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Development and use of a clinical decision support system for the diagnosis of social anxiety disorder

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ABSTRACT

Background: Mental disorders, according to the definition of World Health Organization, consist of a wide range of signs, which are generally specified by a combination of unusual thoughts, feelings, behavior, and relationships with others. Social anxiety disorder (SAD) is one of the most prevalent mental disorders, described as permanent and severe fear or feeling of embarrassment in social situations. Considering the imprecise nature of SAD symptoms, the main objective of this study was to generate an intelligent decision support system for SAD diagnosis, using Adaptive neuro-fuzzy inference system (ANFIS) technique and to conduct an evaluation method, using sensitivity, specificity and accuracy metrics.

Method: In this study, a real-world dataset with the sample size of 214 was selected and used to generate the model. The method comprised a multi-stage procedure named preprocessing, classification, and evaluation. The preprocessing stage, itself, consists of three steps called normalization, feature selection, and anomaly detection, using the Self-Organizing Map (SOM) clustering method. The ANFIS technique with 5-fold cross-validation was used for the classification of social anxiety disorder.

Results and conclusion: The preprocessed dataset with seven input features were used to train the ANFIS model. The hybrid optimization learning algorithm and 41 epochs were used as optimal learning parameters. The accuracy, sensitivity, and specificity metrics were reported 98.67%, 97.14%, and 100%, respectively. The results revealed that the proposed model was quite appropriate for SAD diagnosis and in line with findings of other studies. Further research study addressing the design of a decision support system for diagnosing the severity of SAD is recommended.

1. Introduction

Planning, organizing, controlling, and managing high-quality care, which mainly depends on the decision-making process, are the key responsibilities of health care providers [1]. Developing, applying, and evaluating a new method for decision-making by using information technology is the new trend in recent studies of psychiatry [2] Decision Support System (DSS) is the employment of a collection of individuals, procedures, software, databases, and tools with a focus on solving the problem and supporting decision-makers [1]. In a more specific view, Clinical Decision Support System (CDSS) is a computer system created to facilitate clinicians' decision-making procedures about patients with a major focus on avoiding medical errors and improving quality of care [3].

1.1. Overview of mental disorders

Mental disorders, also called mental illnesses, according to World Health Organization's (WHO) definition, contain a wide range of problems and symptoms, typically specified by a combination of unusual thoughts, feelings, behavior, and relationships with others [4]. Apparent inability to adapt to social situations is associated with these disorders. However, expected-reaction to an acute tense situation, like the loss of one's close relative, is not a mental disorder [5]. Psychiatric problems or mental disorders are increasingly growing in developing countries. It has been reported that about 50% of the patients referred to primary care departments have a kind of psychiatric problems [2] Steel has remarked that 29.2% of participants in his study experienced at least one of the

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signs of mental disorders, once in their lifetime, and the 12-month prevalence rate was 17.6% [6].

1.2. Social anxiety disorder

Anxiety disorder, with a 12-month prevalence rate of 6.7%, is the most prevalent mental disorder worldwide [6]. Bandelow has mentioned that an anxiety disorder affects at least one-third of the population during the lifetime, and its heavy burden is often notable and more than other mental diseases; the cost of the disorder was estimated about 41 billion Euros in the European Union [7].

Social anxiety disorder (SAD), also known as social phobia, is one of the most prevalent anxiety disorders described as permanent and severe fear or feeling of embarrassment in social situations such as lecturing or eating in public, being faced with others' judgment, being the center of attention, etc. [8,9]. According to National Comorbidity Survey-Replication (NCS-R), SAD with the lifetime prevalence rate of 13%, is the second most common anxiety disorder after specific phobias with the prevalence rate of 13.8% [7]. It has also been reported to have the 12-month prevalence rate of 7% by the DSM-5 manual in the United States [5]. Hence, it becomes increasingly difficult to ignore the disorder, which has recently been addressed by several researchers.

The patients who suffer from SAD often remain undiagnosed and untreated; the situation which might lead to other substantial disorders such as depression, eating disorder, and drug abuse. The detection is usually challenging for psychiatric healthcare providers, due to patients' unawareness of the disorder they suffer from. Therefore, designing a system to diagnose SAD could be useful to avoid additional problems [10].

In this study, an Adaptive neuro-fuzzy inference system (ANFIS) is used to model a DSS to diagnose SAD. The ANFIS is an artificial intelligence approach that combines Neural networks (NN) and the fuzzy logic techniques to learn a system, using the advantages of both. These advantages address uncertainties and vagueness by fuzzy approach and handle noisy data by NN [11]. Hence, the main contributions of the study are given as follows:

1) Considering the imprecise nature of SAD symptoms, we proposed an ANFIS-based model to diagnose SAD, which is the first study of its kind performed on that disorder. Furthermore, we added a *hardlim(x)* transfer function to the output of ANFIS, due to binary type of the target feature.
2) We used a multi-step preprocessing manner to improve the model performance consisting of normalization, feature selection, and clustering-based anomaly detection by Self-Organizing Map (SOM) method. To highlight the effect of the anomaly detection step on performance, we also compared the created models before and after this step.

