can be considered as a function of characteristics and this is because trust is a mental concept, and it takes different interpretations depending on the conditions and applications.However, to show the usability of the fuzzy inference system presented through simulation, 5 attributes have been selected. That is, trustworthiness is considered as a function of 5 attributes. Also, the presented approach does not have any restrictions on the scales used to rate experiences for simulation. In general, each rating scale from -S to + S, where S> 0, can be used. Experiences record, in the form of rating various characteristics during different interactions, is maintained by the user about the other user he interacts with. With these experiences, the experience matrix can be formed. Experiences with different parameters in various interactions are stored in the experience matrix.The experience matrix is used as the input of the adaptive neurofuzzy inference system to analyze the trust of others. In evaluating the characteristics of the experience, consider that user U1 interacts with user U2 with n interactions.EC_{att} (u1, u2) is a set of experience consisting of n values that represent the experience of feeling of user u1 about user u2 in n interactions according to the characteristic defined as follows.

$$EC_{att}(u1, u2) = \{exp_{att}1, exp_{att}2, \ldots, exp_{att}\, n\}$$

so that exp_{att} n is the experience felt by user U1 about user U2 according to the attribute $_{att}$ in interaction n. EC_{att} values are recorded by each user for all users they interact with. In this way, we can define the whole experience perceived by user U1 for user U2 according to the attribute $_{att}$.

$$EC_{att}(u1, u2) = mode(EC_{att}(u1,u2))$$

EC_{att} (u1, u2) is the total experience that user U1 feels about user U2 according to the attribute att, and mode(EC_{att}(u1, u2)) is the frequency value of the set EC_{att} (u1, u2). This process can be generalized to get user experience about others due to different features. Figure 2 is a pseudocode that shows a method to calculate users' experience from other users. Low values In and Out-degree between U1 and U2 provide less accuracy EC_{att} (U1, U2), while High values provide greater accuracy EC_{att}(U1,U2) Results.

```
U1: first user
Un: nth user
X,Y: Temp user variables
k = the number of attributes
X=U1;
While (X<=Un)
{
        While (Y<=Un)
        {
            If (X!=Y)
            {
             For (att=att1; att<=attk; att++)
                 {
                  Eatt(X, Y) = mode (ECatt)
                  }
              }
          J++;
           }
    I++;
  }
```

Fig. 2. Pseudo code to calculate user experience

4.1 Generating of Matrix of Experience(EM)

Figure2 shows the pseudo code for calculating the experience matrix. For example, Table 2 shows Ratings for first user interaction with another user on the five attributes.For example, table 2 shows the ranking of the person from other people in the social network. Using the pseudo code written in Figure 2, Table 3 is obtained from Table 2. From Table 3, the experience matrix is obtained, which is shown in Figure 3.After the matrix of experience is obtained, depending on one or more attributes, trust can be calculated.The user can pick the attributes. In fact, the user chooses the specific attributes according to his needs and understanding of trust. The fuzzy inference system we presented can be used to evaluate trust as a function of one or multiple attributes.Here, it's important to note that choosing the attributes of trust may vary for each user. This type of approach enables a user to model trust based on their understanding of what happens in the real world.

Table 2. Rating of the user from other users in the social network

Users	Count of interaction	Attributes				
		Reliability	Availability	Interest	Patience	Adaptability
U_2	8	-1,-1,0,1,2,-1,0,1	-2,-2,0,-1,-2,1,0,2	-1,1,0,-1,2,0,1,-1	-1,-2,-1,-2,1,2,-1,0	-2,-1,-1,0,1,-2,-2,-1
U_3	6	2,1,1,2,1,2	1,2,2,1,1,1	1,1,0,2,1,0	-2,-2,1,1,0,-2	2,1,1,0,2,2
U_4	5	1,2,0,2,1	0,1,2,2,2	-2,2,-2,1,0	-1,2,-1,0,1	1,1,1,2,1
U_5	4	-1,-2,-1,-1	-2,-2,-2,-1	-2,-1,-1,-1	-1,-2,-2,-2	-1,-1,-2,-1
U_6	9	1,0,0,1,1,0,1,0,0	0,1,1,1,0,1,0,1,1	1,0,0,1,0,0,1,1,0	1,0,0,-1,-1,0,-1,-1,1	1,1,1,1,0,0,1,0,0

