Short Communication

Classification of COVID-19 Individuals Using Adaptive Neuro-Fuzzy Inference System

Abstract

The COVID-19 has become an important health issue in the world and has endangered human health. The purpose of this research is to use an intelligent system model of adaptive neuro-fuzzy inference system (ANFIS) using twelve variables of input for the diagnosis of COVID-19. The evaluation of the model was performed using the information of 500 patients referred to and suspected of the COVID-19. Three hundred and fifty people were used as training data and 150 people were used as test and validation data. Information on 12 important parameters of COVID-19 such as fever, cough, headache, respiratory rate, Ct-chest, medical history, skin rash, age, family history, loss of olfactory sensation and taste, digestive symptoms, and malaise was also reported in patients with severe disease. ANFIS identified COVID-19 in accuracy, sensitivity, and specificity with more than 95%, 94%, and 95%, respectively, which indicates the high efficiency of the system in the correct diagnosis of individuals. The proposed system accurately detected more than 95% COVID-19 as well as mild, moderate, and acute severity. Due to the time-constraint, limitations, and error of COVID-19 diagnostic tools, the proposed system can be used in high-precision primary detection, as well as saving time and cost.

Keywords: *Accuracy, adaptive, COVID-19, diagnosis, neuro-fuzzy*

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Mohammad Dehghandar, Samaneh Rezvani

Departments of Applied Mathematics, Payame Noor University, Tehran, Iran

Introduction

At present, with the advancement of science, the importance and complexity of the decision-making process are undeniable and increasing. Since the decision-making process is influential in the next process, you must be careful to do so. Therefore, it seems necessary to need information systems to help the decision-making process. On the other hand, with the addition of large and uncertain variables, complexity and disruption in decision-making increase.[1] Due to the interference of variables, physicians can use the information system by extracting specialized knowledge from clinical experts and specialists and entering it into their knowledge base. Therefore, in today's world, the use of medical information systems is very important in improving the decision-making process of physicians.[2] COVID-19 is a new virus called SARS-COVID-2, which was first reported to Chinese citizens on December 31, 2019, and approved by the World Health Organization.[3] In a very short time, the virus went beyond the epidemic and became a pandemic.[4] COVID-19 belongs to the family of Respiratory Syndrome Middle East and Respiratory Syndrome viruses.[5] Among the most widely used modeling methods, we can refer to artificial neural networks (ANNs), which are based on the learning model of the human nervous system. Neural networks and fuzzy systems play a valuable role in the diagnosis of diseases. Sanchez pointed to medical science as a fuzzy relationship between symptoms and disease, and Adlassnig carefully described it.[6,7] In 2015, Dehghandar *et al*. used fuzzy theory to rank the temperature of febrile diseases in traditional Iranian medicine. The authors presented their proposed model by presenting eleven input variables, five output variables, and 32 rules.[8] In another study, Dehghandar *et al*. used fuzzy theory to determine the cause of the body pulse mask with the help of pulse parameters in traditional Iranian medicine. They presented their proposed model assuming

Address for correspondence:
Dr. Mohammad Dehghandar, Department of Applied Mathematics, Payame Noor University, PO Box 3697-19395, Tehran, Iran.
E-mail: m_dehghandar@pnu.ac.ir

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ten input parameters, three output parameters, and 25 rules.[9]

Numerous studies have been performed on the use of fuzzy inference systems and neural networks associated with COVID-19, some of which are briefly mentioned. Painuli *et al*. using the input variables of fever, cough, age, diabetes, travel history, respiratory problems, flu, hearing problems, olfactory loss, body aches, and sore throats designed a fuzzy expert system.[10] Nitesh Dhiman and Sharma proposed a fuzzy inference system for the detection and prevention of COVID-19 using the gaussian membership function and six input variables.[2] Melin *et al*. presented the overall effect of the neural-fuzzy network model for predicting time series, COVID-19 using a Mexican case study. They first trained the neural network to predict the data and then provided the results of the three parameters to the fuzzy system.[11] In another study, Shaban *et al*. diagnosed COVID-19 based on a fuzzy inference engine, and deep neural network.[12] Abeer Fatima *et al*. demonstrated the internet of thing's ability to intelligently monitor COVID-19 using a fuzzy inference system.[13]