2. Literature review

Suhasini et al. [2] presented a multi-model decision support system to diagnose psychiatric problems. They used a hybrid approach in which Back propagation neural network (BPNN), Radial Basis Function Neural Network (RBFNN) and Support Vector Machine (SVM) were combined to create the DSS. The system reached a good accuracy of 98.75% for identifying psychiatric problems. However, it failed to consider the imprecise nature of some symptoms.

Ekong et al. [11] designed an intelligence neuro-fuzzy case-based reasoning (CBR) approach for depression severity diagnosis. Similar to the previous study, the proposed framework was a hybrid method, with the only difference that they used fuzzy method to handle vagueness in their data.

Windriyani et al. [12] proposed an expert system to diagnose mental disorders by the forward chaining method. They used the experts' knowledge and MINI ICD-10 as an instrument to design the system. Although it was based on experts' knowledge, the accuracy of the system was 96%, which appears to be satisfactory.

Devi, et al. [13] in their study, which is the most similar one to ours, used an ANFIS method to predict anxiety in students. They used two personality parameters, neuroticism, and extraversion, as the input of the model. These parameters were collected by the Maudsley personality inventory (MPI), and Sinha's comprehensive anxiety test (SCAT) questionnaires to measure raw data for anxiety in 36 students participating in the study. The prediction error, calculated by MAPE and RMSE measurements, were 21.0 and 3.280, respectively, which were lower than other methods. It seems that the number of input parameters and participants could be increased to improve the generalizability of the model.

In other areas, fuzzy logic and ANFIS have been extensively deployed for advantages such as dealing with vagueness and uncertainties. For example, Ali et al. [14] proposed a type-2 fuzzy ontology-based recommendation system for diabetes. They used IoT based healthcare system for patient monitoring and information gathering. Using type-2 fuzzy logic, they were able to address many blurred and unpredictable risk factors of diabetes. In terms of accuracy, they compared the proposed system with classical ontology-based and type-1 fuzzy-based ontology systems as well. They found the proposed system more accurate than the others.

Addeh et al. [15] proposed an optimized ANFIS-based with feature selection method for early detection of breast cancer. They used association rules for feature selection and cuckoo optimization algorithm (COA) for optimizing ANFIS algorithm. Upon feature selection step, eight features were selected as input and the accuracy of 99.26% was obtained. The feature selection step improved the accuracy of the model by about 2%, which confirms the importance of this step.

Toghroli et al. [16] compared the ANFIS method with linear regression (LR) in predicting the shear strength connectors in the steel-concrete composite beam. The higher accuracy and precision of ANFIS method as compared with LR have been reported. In another work carried out by the same research team, the ANFIS method team was used to find the factors affecting the shear strength steel-concrete composite beam, in which concrete compression strength had the highest effect on shear strength capacity of the composite beam [17].

3. Methodology

This study proposes a machine learning-based decision support system for the diagnosis of social phobia, using real-world dataset. The method involves a combination of steps to preprocess the raw data, using triangulation method to validate the actual results of the disorder, feature selection to dimension reduction, clustering to anomaly detection, 5-fold cross-validation to avoid overfitting and ANFIS to create the trained model.

In the next section, first, the acquisition of a real-world dataset and triangulation method are described. Then, the preprocessing steps focusing on normalization, feature selection, and self organizing map (SOM) clustering are presented. Ultimately, the ANFIS technique with cross-validation is described for social phobia diagnosis.

3.1. The acquisition of the dataset

At this stage, the raw dataset was collected through a website. The dataset consisted of 11 attributes of SAD, known as significant symptoms based on DSM-5 and International Classification

Table 1
Social anxiety disorder attributes.

Category	Attributes	Range	Code
Demographic information	Gender	0–1	GEN
	Has a family history of anxiety or depression disorders	0–1	HFH
Emotional Characteristics	The fear of being at the center of attention	0–10	ATF
	The fear of eating in front of another person	0–10	EAF
	The fear of speaking in public	0–10	TKF
	The fear of attending parties	0–10	CMT
	The fear of eating and drinking in public places	0–10	DEF
	The fear of meeting or having contact with strangers	0–10	SMF
	The fear of getting in a room where others are sitting	0–10	ERF
	The fear of disagreement with strangers	0–10	DAF
Physical characteristics	The number of physical symptoms	0–13	NPS

of Disease, 10th revision, Diagnostic Criteria for Research (ICD-10-DCR) guidelines. These attributes and their categories and ranges are shown in Table 1.

Afterward, two standard tests, Social phobia inventory (SPIN) and Liebowitz social anxiety scale (LSAS) were used to assess participants for social anxiety disorder. Taking the second test (LSAS) was optional, and it was used to validate the first test as a part of the triangulation method.

