Iran J Sci Technol Trans Sci (2022) 46:1327–1338
https://doi.org/10.1007/s40995-022-01344-z

RESEARCH PAPER

Change in Normal Health Condition Due to COVID-19 Infection: Analysis by ANFIS Technique

Rabindranath Majumder[1,2] · Sayani Adak[3] · Soovoojeet Jana[4] · Sova Patra[5] · T. K. Kar[3]

Received: 22 June 2022 / Accepted: 3 August 2022 / Published online: 10 September 2022

Abstract

The COVID-19 pandemic has crippled the world population. Our present work aims to formulate a model to analyze the change in normal health conditions due to COVID-19 infection. For this purpose, we have collected data of seven parameters, namely, age, systolic pressure (SP), diastolic paper (DP), respiratory distress (RD), fasting blood sugar (FBS), cholesterol (CHL), and insomnia (INS) of 156 persons of Birnagar municipality, Nadia, India; before and after COVID-19 infection. Ultimately, using an adaptive neuro-fuzzy inference system (ANFIS), we have formulated our desired model, a Takagi–Sugeno fuzzy inference system. Further, with the help of this model, we have established one's change in health condition with age due to COVID-19 infection. Finally, we have derived that older people are more affected by COVID-19 infection than younger people.

Keywords Age · Normalized Health Condition (NHC) · ANFIS · Subtractive algorithm · COVID-19

1 Introduction

In December 2019, in the Hubei Province of China, some unidentified pneumonia cases were reported. Later, this disease was discovered as SARS-COV-2, which from a local epidemic spread globally, making the disease the first pandemic of the twenty-first century. The disease crippled the whole world within a brief period of time. Several studies on disease transmission, control measures to contain the disease have been done (Sornette et al. 2020; Mandal et al. 2022). Age seems to play a vital role in how a person gets affected by the disease, and older adults are most vulnerable to the disease. Several studies on effect of COVID-19 on aged person have been done (Banerjee 2020; Liu et al. 2020). Most of the studies have emphasized older people. In our present work, we intend to find how the health of a COVID infected person changes according to their age. We have studied 156 persons from Birnagar municipality, Nadia, West Bengal, India, whom SARS-COV-2 infected. Here, we have collected the data of seven parameters, namely, age, systolic pressure (SP), diastolic pressure (DP), respiratory distress (RD), fasting blood sugar (FBS), cholesterol (CHL), and insomnia (INS) of the 156 persons before and after COVID. With the help of these data, we have formulated an adaptive neuro-fuzzy

✉ Soovoojeet Jana
soovoojeet@gmail.com;
soovoojeet_maths@ramsadaycollege.com

Rabindranath Majumder
dr.rabindranath.majumder@gmail.com

Sayani Adak
sayaniadak1994@gmail.com;
2020map007.sayani@students.iiests.ac.in

Sova Patra
sovapatra@gmail.com

T. K. Kar
tkar1117@gmail.com; tkar@math.iiests.ac.in

1 Department of Physiology, Tamralipta Mahavidyalaya, Tamluk, Purba Medinipur, West Bengal 721636, India

2 Birnagar Municipality Hospital, Birnagar, Nadia, West Bengal 741127, India

3 Department of Mathematics, Indian Institute of Engineering Science and Technology, Shibpur, Howrah 711103, India

4 Department of Mathematics, Ramsaday College, Amta, Howrah 711401, India

5 Department of B.Ed., Bijoy Krishna Girls' College, Kadamtala, Howrah 711101, India

inference system (ANFIS). The adaptive neuro-fuzzy inference system (ANFIS) is an artificial neural network that is based on Takagi–Sugeno fuzzy inference system (Jang 1993). Fuzzy inference system is a mapping between user defined input parameters and output parameters. There are two types of fuzzy inference systems (i) Mamdani and, (ii) Takagi–Sugeno type fuzzy inference system. Both the fuzzy inference systems behave alike except the way the output is computed. ANFIS integrates neural networks and fuzzy logic principles into a single framework with the learning capability to approximate nonlinear functions. In this method, we obtain a Takagi–Sugeno type fuzzy inference system. At present, fuzzy set theory and soft computing-based tools have been used effectively to study the behavior of a disease (Adak and Jana 2020, 2021; Zhao et al. 2017; Golafshani et al. 2020; Adak and Jana 2022; Adak et al. 2022, etc.). Many researchers of several fields are contributing to understand the behavior of the disease in a better way (Abu Arqub et al. 2021, 2021a; Abu Arqub 2017; Abu Arqub et al. 2015; Khatua et al. 2020, etc.).

The whole paper is organized in the following way. In Sect. 2, we have discussed the materials and methods of the work. In Sect. 3, we have obtained the result and discussed it thoroughly. Finally, the last section is dedicated to a precise conclusion of the whole work.

2 Adaptive Neuro Fuzzy Inference System (ANFIS)

In order to understand Adaptive Neuro Fuzzy Inference System (ANFIS), we will first give a very brief introduction to fuzzy inference system and neural network. A fuzzy inference system consists of an input space, an output space, and some user-defined rules which are of the form 'if-then.' The input space consists of input variables, and the output space consists of output variables both of which are characterized by linguistic variables. These linguistic variables are defined using membership functions, which are characterized by membership grades. The remaining part, i.e., defining the 'if-then' rules is done according to experts' suggestions. So, it can be said that a fuzzy inference system is a rule based system rather than data-based. There are two types of fuzzy inference systems (i) Mamdani type, (ii) Takagi–Sugeno type. Both of them work in a similar manner except the way the output is derived. On the other hand, neural network is a network as its name suggests. It consists of nodes and links between the nodes which specify direction of the flow among the nodes. Neural networks are famous for their learning capability of nonlinear systems and adaptive techniques. ANFIS combines fuzzy inference systems and neural networks. Here, the nodes depend on the parameters involved in the input–output space. There are two ways in which a neural network can learn. They are (i) supervised learning, (ii) unsupervised learning. In supervised learning, the system learns from both input data and output data. On the other hand, in unsupervised learning the system learns from input data only. The characteristic of the adaptive network is determined by the characteristics of the parameters involved in the problem space. When the system learns from the data, the parameters involved in the node functions change. This effects the change in the output, moreover in the adaptive network. The ultimate goal of ANFIS is to create a fuzzy inference system that fits the given set of data using neural network.

