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The impact of COVID-19 on spirituality in Indian adults: A machine learning-based approach

Abstract. Objectives: This research delves into the nuanced impact of the COVID-19 pandemic on the spiritual well-being of adult Indian. The study aims to understand the shifts in spiritual practices, beliefs, and overall religious experiences during this unprecedented global crisis. Methods: A comprehensive quantitative approach was employed, combining in-depth interviews and surveys to capture the multifaceted dimensions of Hindu adults' spiritual experiences during the pandemic. The research utilized validated scales and qualitative coding to analyze the data. Results: The findings illuminate complex patterns of change in spiritual practices, with some individuals reporting heightened engagement in religious activities, while others experienced a reevaluation of their beliefs. The study identifies key factors influencing these variations, such as individual coping mechanisms and the role of virtual religious communities. Discussion: This study contributes to our understanding of the dynamic relationship between external stressors, such as a pandemic, and the spiritual dimensions of individuals' lives within the Hindu community. The implications for promoting resilience and support in the face of crisis are discussed, offering insights for both scholars and practitioners in the field of spirituality and mental health.

Keywords: COVID-19, machine learning, spirituality, mental health, artificial intelligence methods.

Little is known about the impact of major epidemics on public mental health, especially during the critical phase. This knowledge gap means that we are not better equipped to support communities as they face the unprecedented pandemic of COVID-19. The study aimed to provide urgently needed data to inform government policy and current resource allocation and other future issues. The new coronavirus virus COVID-19 has never existed in recent history, with global consequences including high mortality and morbidity, loss of income and the continued segregation of billions of people from society (Wilinski et al. 2021). The impact this problem will have on human mental health, in the short and long term, is unknown. There is little evidence of the mental health effects of the acute phase of epidemics in all societies. Existing work focuses on those people most affected by the disease (e.g., infected people and their families, health workers (Gardner & Moallef, 2015; James et al., 2019; Ricci-Cabello et al., 2020; Wu et al.; 2009, Van Bortel et al., 2016) and assesses the effects of mental health on the wider community only after the onset of severe phase (Gardner & Moallef, 2015). However, fears about exposure to infection, job loss, and financial hardship may also increase the stress on many people (James et al., 2019; Wu et al., 2009; Van Bortel et al., 2016), the risk of depression and suicide may increase (Holmes et al., 2020; James et al., 2019; Ma et al., 2016).

Spirituality is a very ancient concept in Indian culture. The Indian subcontinent is considered the place of one of the earliest civilizations on the planet. India is also considered the birthplace of many religions such as Hinduism, Sikhism, Buddhism, etc. The richness of spiritual texts in this land has led us to believe that spirituality has been one of the most integrating factors in Indian society. However, India has evolved a lot over multiple centuries with the series of invasions by Islamic rulers, and continuous proselytism by the ruling elite has created a lot of marginal groups. India since then has faced multiple crises in the form of religious persecution, epidemic fallout, and economic depressions. Various studies have established the fact that spiritual values improve people's well-being, studies such as Richards & Bergin (2000) and Young et al. (2007) have discussed the connection between spirituality with mental health and well-being (Del Castillo et al., 2020; Kapitsinis, 2020, Kim & Bostwick, 2020, Lindstrom, 2020; Lalmuanawma et al., 2020; Oronce et al., 2020). Therefore, we can say that as India has been a land where spirituality is a part of everyday life, this would have helped India at large to cope with these crises.

Indian society today looks vastly different from what it used to be a few decades ago, with globalization at its peak the cultural value exchanges between communities have been the prime story. The West has always been the dominating force across the globe in the recent past, some even argue about the erosion of Indian culture by Western forces which might have hampered India's rich spiritual past. With this current situation in place understanding the effect of spirituality on mental well-being can result in an exciting, yet less-researched study. But little did we know that the next couple of years will arguably be the highlight of the past century.

The year 2020 has been one of the pivotal points in the entire human history. The whole world has faced an unprecedented crisis, which has led the world to a standstill. The SARS-CoV-2 virus also known as coronavirus originated in China around late

2019. Coronavirus crossed all geopolitical boundaries, and India, one of the most populated countries, has suffered the most. Cases on an exponential rise and overwhelming pressure on the country's medical infrastructure created havoc in the country. Indian government enforced a country-wide lockdown on 23rd March 2020, with only essential services working, every other service such as public transport, educational institutes, shopping complex, etc., were forced to shut their operations. An economic crisis was emerging under an existing medical one, people were losing their jobs, businesses going bankrupt, and gig workers were forced to leave the town because of no employment. With some to no social interactions, the development of anxiety among adults was at an all-time high. The uncertainty in the treatment of coronavirus and the lack of effective precautions was the reason for developing the fear of getting the disease. According to the world health organization, the COVID-19 pandemic triggers a 25% increase in the prevalence of anxiety and depression worldwide (Shams et al. 2020; Tan et al. 2021; Wilinski et al. 2022). These statistics give us a direct relation between a decrease in mental well-being and the COVID-19 pandemic. Our study would effectively like to figure out how exactly this pandemic has affected people's life.