The overall scores for SPIN and LSAS varied from 0 to 68 and 0 to 144, respectively. On the basis of experts' ideas, the cut-off points of 21 and 35 were selected for SPIN and LSAS tests, respectively. The number of participants included in the experiments was 214 cases. However, some of them were removed from the study because of mismatches in the test results. Finally, the raw real-world dataset of SAD was prepared. It is noteworthy to mention that the target variable was the result of the aforementioned tests.

3.2. Preprocessing

Due to the mandatory condition of filling out all attributes, there was not any missing value in the dataset.

3.2.1. Normalization

Given the different ranges of attributes, the first step was to normalize the values to avoid the variable's different effects on the learning algorithm. Hence, all variables rescaled to the values 0–10 through min-max feature scaling, which is presented in Eq. (1).

$$\boldsymbol{X'} = \frac{(\boldsymbol{X} - \boldsymbol{X_{min}}) \times 10}{\boldsymbol{X_{max}} - \boldsymbol{X_{min}}} \tag{1}$$

3.2.2. Feature selection

Feature selection or attribute selection is the process of selecting relevant features from a set of features in which the selected features represent the original data. Feature selection is used for some reasons such as reducing the complexity of models, reducing the learning time, avoiding overfitting, and the curse of dimensionality [18,19].

The complexity of the ANFIS model mainly depends on the number of generated rule nodes in which there is an exponential relationship between the number of attributes and fuzzy terms. In other words, if there are n attributes and m fuzzy terms, the ANFIS generates m^n rules [20]. So the main reason for using feature selection in this study was to reduce the complexity of the model, which leads to reducing the learning time. Furthermore, it helps to enhance the generalizability of the model by avoiding overfitting.

The feature selection process was applied by using IBM SPSS Modeler software V18.0, which is a standard and common tool for data mining applications. First, the normalized dataset was added to IBM SPSS Modeler environment. The SAD attribute was selected as target and the others as input features. Then, the algorithm was applied to find which input features have a strong correlation with the target feature. The importance value of each attribute is calculated on the basis of a statistical test of association between the input and target feature.

Table 2
The results of the feature selection algorithm done by IBM SPSS Modeler 18.0.

Rank	Feature	Is important	Value	Is selected
1	ERF	Y	1.0	Y
2	TKF	Y	1.0	Y
3	CMT	Y	1.0	Y
4	SMF	Y	1.0	Y
5	ATF	Y	1.0	Y
6	DAF	Y	1.0	Y
7	EAF	Y	1.0	Y
8	NPS	Y	1.0	N
9	DEF	Y	1.0	N
10	HFH	N	0.499	N
11	GEN	N	0.188	N

Regarding the fact that the high complexity of model, results in overfitting and low performance, the number of generated rule nodes in ANFIS model will be significantly reduced by selecting a subset of important features, leading to a decrease in the complexity of model and avoidance of overfitting as well [21].

The selected features, with their importance and ranks, are presented in Table 2.

As shown in Table 2, the last two features, gender (GEN) and family history of depression and anxiety (HFH), in the ranking, are irrelevant and were therefore removed from the final set of features. Also, the next two least important features, the fear of eating and drinking in public places (DEF) and the number of physical symptoms (NPS), were removed to reduce the complexity of the model and overfitting. Finally, the seven top rank features were selected as final variables of the dataset.

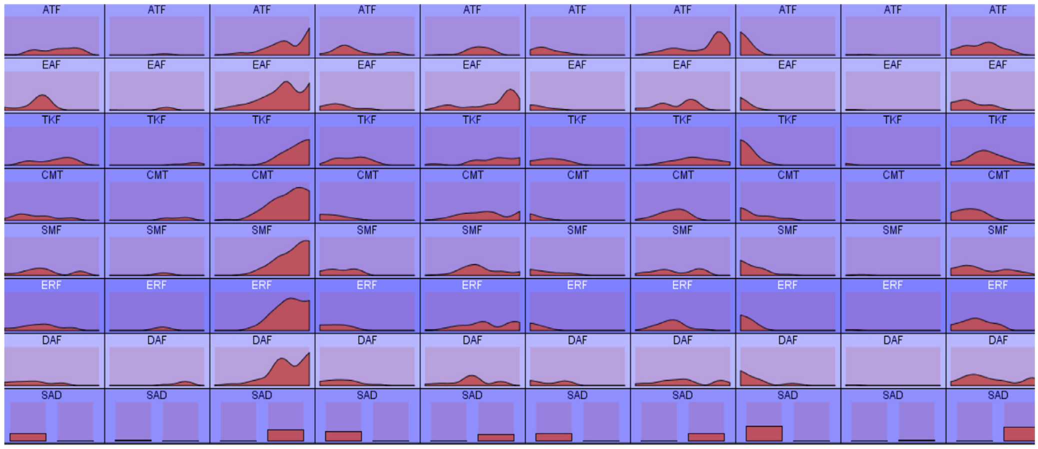
3.2.3. Anomaly detection using clustering

Anomalies (also called outliers, deviations, etc.) refer to patterns or points in a dataset that do not conform to well-defined and normal behavior. The process of finding these patterns is called anomaly detection [22,23]. These anomalies often have a destructive effect on accuracy in classifications. Hence, the anomaly detection plays a vital role in the classification process.