Now, we present a brief discussion on the structure of ANFIS where the system learns from both the input and output data. There are five layers in ANFIS. All of them are made of nodes and directional links among the nodes. In some of the nodes, the parameters are adaptive (square nodes), and in some the parameters are fixed (circular nodes). The parameters are updated by a supervised learning rule. There are several learning rules like back-propagation, hybrid learning rule. In the back-propagation method, the parameters in input space more specifically in the antecedent part are updated using steepest decent method. The hybrid learning algorithm is a combination of the forward pass and backward pass. In the forward pass, the output parameters, i.e., the consequent parameters are optimized by the method of least square. In the backward pass, new firing strengths are calculated using the gradient descent method. These new values are used in the forward pass to compute the updated output. This process continues till the desired error measure is achieved. In ANFIS, a Takagi–Sugeno (TS) type fuzzy inference system is created. In a TS fuzzy model, the consequent part is either a constant or linear function of the input variables. The 'if-then' rules are of the form:

$$Rule_i(R_i):\ If\ (x_1\ is\ a_{1i})\ and\ x_2\ is\ (a_{2i})\ and\ldots(x_n\ is\ a_{ni})$$
$$then\ y=f_i(x_1,x_2,\ldots,x_n)\ for\ i=1,\ 2,\ldots,\ k.$$

Here, $x_1,\ x_2,\ldots,\ x_n$ are input variables, $y_1,\ y_2,\ldots,\ y_n$ are the output variables, k is the number of rules and a_{ni} are the membership functions.

The diagram of the ANFIS model with the rule if

x_1 is a_{11} and x_2 is a_{12}then $y=b_1$

x_1 is a_{21} and x_2 is a_{22} then $y=b_2$

is shown in Fig. 1.

In Fig. 1, x_1 and x_2 are the input data. In layer 1, all the input variables are assigned a membership value according to their membership function. One can choose membership functions as per their choice. In general, Gaussian type

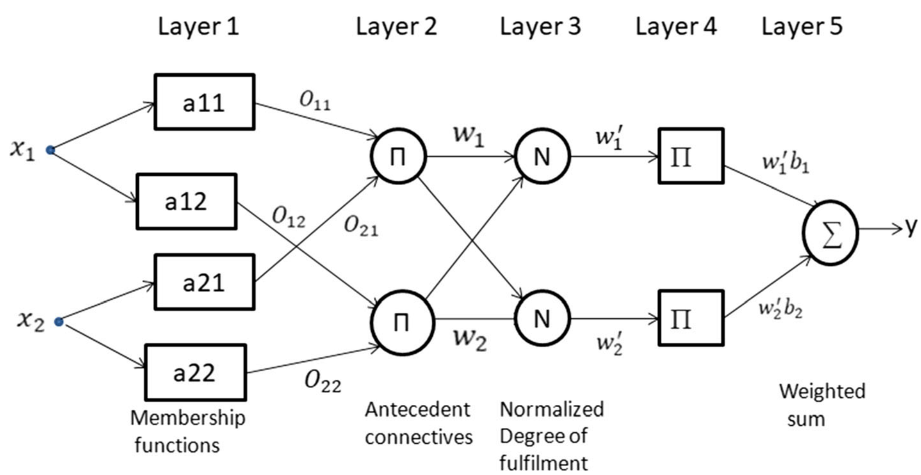


Fig. 1 Pictorial representation of ANFIS model

membership functions are chosen for the input variables. The membership function of Gaussian type fuzzy number is of the form (1).

$$f(x; m, \sigma) = e^{\frac{1}{2}\frac{(x-m)^2}{\sigma^2}} \tag{1}$$

In layer 1, the parameters m and σ are the parameters of the node function. As, parameters are involved in this layer, and the nodes are adaptive. Hence, represented as square nodes. The output of layer 1 is $O_{ij},\ i,\ j = 1,\ 2$ where $O_{ij}\ 's$ are the membership grades of each of the input variables according to their description. In layer 2, the firing strength is calculated. The degree of matching of the input variables is called firing strength. The firing strength is calculated by the 'and' conjunction between the degree of matching of the input variables. The 'and' conjunction is computed using the product operator. So, $w_1 = O_{11} * O_{21}$ and $w_2 = O_{12} * O_{22}$. The nodes of layer 2 are considered as constant. Hence, represented using circular node. In layer 3, the outputs of layer 2 are normalized. The rules of normalization are $w_1' = \frac{w_1}{w_1+w_2}$ and $w_2' = \frac{w_2}{w_1+w_2}$. The nodes in this layer are again fixed nodes. In layer 4, the nodes are computed by multiplying the normalized weight $w_i',\ i = 1,\ 2$ and the consequent part b_i. In this layer, the parameter is 'b'. The nodes in this layer are adaptive. In the final layer, i.e., the fifth layer the final output is computation of a crisp value using the rule $\sum_{i=1}^{i=2} \bar{w_i} b_i$. When the learning algorithm starts, the parameters in layer 1 and layer 4 change and try to fit the data.

There are two steps in identifying the suitable fuzzy model, (i) identification of the structure of the TS model and (ii) estimation of optimal consequent parameters. The learning network of a TS model can be obtained by methods like grid partitioning or subtractive clustering. To overcome the problem of complexity related to more number of inputs, clustering method is used (Mola and Amiri-Ahouee 2020; Chiu 1994).

2.1 Subtractive Clustering

A clustering algorithm accumulates the like data points in several clusters. The learning algorithm is then applied from clusters to clusters instead of data to data. There are techniques like (i) fuzzy c-means clustering (ii) subtractive clustering, which are used in ANFIS learning algorithms to create clusters. In this work, we will use subtractive clustering. In this method, all the input data points are considered as potential cluster centers. The density of measure of each data point is computed using rule (2). In (2), d_k is the density of the x_k the data point, $x_i' s$ are the remaining data points and r_a is called the influence radius. The point with the highest density, say d_k^*, is considered as the first cluster center.

$$d_k = \sum_{i=1}^{n} exp\left(-\frac{||x_k - x_i||^2}{(\frac{r_a}{2})^2}\right) \tag{2}$$

Once the first cluster center is determined, the value of d_k^* is discarded, and a new measure of density is computed for the remaining data points using the rule (3).

$$d_{new} = d_i - d_k^* exp\left(-\frac{||x_i - x_k||^2}{(\frac{r_b}{2})^2}\right) \tag{3}$$

Here, r_b is the positive constant which measures the reduction in density measures of the neighboring points of the first cluster center. r_b is chosen quite large than r_a to avoid more cluster centers. The recommended r_a lies in the range 0.1 to 2.0 with increment of 0.1. $r_b(>r_a)$ is taken as $1.5r_a$ to avoid closely spaced cluster centers. The process stops after partitioning the data into an adequate number of clusters. Finally, the membership degree of each cluster is assigned using (4).

$$\mu_{ik} = exp\left(-\frac{4}{r_a^2}||x_i - x_k||^2\right) \tag{4}$$

2.2 Data Preparation

2.2.1 Choosing Input and Output variables

In this study, we have taken data of seven parameters namely Age, Blood Pressure (BP both SP and DP), Respiratory Distress (RD), Fasting Blood Sugar (FBS), Cholesterol (Chl) and Insomnia (Ins) of 156 people who were affected by COVID-19. We have collected the data of these aforesaid parameters pre-COVID and post-COVID.