Abbas Khan *et al*. presented internet-based hierarchical inference systems, objects, and medicine for the diagnosis of COVID-19 using input-input variables in two layers.[4] In another study, Dehghandar *et al*. designed a fuzzy expert system for the diagnosis of COVID-19 using twelve input variables and extracting 29 rules using a Look-up Table.[14]

In another study, Hossam *et al*. used an ANN, support vector machine, and decision tree to classify Ct-chest images of people with COVID-19 and non-COVID-19.[15] Using adaptive neuro-fuzzy inference system (ANFIS), Deif *et al*. used white blood cells and platelet counts to diagnose COVID-19 disease.[16]

Current research, uses an adaptive fuzzy inference system based on artificial neural and twelve variables such as fever, cough, headache, respiratory rate, Ct-chest, Medical history, skin rash, age, family history, loss of olfactory sensation and taste, digestive symptoms, and malaise are presented. The system determines the severity of a patient with COVID-19 by comparing the symptoms of COVID-19 declared by the World Health Organization. Timely diagnosis of the disease and use of the proposed system at any time and place will increase the speed, of decision-making and reduce errors in nondiagnosis by physicians. Individuals can evaluate their symptoms using this model and, if the results are positive, begin quarantine without endangering the lives of others. In summary, the research performed and its comparison with the present research are given in Table 1.

Materials and Methods

The present study is a diagnostic study that, in addition to identifying COVID-19, also detects its severity with high accuracy, which is of particular importance in COVID-19 screening. To design the neural-fuzzy system, we used the information of 500 patients. The following is a brief description of the ANFIS. The ANFIS is used to study phenomena with nonlinear equations that, while preserving the advantages of the fuzzy inference system, also con be taught.[17]

A fuzzy system consists of four main parts, which include fuzzifier, inference mechanism, knowledge base, and defuzzifier.[1] Fuzzy systems cannot learn independently, and the ability to learn is enhanced by combining neural networks. After receiving the inputs, the system estimates the output, then compares the output with the actual output, and corrects the deviations by methods. This cycle continues as long as the estimated deviation of the estimated outputs from the actual output has the least acceptable deviation. One of the important features of the ANFIS is that its output follows the Sugeno method, a first-order polynomial of input variables as a result. In this method, to approximate the function f, a set of if-then fuzzy rules of type Tagaki-Sugeno-Kang (TSK) is designed for the number of m vectors including the number of n inputs and one output. If the output of a fuzzy system is a combination of inputs, it is called a TSK system and its rules are as follows:[18,19]

$$Rule: IF x_1 \ is \ A_1^L \ \text{AND} \ x_2 \ is \ A_2^L \ \text{AND}, \dots, x_n is \ A_n^L \ \text{THEN} \ y^L = \alpha_0^L + \alpha_1^L x_1 + \dots + \alpha_n^L x_n \tag{1}$$

wherein $L = \{1, 2, \dots, r\}, \alpha^L = \{\alpha_0^L, \alpha_1^L, \alpha_2^L, \dots, \alpha_n^L\}$

Therefore, fuzzy sets are expressed as follows:

$$A_i = \{A_i^1, A_i^2, \dots, A_i^L\} \tag{2}$$

And if $x = (x_1, x_2, \dots, x_n)^T$ then the weighted average output for the number of r rules is as follows:

$$f(x) = \sum_{L=1}^{r} y^L \bar{w}^L \tag{3}$$

wherein $w^L = \prod_{i=1}^{n} \mu_{A_i^L}(x_i), \bar{w}^L = \frac{w^L}{\sum_{L=1}^{r} w^L}$