In this study, the Kohonen algorithm, which is a self-organizing map (SOM) clustering method, was used for anomaly detection. Clusters with few samples (one or two instances) were considered point anomalies, and clusters in which the instances behave anomalously, with regard to the actual results of SPIN and LSAS tests, were called a contextual or collective anomaly. SOM is an unsupervised neural network-based clustering method. It has a feed-forward single layer of neuron architecture. When an input sample is given to SOM, the neurons of the output layer compete with each other to calculate how much they are similar to the input

Table 3
The result of SOM clustering obtained by IBM SPSS Modeler 18.0.

Cluster	1	2	3	4	5	6	7	8	9	10
Size	20	2	31	23	18	19	21	39	2	39
Features										



pattern. The weights of the winner neuron and its neighbors are then strengthened. However, the winner neuron's wights are enhanced more than its neighbors [22]. The result of the SOM clustering is presented in Table 3.

As shown in Table 3, all the eight features, including seven input features and one target feature (SAD) were given to SOM as input. Consequently, ten clusters were identified in the dataset. The label of clusters with their size and the distribution of each feature in each cluster are presented. Clusters *two* and *nine* were point anomaly because of their few members. After more investigation on other clusters, the clusters *one* and *ten* were detected as contextual and collective anomalies. In these clusters, the number of mismatch cases concerning SPIN and LSAS tests was more than other clusters. The distribution of features in these clusters also confirms this action. For a practical example, when the target feature for all instances in a cluster is true, the negative skewness of other features' distribution is expected and vice versa. Otherwise, the cluster is suspected of anomalous behavior. According to the above mentioned, clusters *one* and *ten* are considered outliers and are removed from the dataset.

After detecting anomaly and removing the irrelevant clusters, 151 cases remained in the dataset.

3.3. Classification

After the preprocessing step, the cleaned dataset was ready for the classification process. ANFIS was used for classification purposes due to the fuzzy nature of dataset features and the aforementioned advantages of ANFIS technique.

3.3.1. Adaptive neuro-fuzzy inference system (ANFIS)

ANFIS method, which was first introduced by Jang [24] in 1993, comprises fuzzy logic and neural network approaches. Fuzzy logic is appropriate for addressing incomplete and imprecise information, but it has some drawbacks such as failure to learn the models from data and its high reliance on experts' perception. In contrast, the neural network can thoroughly learn automatically from data, but can not deal with imprecise conditions [25]. ANFIS combines these two approaches and relies on their advantages to overcome their constraints. The architecture of the ANFIS, used for social anxiety disorder diagnosis is presented in Fig. 1.

This architecture has been reported to have some input and a single output with five layers of nodes [11,13,24]. There are two kinds of nodes; the square nodes which are adaptive and circle nodes which are fixed.

The input layer consisted of seven features which prepared the crisp value for layer 1. The fuzzy set of features was {low, high}. Thus, two membership functions (MF) were used for each of them in this study, leading to layer one consisting of 14 nodes. This layer computed the fuzzy membership grade of each feature. See Eq. (2) and 3 for the first four nodes where $O_{j,i}$ is the output of the jth layer and ith node.

$$O_{1,i} = \mu_{A_i}(X_1), \ \ i = 1, 2 \tag{2}$$

$$O_{1,i} = \mu_{B_{i-2}}(X_2), \ \ i = 3, 4 \tag{3}$$

The generalized bell-shaped membership function was used in Eq. (2) because of its impact on accuracy, which is described in Eq. (4).

$$f(x; a, b, c) = 1/\left(1 + \left|\frac{x-c}{a}\right|^{2b}\right) \tag{4}$$

where the parameter 'a' determines the width of the MF, 'b' determines the shape of the curve, and 'c' is the center of the curve.

The layer two takes the output of the layer one as input and calculates the firing strength of each rule antecedent. Typically, this layer consists of rule nodes in which the number of these nodes are the exponential relation between the number of MFs and features; hence, in this study, there were 2^7 rule nodes. The output is shown in Eq. (5).

$$O_{2,i} = \omega_i = \mu_{A_i}(X_1) \times \mu_{B_i}(X_2) \times \mu_{C_i}(X_3) \times \mu_{D_i}(X_4) \times \mu_{E_i}(X_5) \times \mu_{F_i}(X_6) \times \mu_{G_i}(X_7), \ \ i = 1, 2, \ldots, 7 \tag{5}$$

The output of layer three, called normalization layer, is given as follows:

$$O_{3,i} = \varpi_i = \frac{\omega_i}{\sum_{i=1}^{7} \omega_i}, \ \ i = 1, 2, \ldots, 7 \tag{6}$$

The output of layer four is the product of ϖ_i, and the output of the rule is as follows:

$$O_{4,i} = \varpi_i f_i = \ \varpi_i(p_i X_1 + q_i X_2 + \ldots + r_i), \ \ i = 1, 2, \ldots, 128 \tag{7}$$

where the p_i, q_i, … and r_i are consequent parameters, the single neuron in output layer computes the overall output by summing