2.2.2 Systolic Pressure (SP) and Diastolic Pressure (DP)

Measuring blood pressure is considered as measurement of health condition. Normal blood pressure implies good health. Both systolic pressure (SP) and diastolic pressure (DP) gives blood pressure measurement. A person suffers from hypertension if SP is higher than the standard measurement, and hypotension occurs when DP is lower than normal. Hypertension increases the chance of heart diseases, heart attack, stroke. On the other hand, hypotension causes hazards, especially for the elderly. According to [10], the distribution of blood pressure is given in Table 1.

2.2.3 Respiratory Distress (RD)

Respiratory distress occurs when fluid builds up in the tiny, elastic air sacs in one's lungs. The fluid keeps one's lungs from filling with air, due to which enough oxygen does not reach the organs. This leads to breathing problems. Respiratory distress occurs mostly in the elderly. The distribution of respiratory distress is given in Table 2.

2.2.4 Fasting Blood Sugar (FBS)

Fasting blood sugar (FBS) measures the level of blood sugar after overnight fasting. A fasting blood sugar level of 99 mg/dL or lower is considered as normal, 100–125 mg/dL indicates prediabetes. Change in blood sugar can cause low vision, headaches, fatigue, frequent urination, etc. The distribution is given in Table 3.

Table 1 The chart of weights for SP and DP

Description	SP	DP
Low	< 90	< 60
Normal	90–120	60–80
Pre-hypertension	120–139	80–89
Stage 1 hypertension	140–159	90–99
Stage 2 hypertension	≥ 160	≥ 100
Isolated systolic hypertension	≥ 140	< 90

Table 2 The chart of weights for RD

Description	RD
No RD	0
Low	1
Medium	2
High	3

2.2.5 Cholesterol (CHL)

Cholesterol is fat that moves throughout the human body on its own. It does not dissolve into blood. Cholesterol travels through the blood on proteins called 'lipoproteins.' There are two types of lipoprotein:

(i) High-density lipoprotein (HDL): This lipoprotein absorbs cholesterol and carries it back to the liver. The liver then flushes it from the body. High levels of HDL cholesterol can lower the risk of heart disease and stroke.

(ii) Low-density lipoprotein (LDL). One is said to be diagnosed with high cholesterol if the blood contains too much of LDL. Stroke, heart attack are caused by high cholesterol. When our body has too much LDL cholesterol, it can build up on the walls of our blood vessels. Due to this wall, the insides of the vessels narrow. This narrowing blocks blood flow to and from the heart and other organs. This results in heart attack, chest pain, stroke. On the other hand, low cholesterol indicates cancer, depression, hemorrhagic stroke, etc. The distribution of normal cholesterol in is provided in Table 4.

2.2.6 Insomnia (INS)

According to [10], insomnia is a sleeping disorder in which one faces trouble sleeping. Person suffering from insomnia may have a problem in falling asleep or staying asleep. Insomnia can be acute or chronic. Stress, anxiety, depression may lead to insomnia. One may also face insomnia

Table 3 The chart of weights for FBS

Description	FBS
Low	< 70
Normal	70–126
Pre-diabetic	126–200
Diabetic	> 200

Table 4 The chart of weights for CHL

Description	CHL
Low	< 120
Desirable	120–200
Borderline high	201–239
High	> 240

Table 5 The chart of weights for INS

Description	INS
No insomnia	0
Low	1
Medium	2
High	3

due to a change of habits, new shifts at work, genes (Table 5).

2.2.7 Normalized Health Condition (NHC)

The measurement of a good health of a person is based on some basic parameters that we have discussed earlier. To represent all the six parameters via one parameter, we have defined the term normalized health condition (NHC). (Adak et al. (2022)) have defined the term NHC in their work. Though in our present work we have defined the term in different manner. We have taken the mean of all the six inputs after covid-19. For example, if the SP, DP, RD, FBS, CHL and INS of a person after covid-19 be 166, 96, 2, 152, 122, 2, then the computed output is $(166 + 96 + 2 + 152 + 122 + 2)/6 = 90$. The process is performed for each of 156 persons. Finally, we have obtained the range of the output as [70.1667 144.833]. To understand the output variable in a more explicit way, we have computed the value of NHC when the input variables are in different range. For example,

(i) When SP = 60, DP = 70, RD = 1, FBS = 90, CHL = 120, INS = 1, then NHC = (60+70+1+90+120+1)/6 = 342/6 = 57.
(ii) When SP = 120, DP = 80, RD = 0, FBS = 126, CHL = 200, INS = 0, then NHC= (120+80+0+126+200+0)/6 = 526/6 = 87.66.
(iii) When SP = 140, DP = 90, RD = 2, FBS = 200, CHL = 240, INS = 2, then NHC = (140+90+2+200+240+2)/6=342/6 = 111.66.
(iv) When SP = 160, DP = 100, RD = 3, FBS = 250, CHL = 250, INS = 3, then NHC = (60+90+1+70+120+1)/6 = 766/6 = 127.66

Hence, we can observe that when NHC decreases after certain value, we can say that health of a person deteriorates. Similarly, when the value of NHC increases and crosses some fixed value, we can say that a person suffers poor health. Thus, when NHC lies within a certain range, we can say that a person experiences good health. Moreover, the Takagi–Sugeno fuzzy inference system can have only one output. To provide the output for the learning of the supervised network, we have provided 156 scalars as the output by defining NHC.

2.2.8 Normalization

Normalization is done when there are several attributes. Each of them belong to different ranges. To make a uniform scaling for all the data, normalization is performed. In our present work, all the seven inputs lie in different scales. To enhance the performance of the system, we have converted the raw data into normalized data. There exist several methods in which normalization can be done such as Min-max, Z score, Simple Feature Scaling, etc. Due to the advantage of linear scalability in the min-max normalization process, we have used the normalization technique in our present work. The rule of normalization is given in (5).

$$x_{\text{norm}} = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \tag{5}$$

where x_{min} and x_{max} represents the minimum and maximum values among the set of data x. After normalizing, we have derived that, when NHC lies within 0.18-0.56, then NHC represents good health. If the value of NHC lies outside this range, then we can imply health is deteriorating.