If the fuzzy sets are as a Gaussian membership function and in the interval $[-\alpha_i, \beta_i]$ then each $x_i \in [-\alpha_i, \beta_i]$ of the domains are defined as A_i existing in Eq. 2 and the degree of the membership function is non-zero, That is $\mu_i^L(x_i) \neq 0$. The Gaussian membership functions of each fuzzy set A^L, $L \in \{1, 2, \dots, r\}$ are considered according to Eq. 4:[1]

$$\mu_{A_i}(x_i) = e^{-\frac{1}{2}\left(\frac{x_i - m_i}{\sigma_i}\right)^2} \tag{4}$$

Where m_i and σ_i are the centers and variances of the adjustable and the set of parameters of the antecedent section, respectively. Figure 1 shows the general diagram of the TSK ANFIS architecture.[20]

The proposed system includes various factors such as fever, cough, headache, respiratory rate, Ct-chest, medical history,

Table 1: The research was done and their comparison with the present research

Reference	Input variable											Membership function			Description
	Fever	Cough	Headache	Respiratory rate	Ct-chest	Medical history	Age	Family history	Loss of olfactory and taste	Digestive symptoms	Other	Trapezoidal	Triangular	Gaussian	
Painuli *et al.*[10]	*	*		*		*	*		*		*		*		Solve the model using MATLAB
Dhiman and Sharma[2]											*			*	Solve the model using MATLAB
Abeer Fatima *et al.*[13]	*	*									*	*			Internet of medical things based smart monitoring system
Abbas Khan *et al.*[4]	*	*	*	*	*		*	*			*	*			Provide input variables in two layers
Shaban *et al.*[12]											*	*	*		Design with deep neural network
Melin *et al.*[11]											*			*	Use of neural network
Dehghandar *et al.*[14]	*	*	*	*	*	*	*	*	*	*	*		*		Use the look-up table method
This research	*	*	*	*	*	*	*	*	*	*	*	*		*	Use of ANFIS

ANFIS – Adaptive neuro-fuzzy inference system

skin rash, age, family history, loss of olfactory and taste, digestive symptoms, and malaise determines while they are directly involved in the diagnosis and treatment of the disease. In this research, to convert real numbers to fuzzy sets, Gaussian and trapezoidal membership functions have been used. For system training, 70% of the data is equivalent to the information of 350 patients. In addition, 15% of the data equivalent to the information of 75 patients were used to test the model and 15% of the data equivalent to the information of 75 patients were used to validate the model.

For designing ANFIS models, there are three fuzzy inference system structures namely grid partition, subtractive clustering, and fuzzy c-means.[21] The main difference between the two methods is in how they determine membership functions. In the Grid Partitioning method, the type and number of membership functions are determined by the user with the input information vector. However, in the Sub-Clustering method, the type of membership functions is determined by the ANFIS model according to the specificity of the input information vector and their classifications.

The fuzzy sets used to describe the behavior of the system are obtained by experts or by trial and error and should be considered to cover input and output variables. To improve the performance of the system, membership functions, variables, inputs, dependents, and factors with common factors were combined and considered as a variable. In this research, the method of Sub-Clustering and reduction of Gaussian functions and trapezoidal membership function with eight input variables and 30 epochs has been used, which leads to the production of the desired output, namely COVID-19 detection. An output variable is divided into three modes: mild, moderate (be cautious), and acute (quarantine and the need for special attention), indicating the severity of patients with COVID-19. Table 2 shows the input and output variables of patient identification status.

Confusion matrix

In general, confusion matrices are used in disease classification and diagnosis systems to evaluate the success and efficiency of these systems.[15] The criteria used in this view are as follows:

TP: All sick people who have been correctly diagnosed.

FP: All people with the disease who have been mistaken for healthy.