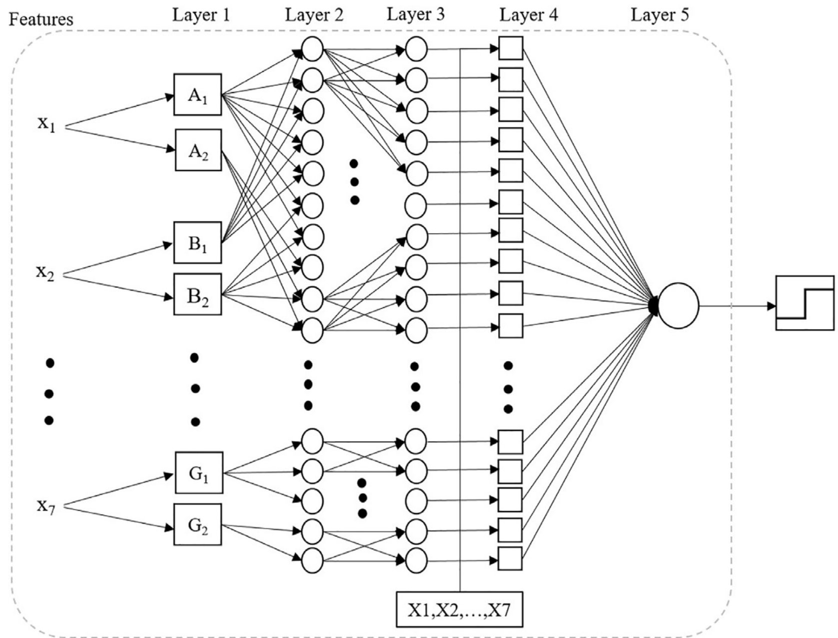


Fig. 1. ANFIS architecture of social phobia diagnosis.

up all incoming signals, as shown in Eq. (8).

$$O_{5,1} = \sum_{i=1}^{128} \varpi_i f_i = \frac{\sum_i^{128} \omega_i f_i}{\sum_i^{128} \omega_i} \tag{8}$$

Due to the binary value of the real target feature, the results of ANFIS must be transferred to the binary form. As a result, the accuracy, sensitivity, and specificity of the model can be measured. To this end, the final output of ANFIS was given to a *hardlim(x)* transfer function, which is described in Eq. (9).

$$Result = \begin{cases} 1 \ if \ O_{5,1} \geq 0.5 \\ 0 \ if \ O_{5,1} < 0.5 \end{cases} \tag{9}$$

3.4. Evaluation

After the classification step, the model was evaluated by accuracy, sensitivity, and specificity criteria, the formula of which are given in -Eqs. (10)–(12). K-fold cross-validation technique was used for validation purpose. The dataset randomly split into five subsets called folds; the model was trained and evaluated five times, by picking up a different fold as the test set and other four folds as the training set every time [26]. Thus, 80% of the dataset was selected for training and 20% for the test in every pass.

$$Accuracy = (\mathrm{TP} + \mathrm{TN}) \ / (TP + TN + FN + FP) \tag{10}$$

$$Sensitivity = \ \mathrm{TP}/(TP + FN) \tag{11}$$

$$Specificity = \ \mathrm{TN}/TN + FP \tag{12}$$

where true positive (TP) is the number of actual patients, who are detected true. True negative (TN) is the number of non-patients who are detected true. False positive (FP) is the number of non-patients who are detected incorrectly, and false negative (FN) is the number of patients who are detected incorrectly.

4. Results

The ANFIS technique, with a hybrid optimization learning algorithm, was used to tune the parameters of the fuzzy inference system (FIS). This algorithm uses a combination of least square and

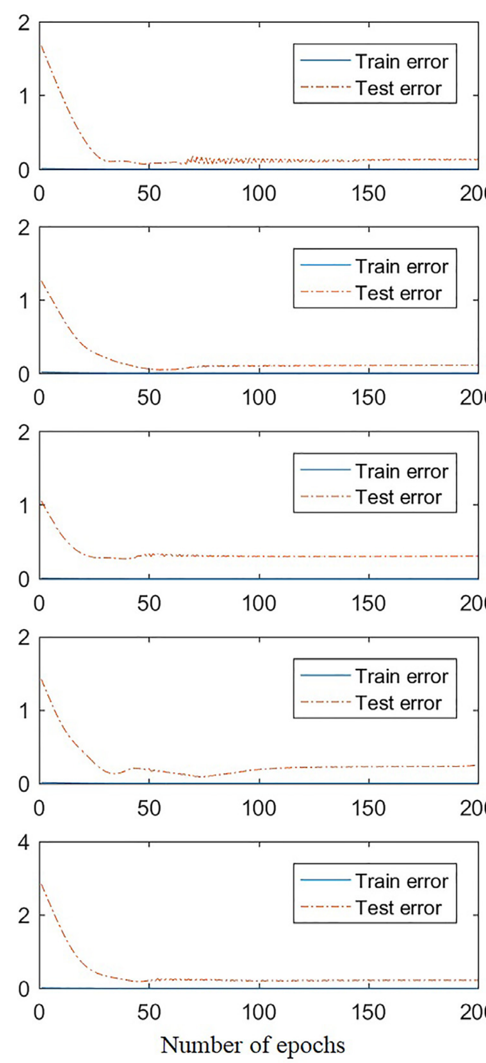


Fig. 2. The complexity of the model graph.