2.3 Cross-Validation

Model validation is performed to check whether a model has achieved its goal. There are many processes in which validation of a model is done, such as (i) Train/test split, (ii) k-fold cross-validation, (iii) Time-series cross-validation, (iv) Nested cross-validation, and many more. In this paper, we have used the k-fold validation process. In the k-fold validation process, the whole data set is divided into k classes. Each of them is called fold. That is why the process is called k-fold validation. Among the k-folds, we have chosen any onefold arbitrarily to use it as testing data and the remaining $k-1$-folds as training data. We compute the training and testing error at this stage. We repeat the process by choosing one fold from the remaining $k-1$, which we had used for training in the previous step for testing, and the remaining $k-1$-fold for training. Further, we have used some of the data set for checking. We also compute the checking error along with the training and testing error in each iteration. We continue this process till all the folds are used for training and testing (Table 6). The error of the application is the average error after each iteration.

Table 6 k-cross-validation

Iteration	Folds for training	Fold for testing
1	2,3,4	1
2	1,3,4	2
3	1,2,4	3
4	1,2,3	4

In our present work, we have total 156 data set. Among them, we have divided the whole data for training, testing, and checking. We have chosen 16 data points for checking. Remaining 140 data are divided for training and testing. Here, we have divided the 140 data into fourfolds, i.e., $k = 4$. So, each fold contains 35 data points. We have used onefold for testing and the remaining folds for training. Total 4 iteration are performed, and RMSE error at each iteration is computed using rule (6). After completion of all the iterations, we see that iteration 2 shows the least error and the difference between the training error, testing error, and checking error is least in iteration 2. Table 7 shows the RMSE errors of all the iterations. The RMSE values are derived using (6).

$$RMSE = \sqrt{\frac{1}{n}\sum_{k=1}^{n}(y(k) - f(x(k)))^2} \qquad (6)$$

where $y(k)$ are the actual value of the output, $f(x(k))'s$, say are the predicted values of the output, $x(k)$ are the inputs where $k = 1, 2, \ldots, n$, and n is the sample size. These parameters evaluate the agreement between actual and predicted values.

3 Results and Discussion

From the section discussed above, we have found a model using the ratio of data set derived in iteration 2. To generate the model, we have used subtractive clustering method as discussed earlier. We have taken range of influence $= 0.5$, squash factor $= 1.25$, accept ratio$= 0.5$, reject ratio $= 0.15$. Hybrid method is taken as learning algorithm.

After performing training, testing, and checking in the above section, we derived the best possible model using ANFIS. Figure 2 represents the change of training error with respect to the number of epochs. We see that the training error finally takes a value of 0.0653. Figure 3 illustrates the graphical representation of FIS predicted output and the provided data for testing. The red color represents FIS generated output, and the blue one represents the output used while testing. In this case, the testing error is 0.1053. The training, testing, and checking errors are computed using the formula (6), i.e., all the errors are Root Mean Square Error.

Ultimately, we have derived a Sugeno-type fuzzy inference system (Fig. 4). In the model, the inputs are taken as Gaussian fuzzy numbers and output as constant. Each of the inputs has three membership functions. The fuzzy inference system is generated by the subtractive fuzzy clustering method. Using the hybrid learning algorithm 7, 'if-then' rules have been created in the system by training and testing the input and output data. The rules are given below. Here, each of the input and the output data are divided in seven clusters. Corresponding to each cluster of the input variable, there exists a rule assigned to a output cluster. Defuzzification is done using the weighted average method. Figure 5a–g represent the membership functions of the input variables after completion of training and testing. Figure 6 represents the 'if-then' rule of the fuzzy inference system. We have presented some surfaces derived from the Takagi–Sugeno fuzzy inference system.

1. If (Age is in1cluster1) and (SP is in2cluster1) and (DP is in3cluster1) and (RD is in4cluster1) and (FBS is in5cluster1) and (CHL is in6cluster1) and (INS is in7cluster1), then (NHC is out1cluster1) (1)
2. If (Age is in1cluster2) and (SP is in2cluster2) and (DP is in3cluster2) and (RD is in4cluster2) and (FBS is in5cluster2) and (CHL is in6cluster2) and (INS is in7cluster2), then (NHC is out1cluster2) (1)
3. If (Age is in1cluster3) and (SP is in2cluster3) and (DP is in3cluster3) and (RD is in4cluster3) and (FBS is in5cluster3) and (CHL is in6cluster3) and (INS is in7cluster3), then (NHC is out1cluster3) (1)
4. If (Age is in1cluster4) and (SP is in2cluster4) and (DP is in3cluster4) and (RD is in4cluster4) and (FBS is in5cluster4) and (CHL is in6cluster4) and (INS is in7cluster4), then (NHC is out1cluster4) (1)
5. If (Age is in1cluster5) and (SP is in2cluster5) and (DP is in3cluster5) and (RD is in4cluster5) and (FBS is in5cluster5) and (CHL is in6cluster5) and (INS is in7cluster5), then (NHC is out1cluster5) (1)

Table 7 Cross-validation for this model

Iteration	Folds for training	Fold for testing	RMSE Value Training	Testing	Checking
1	2,3,4	1	0.0542	0.1638	0.0906
2	1,3,4	2	0.0653	0.1053	0.1101
3	1,2,4	3	0.0571	0.0861	0.0898
4	1,2,3	4	0.0659	0.1060	0.0970