TN: All healthy people who have been correctly diagnosed.

FN: All healthy people who have been mistaken for a patient.

Network accuracy for test and validation data is obtained from Eq. 5 as follows:

$$\text{Accuracy} = \frac{TP + TN}{(TP + TN + FP + FN)} \quad (5)$$

The performance evaluation of the algorithms described above has been done using different criteria based on the sensitivity

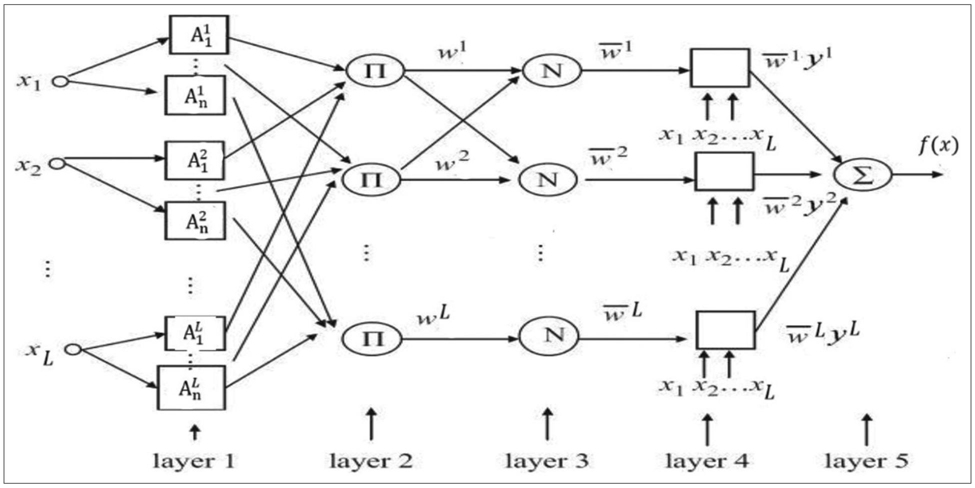

Figure 1: The TSK ANFIS architecture. Layer 1: Each node represents a linguistic label. Here, The Gaussian membership functions of each fuzzy set according to Eq. 4, Layer 2: Every node is a fixed node whose output is the product of all the incoming signals from Layer 1, Layer 3: Every node is a fixed node labeled with "N," Layer 4: Every node L in this layer is a node function $y^L\overline{w}^L$ where $\overline{w}^L$ is the output of Layer 3, Layer 5: The single node in this layer is a fixed node. It computes the overall output as the summation of all incoming signals

Table 2: Input and output variables for diagnosis of COVID-19

Row	Type of risk factor	Type of disease diagnosis variable	Maximum	Minimum	Mean
1	Input	Fever	40	35	37.2
2	Input	Cough	1	0	0.32
3	Input	Headache	1	0	0.52
4	Input	Respiratory rate	97	84	88.5
5	Input	Ct-chest	1	0	0.31
6	Input	Medical history	1	0	0.42
7	Input	Skin rash	1	0	0.38
8	Input	Age	71	15	42.4
9	Input	Family history	1	0	0.43
10	Input	Loss of olfactory and taste	1	0	0.46
11	Input	Digestive symptoms	1	0	0.41
12	Input	Malaise	1	0	0.39
13	Output	Patient identification status	3	1	2.01

and detection perspective. The sensitivity index means the ratio of the number of sick people to the total number of people from Eq. 6 and can be calculated as follows:

$$\text{Sensitivity} = \frac{TP}{(TP + FN)} \tag{6}$$

Also, the specificity index means the ratio of the number of healthy people to the total number of people is calculated from Eq. (7) as follows:

$$\text{Specificity} = \frac{TN}{(TN + FP)} \tag{7}$$

The proposed system according to Equation (5) with an accuracy above 95% determines the severity of COVID-19 in the patient. In addition, the sensitivity of the system according to Eq. 6 is more than 94% and the specificity of the system designed according to Eq. 7 is more than 95%, which indicates the high efficiency of the system in diagnosing severe COVID-19 in the affected person. Table 3 shows the data confusion matrix using the proposed system.