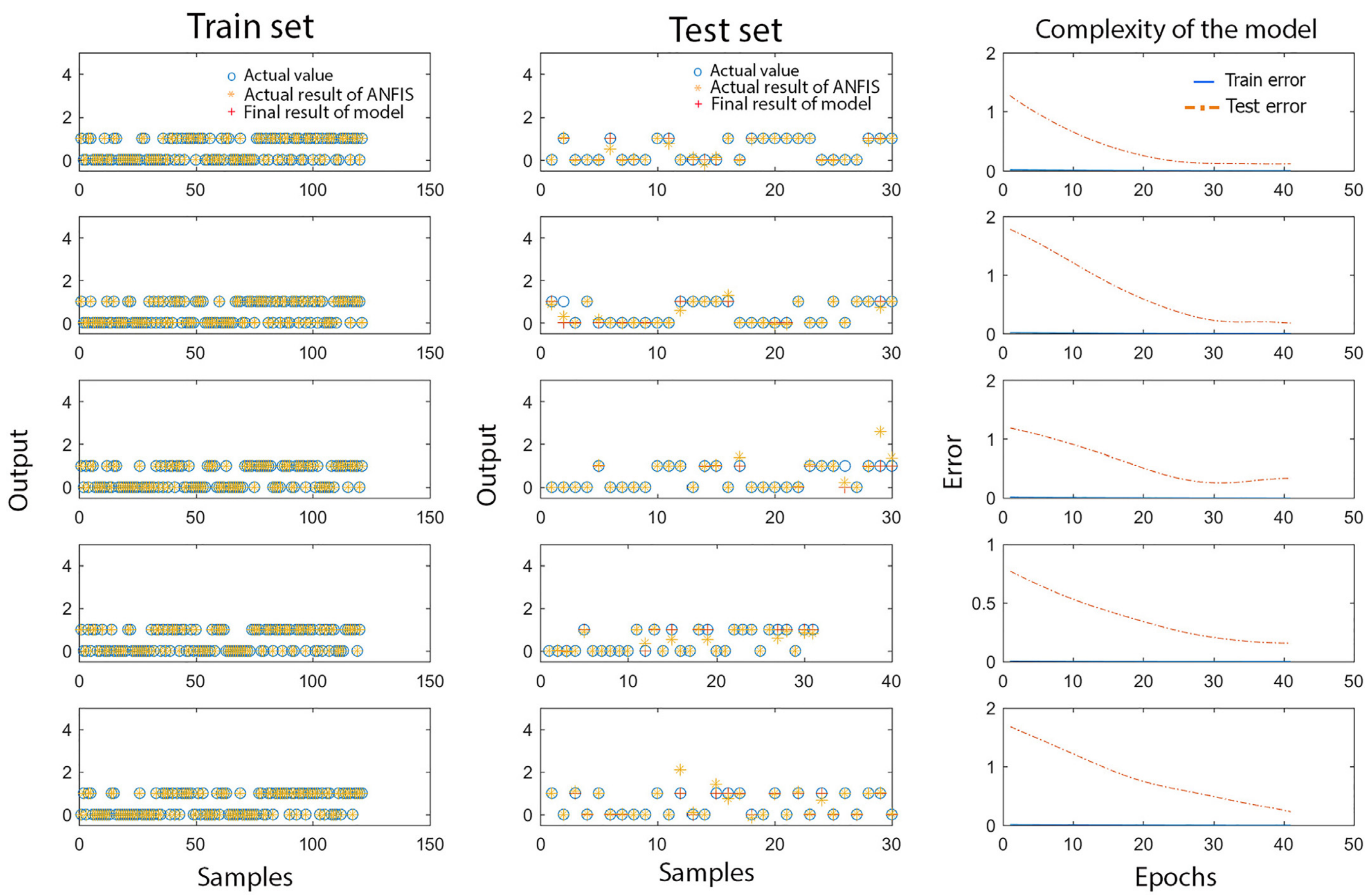


Fig. 3. The result of generated ANFIS model using 5-fold cross-validation.

back-propagation methods to train the model [13]. To find the optimal number of epochs for training the FIS, we used the model complexity graph in which the horizontal axis was the number of epochs, and the vertical one was the model error. At early epochs, the training and test set error begins to decrease, suggesting that the training should be continued. At the point where the test set error starts to increase or fluctuate, the training should be stopped. This point is the optimal point for the number of epochs and the complexity of the model. We started with 200 epochs and finally reached 41 epochs as the optimal point (See Fig. 2). Because of using the 5-fold cross-validation method, a complexity graph was created for every five models.