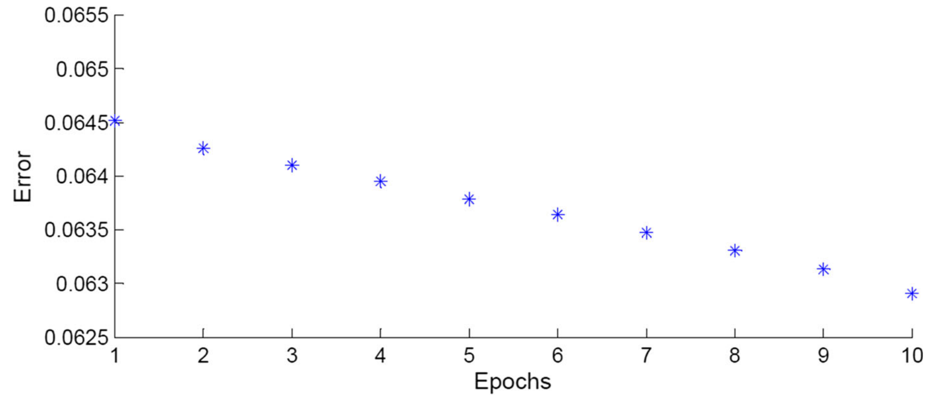


Fig. 2 Graphical representation of training error with the change of epochs

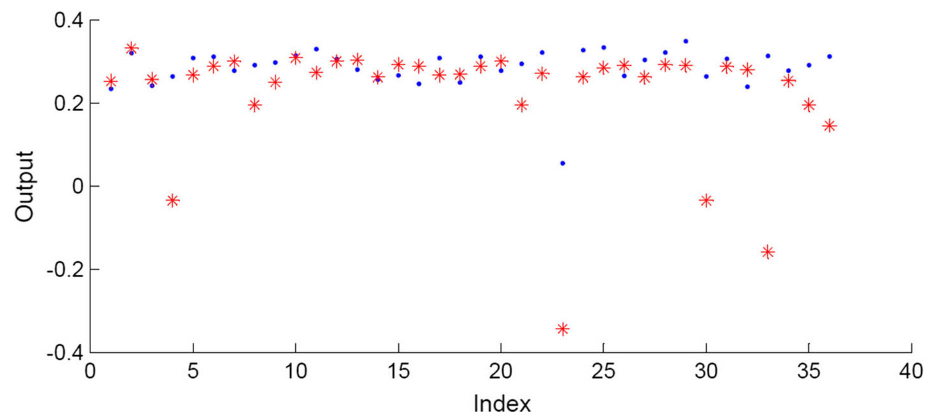


Fig. 3 Graphical representation of FIS predicted output and the given test data

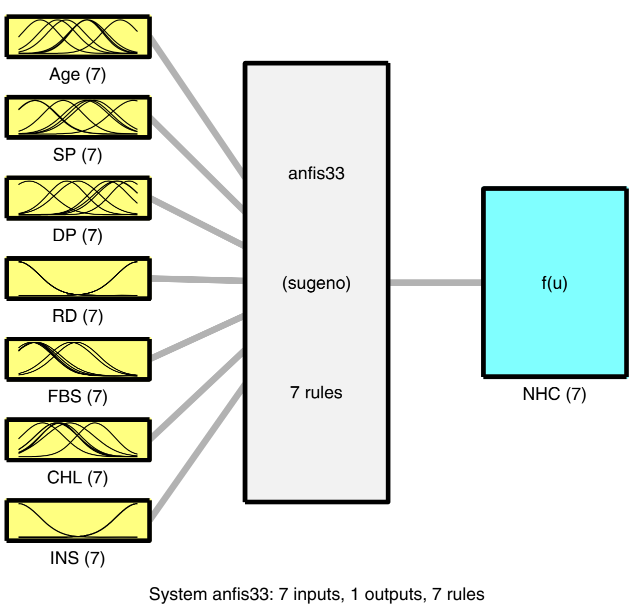
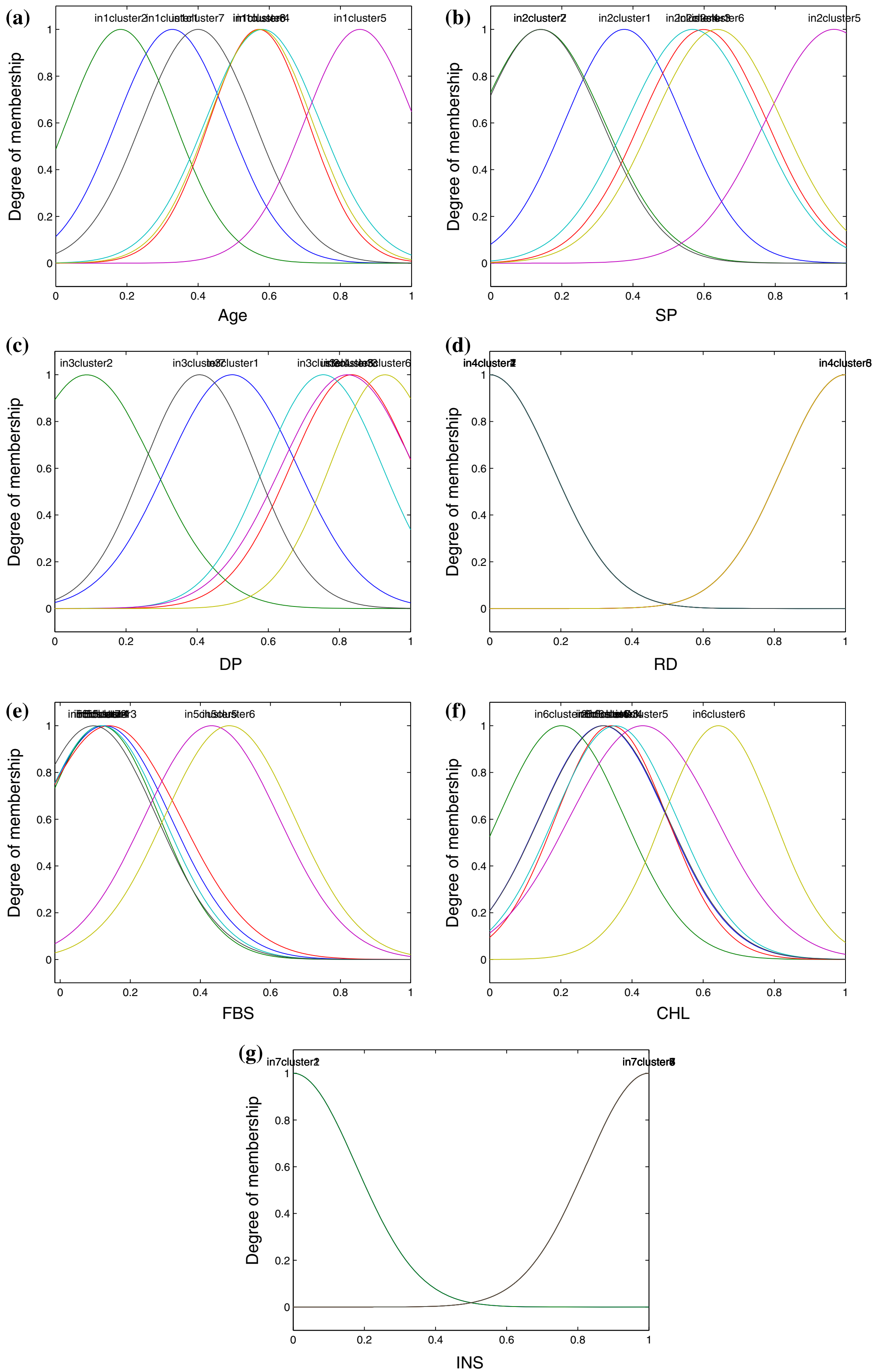


Fig. 4 The adaptive neural network derived FIS

6. If (Age is in1cluster6) and (SP is in2cluster6) and (DP is in3cluster6) and (RD is in4cluster6) and (FBS is in5cluster6) and (CHL is in6cluster6) and (INS is in7cluster6), then (NHC is out1cluster6) (1)
7. If (Age is in1cluster7) and (SP is in2cluster7) and (DP is in3cluster7) and (RD is in4cluster7) and (FBS is in5cluster7) and (CHL is in6cluster7) and (INS is in7cluster7), then (NHC is out1cluster7) (1)