Table 3: Data confusion matrix using the proposed system

Mild	Moderate and acute	Network prediction
2	102	Moderate and acute
40	6	Mild

Results

Using the collected data sets, a new model was developed for COVID-19 diagnosis based on ANFIS capabilities. A computer with an Intel (R) Core (TM) i5-4300 processor, 8 GB of RAM, and MATLAB R2014b software was used to implement the ANFIS. In ANFIS, the software plots the training data into a graph and then delivers the same data to the system. The ANFIS estimates the output based on this data and displays it on the same chart to be comparable to the training data.

To train the system, the information of 350 patients was given to the system in the form of a 350-line matrix (each row related to a patient's information) with 8 columns for eight input variables along with the evaluation results of each case in a separate column. Test and validation data were randomly selected and not used in the training process. For this purpose, to evaluate and efficiently the system of test and validation data in the form of two matrices of 75* 9 was considered. After loading the training, testing, and validation data in the graphical interface, the Sub-Clustering method was used. The membership Function of Fever is defined as a trapezoid membership function and other input variables are in the form Gaussian membership function.

The results of the ANFIS in the testing and validation stages are shown in Figures 2 and 3, respectively.

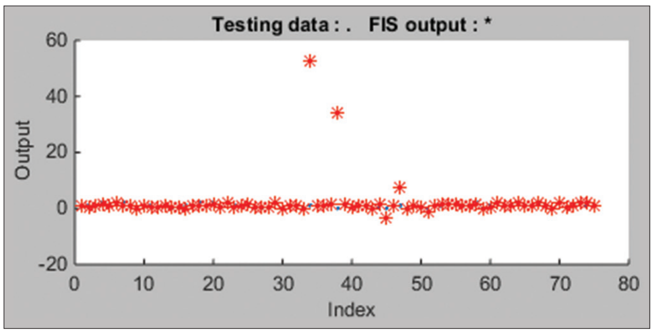

Figure 2: Results for adaptive neuro-fuzzy inference system for test data

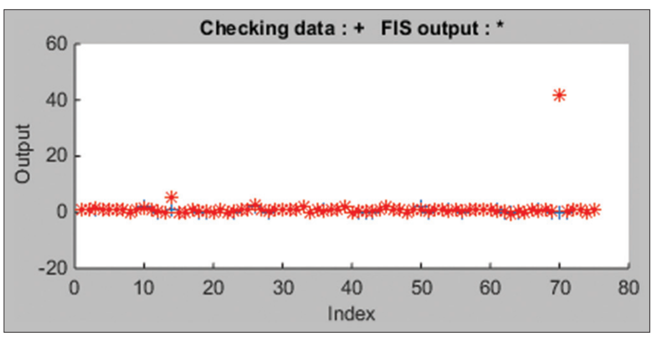

Figure 3: Results for adaptive neuro-fuzzy inference system for validation data

Figures 2 and 3 show that the model has been able to understand the ruler model well and accurately in the training, testing, and validation stages. Thus, in Figure 2, the network output data and the test data are matched. Similarly, in Figure 3, ANFIS outputs with validation data show high system efficiency.

Figure 4 shows an overview of the user interface of the ANFIS for the detection of COVID-19. Fuzzy logic interprets the rules well, but cannot obtain the rules automatically. Therefore using ANFIS 26 rules were determined, some of which are shown in Table 4.

Figure 4 shows a system designed for an elderly patient with a low-grade fever and cough, whose lungs are not infected and who have headaches, skin rashes, and lethargy, and who has lost their sense of smell and taste, who has no gastrointestinal symptoms or underlying disease and breathing rhythm is abnormal and no one in his family has the disease. In this case, the output shows a mild condition, which means that the patient has mild Covid-19 disease, which predicts the designed system to be true.