There is an interesting connection between compassion and spirituality, whether it is self-compassion or compassion for others. Spirituality allows individuals to experience new perspectives on simple human interaction. Greenwald & Harder (2003) found that when talking about spirituality and spiritual experiences, people recognize a loving connection with others and a tendency to help others. In a study conducted to examine the independent effects of spirituality and religiosity on compassion, subjects with high spirituality ratings were found to be more compassionate, while no significant relationship was found between religiosity and compassion. Also, participants who were found to be more spiritual responded compassionately to situations that described someone in distress, rather than simply showing sympathy, the same study also found that compassion mediated the relationship between spirituality and prosocial behavior.

Many studies have proposed a spiritual dimension of humility, which consists of the belief that God is an ultimate power, and has abilities far superior to any human being, suggesting the limited abilities of human beings. Humility does not emphasize human incapacity, but rather the idea that there is a higher power and wisdom that comes when we begin to accept our limitations. A person who has attained humility is no longer the center of his world and instead focuses on the larger community of which he is a part. Humility, as we know it from the literature so far, makes a person aware of his true abilities and at the same time clarifies his limitations. The main domains of self-compassion: self-kindness, common humanity, and mindfulness, all focus on an individual's ability to show self-kindness even in the phase of failure; to perceive one's experiences as those faced by other people and to have a balanced awareness of one's blessings and misfortunes. All this is possible only when a person is completely impartial about himself and has no sense of grandeur or inferiority. Humility ensures the existence of such a state, thereby facilitating the inoculation and growth of self-compassion. Humility gives an individual the ability to take full responsibility for the actions he takes and the various ways he affects himself and those around him. It has been found that humble people are better able to accept negative feedback, and people with high self-compassion respond to negative states with less distress. Our contribution is here to find the correlation interplay between the COVID-19 pandemic, Spiritual conscience, and the mental well-being of society at large. Our hypotheses for this study are as follows.

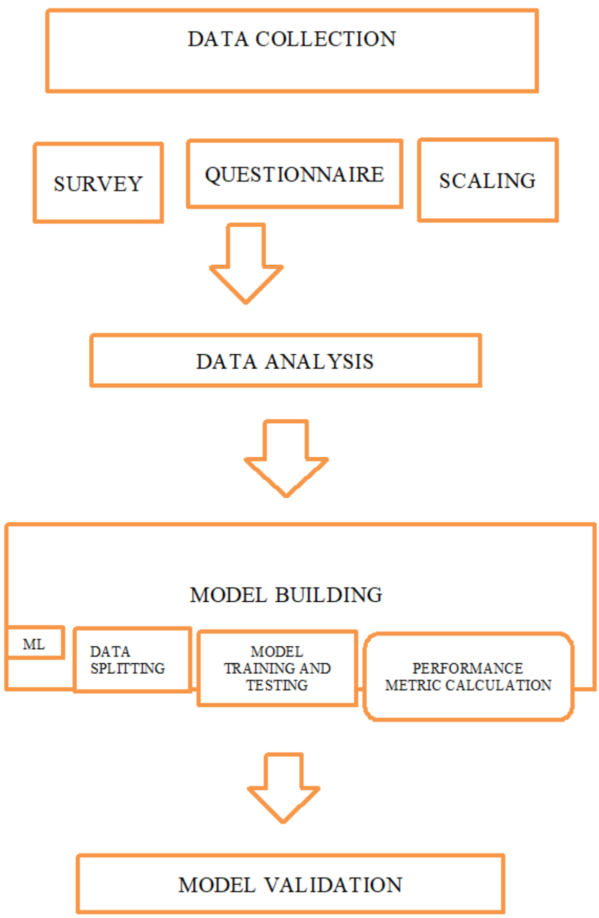
There is a significant relationship between the increase in spirituality and the COVID-19 pandemic and a direct relationship between higher spiritual conscience and mental well-being.

Methodology

We propose to build a ML-based model to analyze the relationship between the increase in spirituality and the COVID-19 pandemic among Indian adults. The flowchart of the adopted method is shown in Figure 1.

Components of Model Building:

Figure 1
Flowchart of the proposed method



1) **Data Collection** – The data has been collected via a survey through the Google Docs platform. The survey link was circulated using media platforms which strictly focused on Indian adults. The survey consisted of a questionnaire that had the particular objective to get information about the spirituality experience scale.