Figure 7a represents the change of NHC with respect to Age and SP when the remaining parameters, i.e., DP, RD, FBS, CHL, and INS, are low. Figure 7c represents the change of NHC with respect to Age and SP when the remaining parameters, i.e., DP, RD, FBS, CHL, and INS, are medium. Figure 7e represents the change of NHC with respect to Age and SP when the remaining parameters, i.e., DP, RD, FBS, CHL, and INS, are high. Figure 7g represents the change of NHC with respect to Age and DP while the remaining parameters remain medium. Figure 7i represents the change of NHC with respect to Age and DP while the remaining parameters remain high. Figure 7k represents the change of NHC with respect to Age and RD, while the remaining parameters are low. In a similar manner, we have presented Fig. 7m, o, q. We can obtain several surfaces to observe the relation between age and normalized health condition, keeping the remaining parameters in different ranges.

In some figures, we can see that the output NHC takes values greater than 1. It is observed that the output attains values greater than 1 when the inputs are taken relatively


(a)
in1cluster5
Degree of membership
Age
(b)
in2cluster1
in2cluster5
Degree of membership
SP
(c)
in3cluster2
Degree of membership
DP
(d)
Degree of membership
RD
(e)
Degree of membership
FBS
(f)
in6cluster6
Degree of membership
CHL
(g)
Degree of membership
INS

◀**Fig. 5** **a** Final membership function of the input variable 'Age,' **b** Final membership function of the input variable 'SP,' **c** Final membership function of the input variable 'DP,' **d** Final membership function of the input variable 'RD,' **e** Final membership function of the input variable 'FBS,' **f** Final membership function of the input variable 'CHL,' **g** Final membership function of the input variable 'INS'

odd in contrast with any real-life scenario. Moreover, the output may attain negative values too due to the same reason. So, we would explain the scenarios when the value of NHC lies within 0–1. In Fig. 7b, NHC lies in the range [0.025,0.45]. We can see from the figure that when SP is low, NHC is low. Thus, when SP, DP, RD, FBS, CHL are in the low range, NHC is low. With increasing SP, NHC increases and lies within the normal range. Thus, due to COVID-19 infection, a person suffering from low blood pressure, low blood sugar has a lower NHC value. In Fig. 7d, here DP, RD, FBS, CHL and INS all lie in normal range. The range of NHC is [0.2–0.9]. NHC attains a value between 0.2 and 0.5 for people of any age group. Thus, when the parameters SP, DP, RD, FBS, CHL, and INS of a person are normal, then COVID-19 infection has less effect on a person's health. In Fig. 7f, the parameters DP, RD, FBS, CHL, and INS remain high. In this case, we see that NHC is not varying with age. With the increasing value of SP, NHC increases. Hence, we can say that a person of any age group suffering from high cholesterol infection due to the COVID-19 virus has a significant effect on their health even if they have normal blood pressure. Figure 7h represents the change of NHC with respect to Age and DP when the remaining parameters lie in the normal range. Here, the output lies in the interval [0.4 1.3]. In this case, people from the lower age group have good NHC values. Hence, it can be said that if SP, RD, FBS, CHL, INS are normal, younger persons are less likely to be affected by infection of COVID-19 than an older person. Figure 7j represents the change of NHC with respect to Age and DP when the other inputs lie in a higher than the normal range. In this case, NHC takes values between 0.4 and 1.4. Here too, we can see that younger people are less affected by COVID-19 infection in spite of high SP, FBS, CHL, INS. Figure 7l represents the change of NHC with respect to Age and RD when the rest of the parameters SP, DP, FBS, CHL, and INS are high. In this case, NHC varies from 0.7–1.3. Hence, the health condition of people of any age group deteriorates due to COVID-19 infection. Figure 7n represents the change in NHC with respect to Age and FBS when the remaining parameters lie in the lower than the normal range. In this case, NHC lies in [0.15–0.4]. If FBS is normal, NHC is good for a person of any age group. Figure 7p represents the change of NHC with respect to Age and CHL whenever the rest of the parameters are assigned values in a normal range. In this case, we see that person from a higher age group suffers more due to COVID-19 infection. Figure 7r represents the change of NHC with respect to Age and INS when the remaining parameters lie in the high normal range. Here, the output takes values between 0.7 and 1.2, i.e., the overall output is high.

4 Conclusion

In this paper, we have proposed a model that shows the change in the health condition of the infected persons by COVID-19. We have collected the data of seven parameters, namely, age, systolic pressure (SP), diastolic pressure