Figure 5 shows the input-output behavior of the system as a three-dimensional representation based on the two input variables Ct-chest-family history and age. Similarly, Figure 6 shows a three-dimensional representation based on the two input variables Ct-chest-family history and fever with Gaussian and trapezoidal membership functions.

Discussion and Conclusion

Due to the importance of the COVID-19 virus, which can endanger human health, in this study, an assistive system was presented for use in medical universities, and hospitals, as well as error reduction in the diagnosis of the COVID-19 virus. COVID-19 was designed. In the present study, an intelligent system using an ANFIS by the information of 500 patients suspected of COVID-19 was suggested. The proposed system is designed with the information of 350 patients referred to treatment centers and is tested and validated on the information of 150 patients. Twelve variables: fever, cough, headache, respiratory rate, Ct-chest,

Table 4: Some fuzzy rules are considered

Rules	Fever	Cough	Headache*	Respiratory rate	Ct-chest family history	Medical history	Age	Digestive symptoms	Rule Output
1	Low	Yes	Yes	Abnormal	Yes	No	Older	Nausea/vomiting	Average
2	Average	Yes	No	Normal	Yes	No	Middle age	Nausea/vomiting	Slight
3	Low	Yes	No	Abnormal	No	Hepatitis	Older	Constipation	Slight
4	Average	Yes	Yes	Abnormal	No	Cancer	Older	No	Acute
5	Average	Yes	Yes	Abnormal	No	Asthma	Young	Constipation	Acute
6	High	No	No	Average	No	No	Middle age	Diarrhea	Average
7	Average	Yes	No	Average	Yes	Asthma	Young	No	Slight
8	High	Yes	Yes	Normal	No	No	Older	Constipation	Average
9	High	No	Yes	Average	Yes	No	Young	No	Average
10	Low	Yes	Yes	Abnormal	No	Cancer	Middle age	No	Acute

*Headache, skin rash, loss of olfactory and taste, malaise

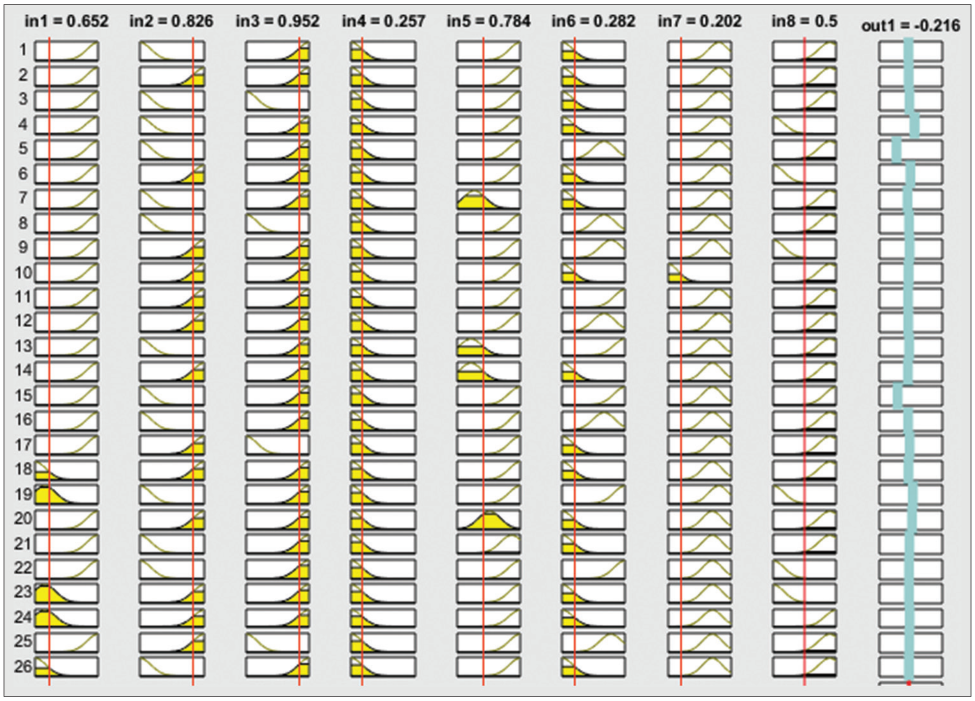

Figure 4: Part of the user interface of adaptive neuro-fuzzy inference system for diagnosis of COVID-19