The results of the generated model using the 5-fold cross-validation on the cleaned dataset are presented in Fig. 3.

As it is displayed, every row shows the results of a generated model in one of the cross-validations pass. Moreover, the three columns show the training phase output, test phase output, and complexity of the model output, respectively. In all passes of the cross-validation, only two cases, related to second and third passes, were incorrectly classified, showing the excellent performance of the model. Corresponding results of validation measures are presented in Table 4.

It can be observed that the sensitivity, specificity, and accuracy of the model using 5-fold cross-validation are 97.14%, 100%, and 98.67%, respectively.

To show the effectiveness of the anomaly detection step, we generated a model before the anomalies deletion and compared it with the generated model after deletion of anomalies; the validation results are illustrated in Table 5.

Table 4
The results of validation measures for test set.

	Test set		
Pass number	Sensitivity	Specificity	Accuracy
1	100%	100%	100%
2	92.86%	100%	96.67%
3	92.86%	100%	96.67%
4	100%	100%	100%
5	100%	100%	100%
Total	97.14%	100%	98.67%

Table 5
The results of validation measures before and after deletion of anomalies.

		Test set		
	Size of dataset	Sensitivity	Specificity	Accuracy
Before	214	50.36%	69.0%	59.26%
After	151	97.14%	100%	98.67%

As shown, the results of the evaluation have significantly improved in all the criteria after the deletion of anomalies. Furthermore, the results of Receiver Operation Characteristic (ROC) curves show a better model after anomalies deletion, presented in Fig. 4. It is noteworthy to mention that the 5-fold cross-validation was used to create the model, and that is why there are five different curves in every graph.

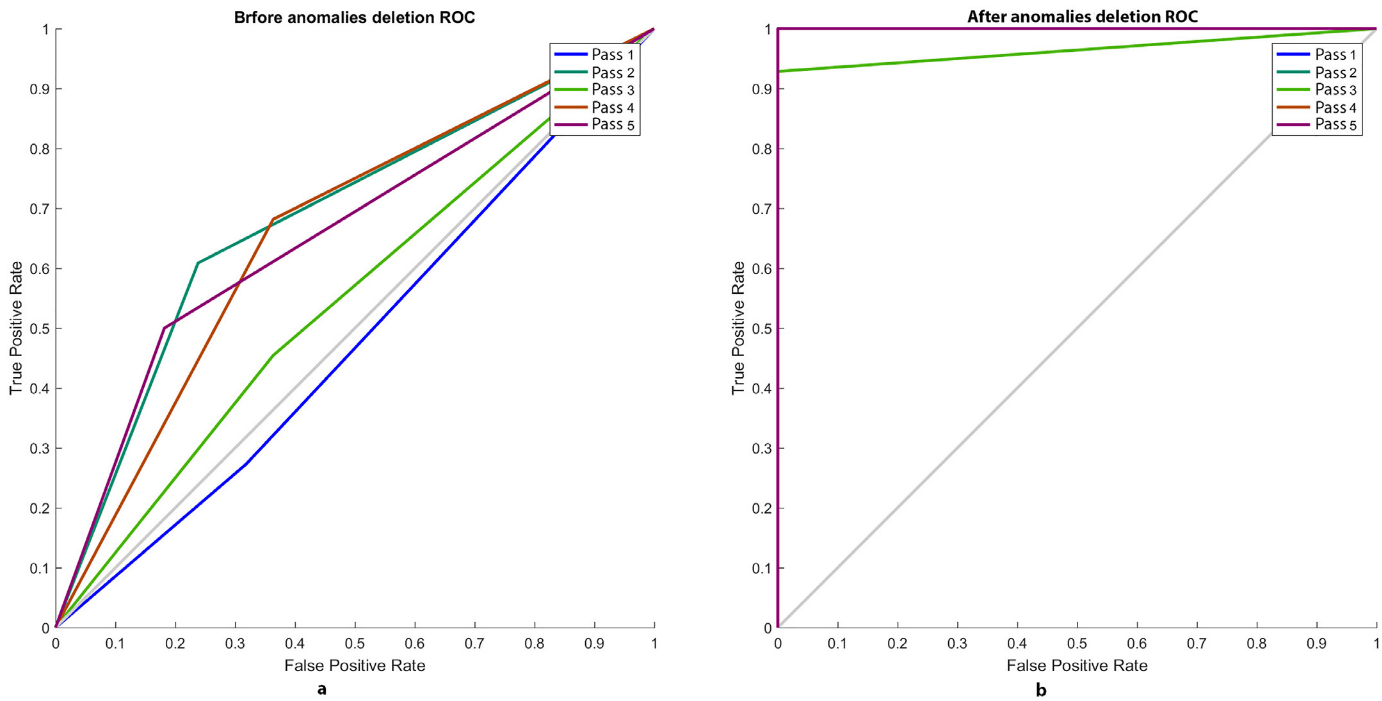


Fig. 4. The results of ROC curves. (a) The before anomalies deletion ROC curves. (b) The after anomalies deletion ROC curves.