Table 3. Calculating attributes values based on interactions

Users	Attributes				
	Reliability	Availability	Interest	Patience	Adaptability
U_2	-1	-2	-1	-1	-2
U_3	2	1	1	-2	2
U_4	1	2	-2	-1	1
U_5	-1	-2	-1	-2	-1
U_6	0	1	0	-1	1

$$EM = \begin{bmatrix} -1 & -2 & -1 & -1 & -2 \\ 2 & 1 & 1 & -2 & 2 \\ 1 & 2 & -2 & -1 & 1 \\ -1 & -2 & -1 & -2 & -1 \\ 0 & 1 & 0 & -1 & 1 \end{bmatrix}$$

Fig. 3. Experience matrix for individual I1

4.2Adaptive neuro-fuzzy inference system for evaluating trustworthiness of users

We used an adaptive neuro-fuzzy inference system to evaluate the trustworthiness of users based on the rating of the 5 considered personality attributes. Adaptive neuro-fuzzy systems, like fuzzy systems, organize two parts. The first part is the preliminary part and the second part is the late part, which are connected to each other in the form of a network by rules. The structure of this system consists of 5layers. The first layer performs the fuzzification process. In this layer, each node represents a membership function, which are the learnable parameters of the front part. In the second layer, the relevant rules are calculated. In the third layer, the rule normalization process takes place. In the fourth layer, the output of each rule is obtained, and finally, the last layer calculates the output of the fuzzy system by adding the outputs of the fourth layer. The adaptive neural fuzzy inference system is a suitable method for solving nonlinear problems. This method is a combination of fuzzy inference method and artificial neural network that takes advantage of both methods. In this research, 5 personality traits of users were used as input to the fuzzy inference system. We used fuzzy logic for the reason that there are no exact boundaries to separate these interdependent features. Figure 4shows an overview of the adaptive neuro-fuzzy inference system. Fuzzy system inputs have five attributes:reliability, availability, interest, patience and adaptabilityand the fuzzy system output is trustworthiness. The final ranking values of these features are processed by the adaptive neural fuzzy inference system.

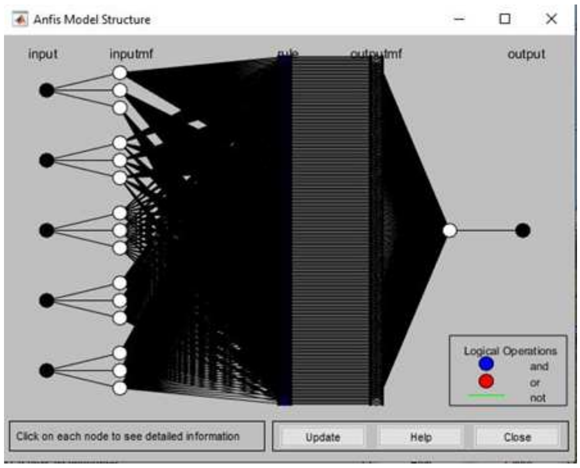

Fig. 4. Overview of the adaptive neuro- fuzzy inference system

5. Evaluating the Proposed Approach

To evaluate the proposed approach, we used the Epinions dataset, which is a social network dataset. One of the advantages of this data set is that it is a real data set and is widely used in research work in the field of social networks. MATLAB tool and adaptive neural fuzzy inference system have been used to simulate and evaluate this approach. In this way, on a part of the data set including the first 2000 nodes and 77589 edges, we read the text file related to the data set line by line by coding in MATLAB software and saved it in the matrix and produced the matrix. Then the desired dataset We divided it into one to five clusters. Figure 5 is related to how to categorize the dataset in the proposed method.According to Figure 5, we considered 80% of the dataset as training data and 20% of the dataset as testing data. Also, we used 5 clusters to cluster the data. Also, the executive structure for each of the clusters in the proposed method is shown in Figure 6. An important point in this dataset is that the available rankings are based on one-to-one interactions. That is, the dataset is an interaction between the nodes by default. Also, the output that we have in the dataset is the degree of trustworthiness between nodes and not the number of their interactions. When simulating the output of the neural fuzzy system, the level of trustworthiness was classified into 5 categories according to table 4.