The first step to collect the data related to spirituality in the Indian adults. For this, we float a google form which contains ten questions. The questions are made in such a way so that one can comment on the his/her connection to the God, nature, love from others, religion, peace and finally spirituality. Specifically, we want to know whether the person becomes more/less spiritual after COVID-19. The participant can mark the answer on a scale of zero to ten. This scale may range from any real value to any other real value. In our experiment, for the ease of calculation, we have chosen the scale from zero to ten.

The survey form consists of 10 questions on the spirituality experience scale (0–10). The first nine questions are considered as input variables and the tenth question is considered as target.

Table 1
Example of Profile of Spirituality

Input/Output Variable	Question	Score (1–10)
I/P 1	I feel God's presence more after COVID-19 pandemic	7
I/P 2	I find strength in my religion or spirituality more after COVID-19 pandemic	6
I/P 3	I find comfort in my religion or spiritualty more after CO-VID-19 pandemic	7
I/P 4	I feel deep inner peace or harmony more after COVID-19 pandemic	7
I/P 5	I feel God's love for me directly more after COVID-19 pandemic	8
I/P 6	I feel God's love for me through others more after COVID-19 pandemic	6
I/P 7	I am spiritually touched by the beauty of creation more after COVID-19 pandemic	4
I/P 8	I feel more closer to the Nature after COVID-19	3
I/P 9	I desire to be closer to God or in union with the divine after COVID-19 pandemic	7
O/P	DO you feel more spiritual after COVID-19?	8

The spirituality experience scale consisted of questions on religion, spirituality, God, and peace of Indian adults.

The above-mentioned questions in the form of Google-form are floated among a group of students, professors, medical practitioners, and a group of corporates. Mostly, all considered person are living in big cities. The selected age group is 18–60 years. It is because of the fact that below 18 years, the people are not mature enough to address the topic of spirituality and above 60 years, most of the people are spiritual in India. We have selected the group of people, which are affected by COVID-19 badly. Because of this disease, colleges are closed, classes are conducted in online mode. Medical practitioners need to work for whole day and night. Many people working in corporate sector lost their jobs or are compelled to work on lower salaries. It affects their mental health badly. Total two fifty-six responses are received. These responses are mixed and among these responses, randomly one ninety-eight responses are selected for the data analysis.

The scaling has been done on a scale of zero to ten. The middle of the scale, i.e., five is defined as having no effect on the spirituality due to covid. If we move towards zero, it is defined as the negative effect on spirituality and as I find strength in my religion or spirituality more after COVID-19 pandemic we move towards ten, it is the maximum effect on the spirituality of an Indian adult after covid. Therefore, the answer of question ten will not be like yes/no, in this paper. it will also on the scale from 0–10.

2) **Data Analysis** – The considered data is taken from randomly selected 198 people from the age group of 18–60 years old. Some statistics have been calculated, as shown in the table 2.

Table 2
Statistics of Survey

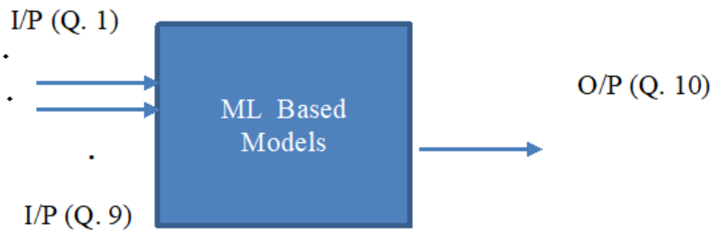
Q. No.	Mean	St. Deviation	Kurtosis	Skewness
1	6.6869	2.6598	3.0588	-0.6577
2	6.6162	2.6600	2.8044	-0.5013
3	6.6061	2.5267	3.0941	-0.5580
4	6.2323	2.5905	2.6479	-0.3850
5	6.0505	2.5650	2.9096	-0.5122
6	6.4444	2.6078	2.8477	-0.5802
7	6.3434	2.3826	3.0179	-0.4756
8	6.7475	2.4384	2.7442	-0.4471
9	6.5960	2.4071	3.0125	-0.4229
10	6.4949	2.2963	3.2297	-0.5322

It can be observed from Table 2 that the mean of input variables, i.e. questions 1 to question 9 is more than 5, which shows that spirituality improves after the pandemic. The standard deviation of the considered data is more than 2 for all input variables, it denotes that data is dispersed for the mean value, but dispersion is not very high. The kurtosis tells how much tailedness is existing in the considered data. Its value is approx. 3 or less than 3, which shows that the distribution has thin tails and its outlier frequency is low. Further, it can also be observed from Table 2 that the skewness of the considered data is negative, which means the distribution of data is not symmetric. If we consider some other set of data, like data of farmers or people living in villages or a group of highly religious community or a group of atheist. The result will change accordingly. The above considered model may not work in that case and a fresh training data is required to train the neural network.