Fig. 6 'if-then' rules of the Fuzzy Inference System

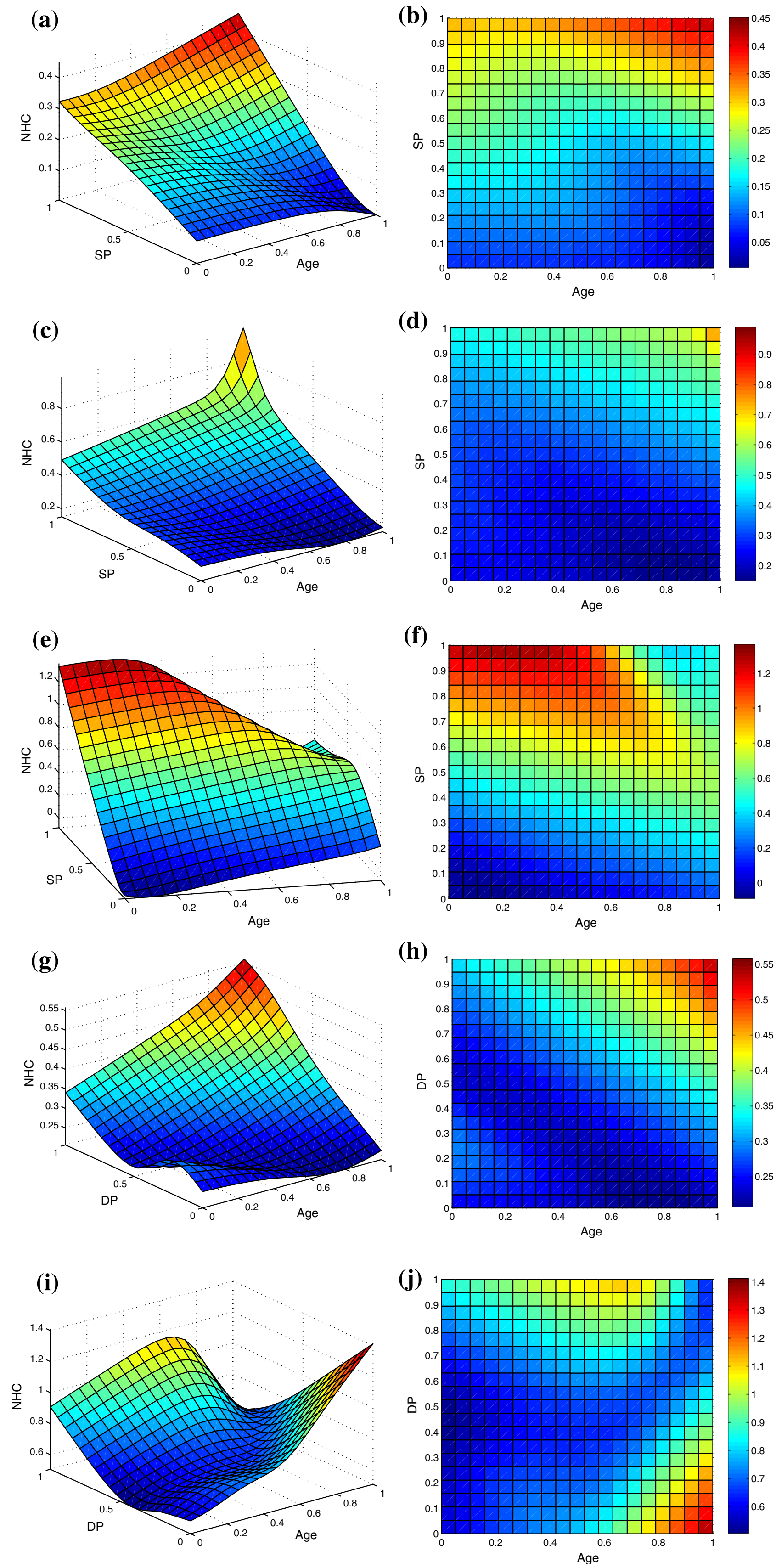


Fig. 7 **a** represents the change in NHC with respect to Age and SP when DP = 0.2, RD = 0.4, FBS = 0.175, CHL = 0.45 and INS = 0.3. **b** represents its projection. **c** Represents the change in NHC with respect to Age and SP when DP = 0.2, RD = 0.4, FBS = 0.175, CHL = 0.45 and INS= 0.3. **d** Represents its projection. **e** Represents the change in NHC with respect to Age and SP when DP = 0.833, RD= 0.7, FBS = 0.175, CHL = 0.7 and INS= 0.6. **f** represents its projection. **g** Represents the change in NHC with respect to Age and DP when SP = 0.285, RD= 0.4, FBS = 0.175, CHL = 0.45 and INS= 0.3. **h** Represents its projection. **i** Represents the change in NHC with respect to Age and DP when SP = 0.45, RD= 0.6, FBS = 0.175, CHL = 0.7 and INS= 0.6. **j** Represents its projection. **k** Represents the change in NHC with respect to Age and RD when SP = 0.65, DP= 0.833, FBS = 0.305, CHL = 0.7 and INS= 0.7. **l** Represents its projection. **m** Represents the change in NHC with respect to Age and FBS when SP = 0.114, DP= 0.2, RD = 0.1, CHL = 0.08 and INS= 0.1. **n** Represents its projection. **p** Represents the change in NHC with respect to Age and CHL when SP = 0.285, DP= 0.45, RD = 0.4, CHL = 0.08 and INS = 0.1. **p** Represents its projection. **q** Represents the change in NHC with respect to Age and INS when SP = 0.65, DP = 0.833, RD = 0.6, FBS = 0.505 and CHL = 0.7. **r** Represents its projection