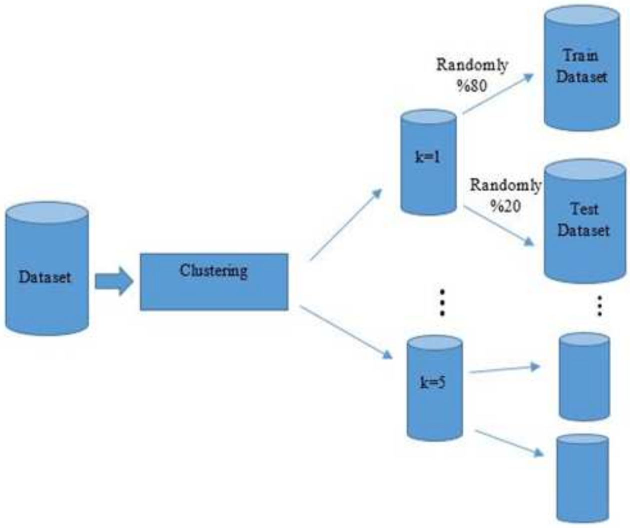

Fig. 5. Dataset classification in the proposed method

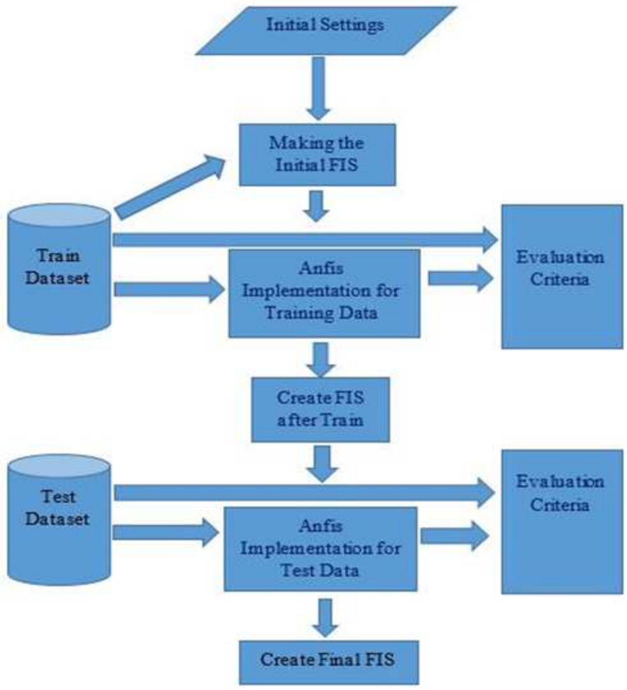

Fig. 6. The execution structure of the proposed method for each clusters

Table 4. Trustworthiness categories of users

Rating Category	Trustworthiness
-2	Ever untrusty
-1	Often untrusty
0	No comment
1	Often trusty
2	Ever trusty

We also used the Pimf membership function for the input and output variables, the general structure of this function is shown in Equation 1.

$$f(x,a,b,c,d)=\begin{cases}0, & x\le a\\ 2\left(\frac{x-a}{b-a}\right)^2, & a\le x\le \frac{a+b}{2}\\ 1-2\left(\frac{x-b}{b-a}\right)^2, & \frac{a+b}{2}\le x\le b\\ 1, & b\le x\le c\\ 1-2\left(\frac{x-c}{d-c}\right)^2, & c\le x\le \frac{c+d}{2}\\ 2\left(\frac{x-d}{d-c}\right)^2, & \frac{c+d}{2}\le x\le d\\ 0, & x\ge d\end{cases} \quad (1)$$

5.1Performance evaluation parameters of adaptive neuro- fuzzy system

After simulating the neural fuzzy system described in section 5, to evaluate the performance of different neuro-fuzzy systems, we considered 20% of the used dataset as test data and examined the performance of the neuro-fuzzy system. To calculate the accuracy of neuro- fuzzy system and clusters, we used different accuracy evaluation criteria including: accuracy, precision, recall and F-score criterion and compared them. How to calculate the accuracy criterion in Equation 2 and precision criterion in Equation 3 as well as how to calculate the recallcriterion and the F-score criterion are given in Equation 4 and 5, respectively. In the mentioned relationships, the concepts TP means true positive, TN means true negative, FP means false positive and FN means false negative. We also calculated the amount of error resulting from the amount of trustworthiness obtained by the Anfis system compared to the amount of trustworthinessavailable in the test data from the original dataset under the title of Mean Absolute Error (MAE), which is given in Equation 6. According to Equation 6, Cti is related to the calculated confidence value and Rti is the real confidence value and N is the total number of test data.