It can be seen that the area under curves in the models, created after the deletion of anomalies, is significantly wider than before the deletion of anomalies.

5. Discussion and conclusion

This study sought to develop a decision support system for the diagnosis of social phobia, using relevant features. It comprised of multi-stage procedures named preprocessing, classification, and evaluation. The preprocessing stage consisted of three steps called normalization, feature selection, and anomaly detection. In the normalization step, all the features were rescaled to the values of 0–10. In the feature selection step, seven top rank features were selected by IBM SPSS Modeler software V18.0, which is a standard tool for data mining aim. These features, by the order of importance, included the fear of getting in a room where others are sitting (ERF), speaking in public (TKF), attending parties (CMT), meeting or contacting strangers (SMF), being the center of attention (ATF), disagreement with strangers (DAF), and eating in front of another person (EAF). In the anomaly detection step, the SOM clustering method was used to determine the anomalies. Four of the ten clusters were identified as anomalies and were removed from the dataset.

Finally, the ANFIS technique with 5-fold cross-validation was used for the classification of social anxiety disorder, and the accuracy of 98.67%, which is desirable, was obtained.

Although the use of artificial intelligence and especially ANFIS method was mentioned for diagnosis of some mental disorders such as depression, to the best of the authors' knowledge, it has not been used for SAD diagnosis yet. The details of some studies which have employed artificial intelligence in mental disorders, are summarized in Table 6.

Devi, in his study [13], which is the most similar to ours, applied ANFIS to predict anxiety in students and used two parameters as input and 30 samples to predict anxiety. Given the prediction aim of that study, the error-based metrics including Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) were used instead of the accuracy, sensitivity, and specificity metrics. However, we used seven features, 151 samples, and the cross-validation method to train the model, resulting in a more generalizable model.

In the studies of Chattopadhyay et al. [27] and Ekong et al. [11], the neuro-fuzzy and ANFIS methods were applied for depression severity diagnosis. The accuracy of 95.50%, which is lower than our finding, has been reported in the former study. Amadin et al. [28] have also introduced an ANFIS based prediction system for delirium disorder. They used five attributes and 30 samples to train the model and reached an accuracy of 99%. Although the accuracy obtained is excellent and close to our work, the number of features and samples are fewer than ours.

In addition, there are some studies, which have used ANFIS method for different aims like prediction, classification, and modeling diseases in other medical areas (See Table 7).

Table 6
A brief review of using artificial intelligence in mental disorders.

Author	Year	Problem Addressed	Method	Accuracy/Error
Suhasini et al. [2]	2011	DSS for psychiatry problem	BPNN+RBFNN+SVM	98.75%
Ekong et al. [11]	2012	Depression diagnosis	ANFIS+CBR	–
Windriyani et al. [12]	2013	Mental disorder detection	Table decision expert system	96%
Devi et al. [13]	2016	Anxiety prediction	ANFIS	RMSE = 3.280
Chattopadhyay et al. [27]	2017	Depression diagnosis	Neuro-fuzzy approach	95.5%
Amadin et al. [28]	2018	Delirium prediction	ANFIS	Err = 0.453

Table 7
A brief review of using ANFIS method in medical areas (except mental disorders).

Author(s)	Year	Sample size	No. of input attributes	description	Accuracy/Error
Hamdan et al. [29]	2010	958	2	Using ANFIS to modeling breast cancer survival	–
Dogantekin et al. [30]	2010	768	7	An intelligent diagnosis system for diabetes	84.61%
Bhardwaj et al. [31]	2013	–	–	Brain tumor image classification	94%
Kalaiselvi et al. [32]	2014	768	7	An ANFIS based approach for diagnosis of both diabetes and cancer	80%
Shrivastava et al. [33]	2018	–	4	An ANFIS based approach to detection of tuberculosis	Err = 0.17
Yadollahpour et al. [34]	2018	465	4	An ANFIS based approach to predict chronic kidney disease progression	Err = 0.05
Kirisci et al. [35]	2019	30	6	An ANFIS based approach for the diabetes type II diagnosis using 10-fold cross-validation	82.16%

All the studies reviewed and shown in Table 7 have used ANFIS method in different fields of medicine. They have reported an accuracy range of 82–94%. Only Kirisci et al. [35] have used cross-validation method to evaluate the model, in which the sample size was smaller, the number of input attributes, and reported accuracy were less than ours. We have found a novel method to generate a decision model for the diagnosis of social anxiety disorder with desirable results. However, it should be remarked that participants from different social classes and educational levels might lead to the varying perception of attributes, thereby resulting in a large number of anomalies in the dataset. This issue highlights the role of the anomaly detection step in which the results show a significant improvement in validation measures after this process. The method we have presented provides a binary classification, which can be used for the diagnosis of those suffering from SAD. Further research on designing a decision support system for diagnosis of severity of SAD is recommended.

Declaration of Competing Interest

We wish to confirm that there are no known conflicts of interest associated with this publication and there has been no significant financial support for this work that could have influenced its outcome.

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