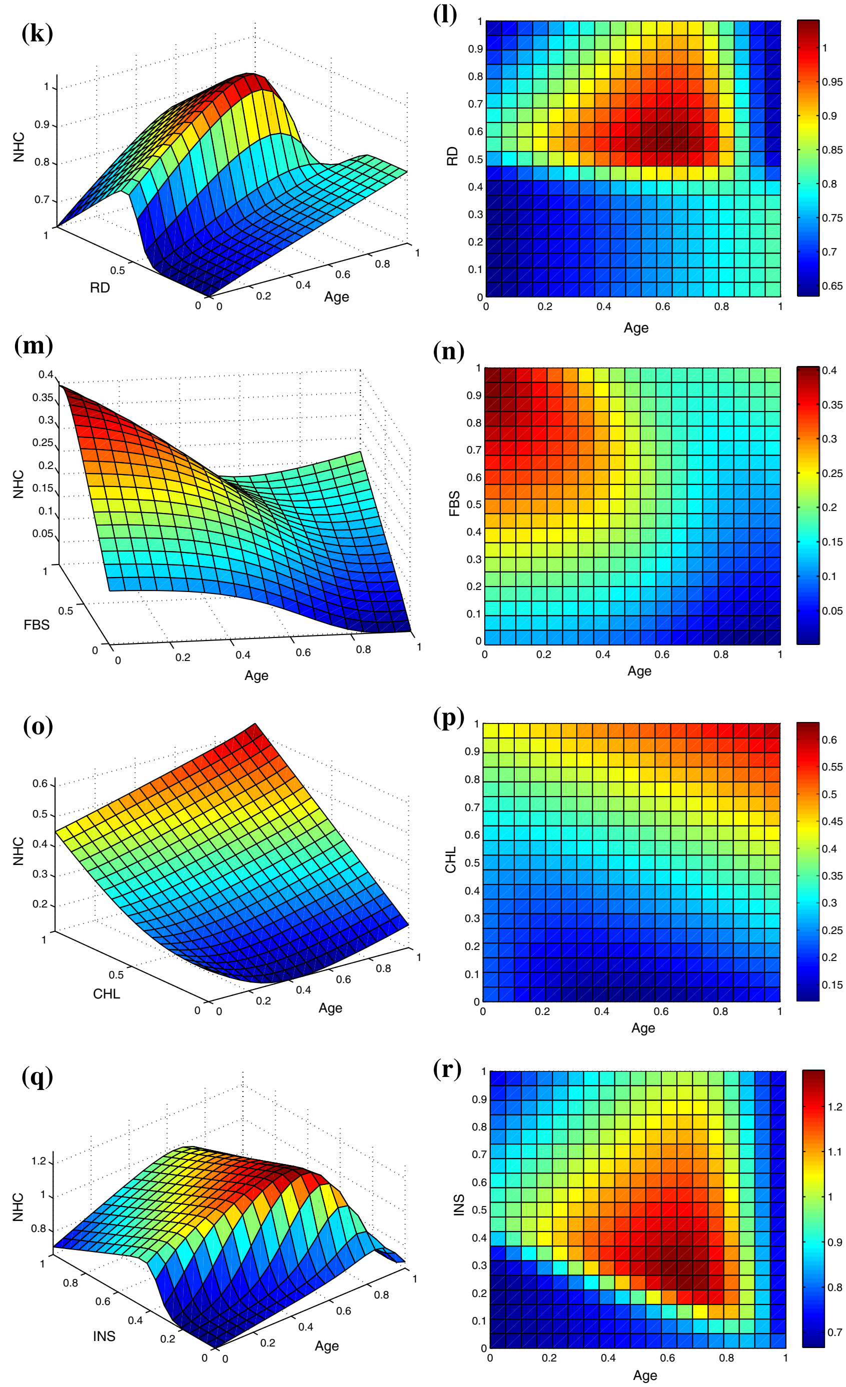


Fig. 7 continued

(DP), respiratory distress (RD), fasting blood sugar (FBS), cholesterol (CHL), and insomnia (INS) of 156 persons who were infected by COVID-19. We collected the data before and after the infection. Finally, we have found the desired model that shows the effect of COVID-19 on a person's normal health. We have also derived that age of a person is a crucial factor in determining the effect of Covid-19 infection. COVID-19 infection has more effect on older adults than younger people even if they have normal SP, DP, no RD, no insomnia. It is also found that if SP, DP, RD, FBS, CHL, and INS of a person are lower than the normal range, NHC does not change much due to COVID-19 infection. On the other hand, if a person has higher values than standard SP, DP, RD, or INS, the COVID-19 infection significantly affects a person's health. Since the obtained results are based on randomly chosen people, therefore, we can conclude that this result will be true in general case also.

In our future work, we will try to collect more data by surveying more individuals in heterogeneous regions by using other soft computing techniques.

Acknowledgements The authors are thankful to the anonymous reviewers for their constructive comments and helpful suggestions to improve both the quality and presentation of the manuscript significantly.

Author Contribution The authors also declare that all the authors have contributed equally in the preparation of the manuscript.

Declarations

Funding The work of S. Adak is supported by Indian Institute of Engineering Science and Technology (IIEST), Shibpur, India (No. 1878/1(5)/Exam, dated: 19th January, 2021).

Conflict of interest The authors declare that there is no conflict of interest.

References

www.WebMed.com

Abu Arqub O (2017) Adaptation of reproducing kernel algorithm for solving fuzzy Fredholm–Volterra integrodifferential equations. Neural Comput Appl 28:1591–1610. https://doi.org/10.1007/s00521-015-2110-x

Abu Arqub O, Momani S, Al-Mezel S, Kutbi M (2015) Existence, uniqueness, and characterization theorems for nonlinear fuzzy integrodifferential equations of Volterra type. Math Probl Eng. https://doi.org/10.1155/2015/835891

Abu Arqub O, Singh J, Maayah B, Alhodaly M (2021) Reproducing kernel approach for numerical solutions of fuzzy fractional initial value problems under the Mittag-Leffler kernel differential operator. Math Meth Appl Sci. https://doi.org/10.1002/mma.7305

Abu Arqub O, Singh J, Maayah B, Alhodaly M (2021) Adaptation of kernel functions-based approach with Atangana–Baleanu–Caputo distributed order derivative for solutions of fuzzy fractional Volterra and Fredholm integrodifferential equations. Math Meth Appl Sci. https://doi.org/10.1002/mma.7228

Adak S, Jana S (2020) A study on stegomyia indices in dengue control: a fuzzy approach. Soft Comput. https://doi.org/10.1007/s00500-020-05179-x

Adak S, Jana S (2022) Dynamical behavior of an epidemic model with fuzzy transmission and fuzzy treatment control. J Appl Math Comput 68:1929–1948. https://doi.org/10.1007/s12190-021-01597-8

Adak S, Jana S (2021) A model to assess dengue using type 2 fuzzy inference system. Biomed Signal Process Control 63:102121

Adak S, Majumder R, Majee S et al (2022) An ANFIS model-based approach to investigate the effect of lockdown due to COVID-19 on public health. Eur Phys J Spec Top. https://doi.org/10.1140/epjs/s11734-022-00621-7

Adak S, Jana S, Kar TK (2022) Investigation of COVID-19 using an artificial intelligence based approach. In: Azar AT, Hassanien AE (eds) Modeling, control and drug development for COVID-19 outbreak prevention. Studies in systems, decision and control, vol 366. Springer, Cham. https://doi.org/10.1007/978-3-030-72834-2-13

Banerjee D (2020) Age and ageism in COVID-19': Elderly mental health-care vulnerabilities and needs. Asia J Psychiatr 51:102154

Chiu SL (1994) Fuzzy model identification based on cluster estimation. J Intell Fuzzy Syst 2:257–78. https://doi.org/10.3233/IFS-1994-2306

Golafshani EM, Behnood A, Arashpour M (2020) Predicting the compressive strength of normal and High-Performance Concretes using ANN and ANFIS hybridized with Grey Wolf Optimizer. Constr Build Mater 232:117266. https://doi.org/10.1016/j.conbuildmat.2019.117266

Jang JSR (1993) ANFIS: adaptive-network-based fuzzy inference system. IEEE Trans Syst Man Cybern 23(3):665–685

Khatua A, Jana S, Kar TK (2020) A fuzzy rule-based model to assess the effects of global warming, pollution and harvesting on the production of Hilsa fishes. Eco Inform 57:101070. https://doi.org/10.1016/j.ecoinf.2020.101070

Liu K, Chen Y, Lin R, Han K (2020) Clinical features of COVID-19 in elderly patients: a comparison with young and middle-aged patients. J Infect 80:14–18

Mandal M, Jana S, Adak S, Khatua A, Kar T (2022) A model-based analysis to predict and control the dynamics of COVID-19. In: Azar AT, Hassanien AE (eds) Modeling, control and drug development for COVID-19 outbreak prevention. Studies in systems, decision and control, 366. Springer, Cham. https://doi.org/10.1007/978-3-030-72834-2-4

Mola M, Amiri-Ahouee R (2020) ANFIS model based on fuzzy C-mean, grid partitioning and subtractive clustering to detection of stator winding inter-turn fault for PM synchronous motor. Int Trans Electr Energ Syst. https://doi.org/10.1002/2050-7038.12770

Sornette D, Mearns E, Schatz M, et al (2020) Interpreting, analysing and modelling COVID-19 mortality data. Nonlinear Dyn 101:1751–1776. https://doi.org/10.1007/s11071-020-05966-z

Zhao Y, Healy BC, Rotstein D, Guttmann CR, Bakshi R, Weiner HL et al (2017) Exploration of machine learning techniques in predicting multiple sclerosis disease course. PLoS ONE 12(4):e0174866