The results obtained from the calculation of these criteria's and the amount of error obtained on the training and testing data set in different clusters, as well as their comparison, are shown in figures 7 to 16, respectively.According to Figure 7, for the precision criterion, k=5 cluster shows a better result in training data than other clusters.Also, in Figure 8, for the precision criterion, k=5 cluster shows a better result than other clusters in the test data.It is shown in figure 9 and 10 that for the recall criterion in cluster k=5, better results have been obtained for both the training data and the test data.Also, in Figures 11 and 12, for the F-score criterion, we see better results in the k=5 cluster than in other clusters for both the training data and the test data.In Figures 13 and 14, for the Accuracy criterion, the k=5 cluster has given the best results compared to other clusters for both the training data and the test data.To compare the MAE criteria according to Figures 15 and 16, we see that for both the training data and the test data, k=5 cluster has the lowest Mean Absolute Error compared to other clusters.Also, in Figure 17,we compared the evaluation results of the criteria stated in this article (black line) with the evaluation results of the approach presented in the article by Shafieiet al (red line). According to Figure 17, in the new approach presented, we see an improvement in the F-score criterion and also a reduction in the average error.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (2)$$

$$Precision = \frac{TP}{TP+FP} \quad (3)$$

$$recall = \frac{TP}{TP+FN} \quad (4)$$

$$Fscore = \frac{2\times recall\times precission}{recall+precission} \quad (5)$$

$$MAE = \frac{\sum_{i=1}^{N} |C_{Ti}-R_{Ti}|}{N} \quad (6)$$

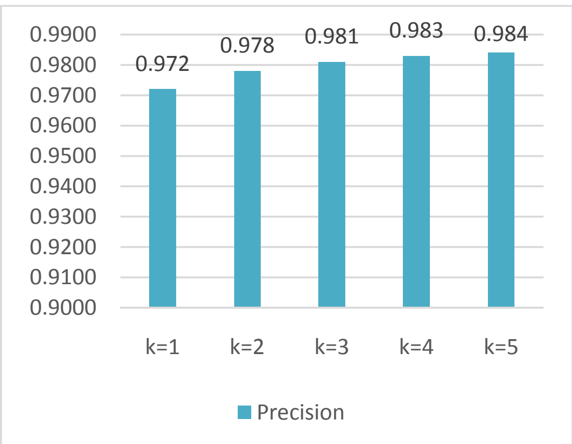

Fig. 7. Precission measure for train dataset

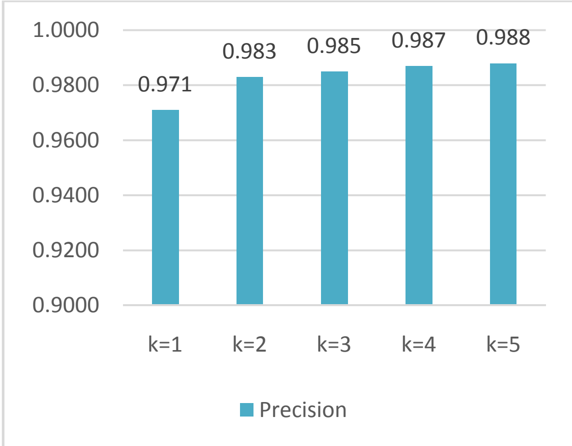

Fig. 8. Precissionmeasure for test dataset

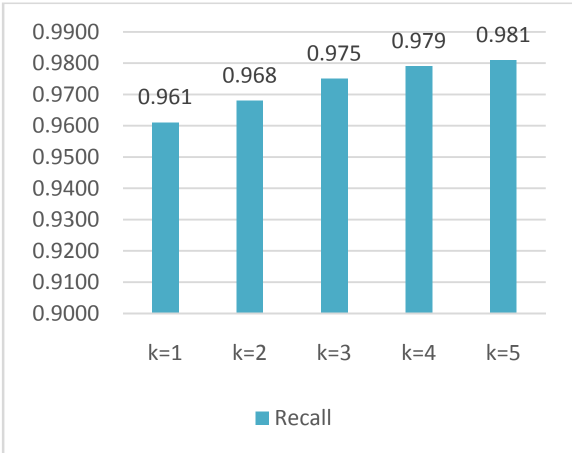

Fig. 9. Recall measure for train dataset

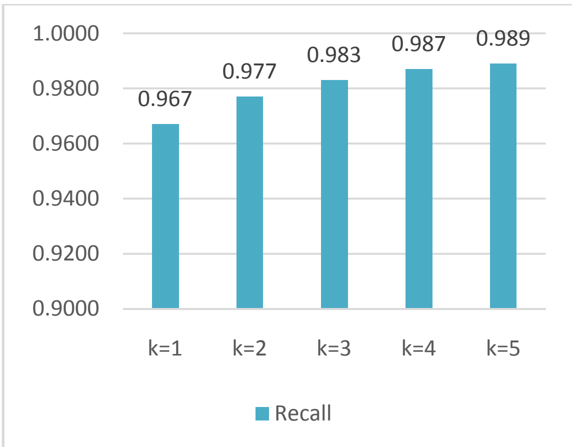

Fig. 10. Recall measure for test dataset

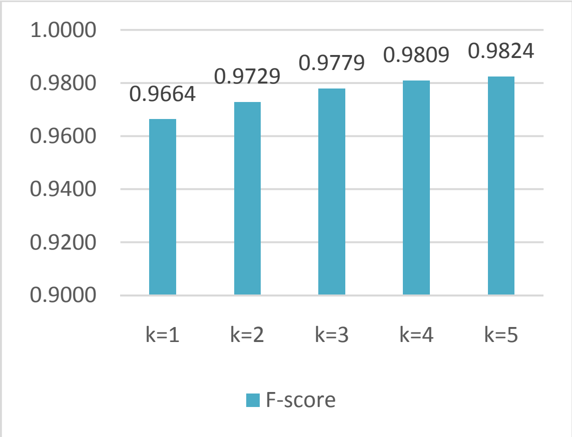

Fig. 11.F-score measure for train dataset

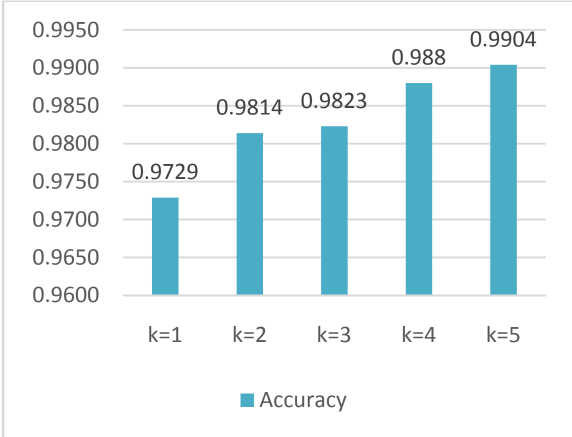

Fig. 14. Accuracy measure for test dataset

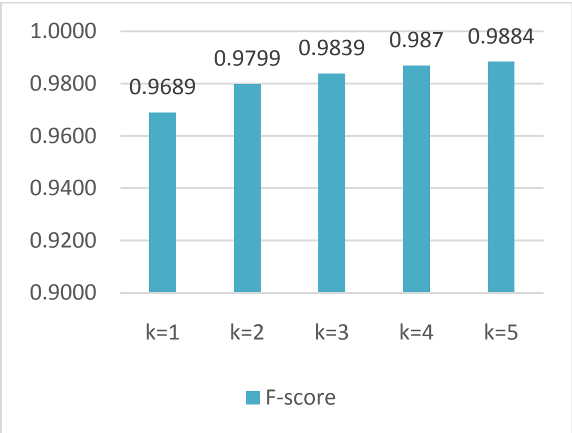

Fig. 12.F-score measure for test dataset

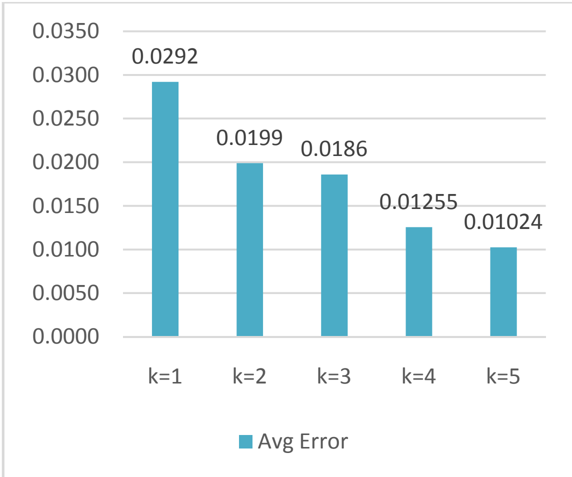

Fig. 15.MAE measure for train dataset

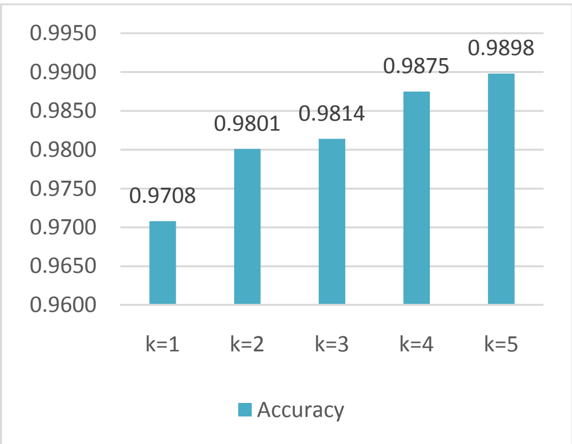

Fig. 13. Accuracy measure for train dataset

Fig. 16.MAE measure for test dataset

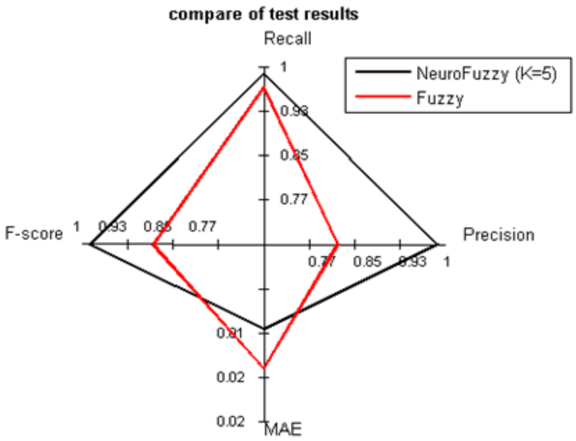

Fig. 17. Comparing the evaluation results of the current approach with the approach of the fuzzy[14]

6. Conclusion and Future Works

Determining and establishing trust relationships with other people is an important and constant concern in almost most fields. In this paper, we presented and discussed anadaptive neuro-fuzzy inference system for evaluating the trustworthiness of users in a social network. In the proposed system, our approach includes rating of 5 personality attributes when users interact with each other. These ratings were processed using an adaptive neural fuzzy inference system to obtain the trustworthiness of the users. An adaptive neural fuzzy inference system was used because these systems have the ability to deal with uncertain and ambiguous information. Trustworthiness can be determined as a function of one or more personality attributes. The proposed approach is flexible and extensible, allowing trust to be determined as a function of any number of personality attributes. The attributes can also be expanded. The information extracted through the use of this proposed neural fuzzy system can be used to identify and predict interesting facts in the field of social networks. According to the obtained results, among all the considered clusters, the cluster corresponding to k=5 has the lowest average error with a value of 0.0095 and also has the highest F-score measure with a value of 0.9884, which according to figure 17 in Compared with the approach presented in the article by Shafiei et al [14], the average error has decreased and the F-score measure has improved.

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