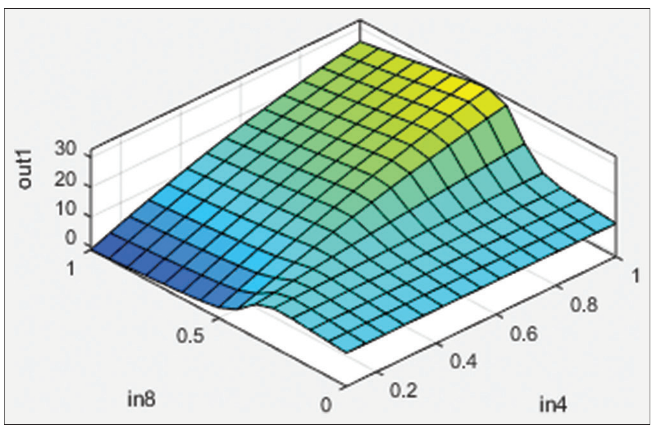

Figure 5: Surface view for two parameters: Ct-chest-family history and age

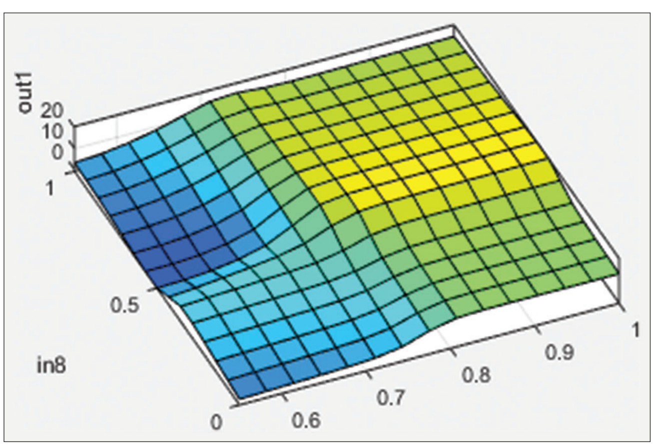

Figure 6: Surface view for two parameters: Ct-chest-family history and fever with Gaussian and trapezoidal membership functions

medical history, skin rash, age, family history, loss of olfactory and taste, digestive symptoms, and malaise used for diagnosis and prediction of COVID-19. In most of the previous research, which is summarized in Table 1, fewer variables were used to diagnose COVID-19 disease. The use of further input variables increases the accuracy and success of the system, indicating that the present research is more comprehensive. The proposed reference system,[14] using the information of 375 patients, identifies 93% accuracy of COVID-19 disease and also the sensitivity of the system is more than 95% and the specificity of the system is more than 87%. In the present study, with the increase in the number of patients to 500 patients, the ANFIS method, which uses neural network learning algorithms and fuzzy logic to design a mapping between input and output space and has good capabilities in training, construction, and classification, has been used and is more accurate than previous research.

According to the results of this ANFIS, the accuracy of the proposed system was above 95%, the sensitivity of the system more than 94%, and the specificity of the system more than 95% were able to detect Covid-19 with mild, moderate, and acute ratings. The results provided by this system are very promising and can be used with high accuracy as well as saving time and cost.

Data availability

The data used to support the findings of this study are available from the corresponding author upon request.

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None.

Conflicts of Interest

There are no conflicts of interest.

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