3) **Model Building**

Figure 2

Model building



An ML-based model is considered as shown in Figure 2. In this case, we define a target value T = f(x_i),iϵ{1,2,…9}, where x_i s are the input variables, i.e., questions 1 to 9, as given in Table 1, and Target value is output variable, i.e., question number 10. Now the question arises which ML algorithm is used to model this problem. We want to train the model and then if any new person comes, we will ask the same survey questions from 1 to 9, and model will generate a number between 0–10. Based on that number we can interpret about the spirituality of that person.

Because of the less data, it is not clear that which algorithm will work efficiently. Therefore, we have tried several algorithms and can select the final algorithm according to their performance in terms of mean square error. Another important issue is how much data is used for training. We have started training with survey responses of 700 people and observed that if we use 120 responses then the training is adequate. However, we are not sure that this is optimal training or not. Answers of questions 1-9 of survey questions are inputs and tenth answer is the pout put. Therefore, the model is trained for a set of 120 responses. Now when new person will come, he/she will answer these 9 questions and based of his/her responses the model will generate an output in terms of a number between 0–10. Therefore, we need to use ML algorithms for prediction/forecasting.

We have implemented the following algorithms (Ray, 2019):

1. **LM Algorithm** – The Levenberg-Marquardt algorithm (LMA) is a popular confidence region algorithm used to find the minimum of a function (either linear or nonlinear) in parameter space. Essentially, the credible region of the objective function is internally modeled using some function such as a quadratic. When an adequate fit

is found, the confidence region expands. As with many numerical techniques, the Levenberg-Marquardt method can be sensitive to initial parameters. The primary application of the Levenberg-Marquardt algorithm is in the least-squares curve fitting problem: given a set of m empirical pairs (x, t) of independent and dependent variables, find the parameters of the beta function of the model curve (x, beta) such that the sum of the squares of the deviations is minimized (Li et al., 2017).

2. **Bayesian Regularization**: This algorithm is used for non-linear types of regression. It minimizes the sum of squared errors.
3. **BFGS Quasi-Newton**: The Broyden, Fletcher, Goldfarb, and Shanno, or BFGS Algorithm, is used for local search optimization. A second-order derivative is used for an objective function. It is the most commonly used algorithm for second-order optimization.
4. **Resilient Backpropagation**: It is a very fast training algorithm for neural networks and it does not require any specifications of free parameters.
5. **Scaled Conjugate Gradient**: It is based on the conjugate directions, but it is not fit for the line search.
6. **Conjugate Gradient with Powell/Beale Restarts**: The conjugate Gradient method require a restart, which depends upon the objective function. Similar gradient methods are Fletcher-Powell Conjugate Gradient, and Polak-Ribiére Conjugate Gradient
7. **One Step Secant**: This algorithm lies in between the quasi-Newton (secant) algorithms and conjugate gradient algorithms. The complete Hessian matrix is not stored and in each next iteration, it is assumed that the previous Hessian was the identity matrix.
8. **Variable Learning Rate Gradient Descent**.
9. **Gradient Descent with Momentum**.
10. **Gradient Descent**: It is a very simple iterative optimization algorithm used in ML to minimize the loss function. It is a first-order optimization technique. It is used to update the coefficients/parameters in regression/neural networks. To improve the convergence of this algorithm, Variable Learning Rate Gradient Descent can be used according to the application. Gradient Descent with Momentum is another variant of this algorithm. It uses the exponentially weighted average of the gradients and then uses this algorithm.

Results

A total of 198 responses are collected of which 120 are used to train the network and the rest are used for testing purposes. Mean square error performance are used for the validation and evaluation.

It can be observed from Table 3. that a total of 12 ML algorithms is implemented. It can be noticed that the best performance is of the Bayesian regularization method. Detailed plots of performance, training state, error histogram, and regression are shown. The worst performance of the gradient descent with the momentum algorithm. All other algorithms are performing closely to 0.1 or 0.2.

Table 3

Performance Comparison

Sr. No. (MSE)	Model Type	Performance
1.	Levenberg-Marquardt	0.1041
2.	Bayesian Regularization	0.0493
3.	BFGS Quasi-Newton	0.1397
4.	Resilient Backpropagation	0.3957
5.	Scaled Conjugate Gradient	0.2673
6.	Conjugate Gradient with Powell/Beale Restarts	0.1065
7.	Fletcher-Powell Conjugate Gradient	0.1394
8.	Polak-Ribiére Conjugate Gradient	0.1590
9.	One Step Secant	1.5077
10.	Variable Learning Rate Gradient Descent	2.3048
11.	Gradient Descent with Momentum	197.7402
12.	Gradient Descent	1.9260

Figure 3

Neural Network Error Histogram

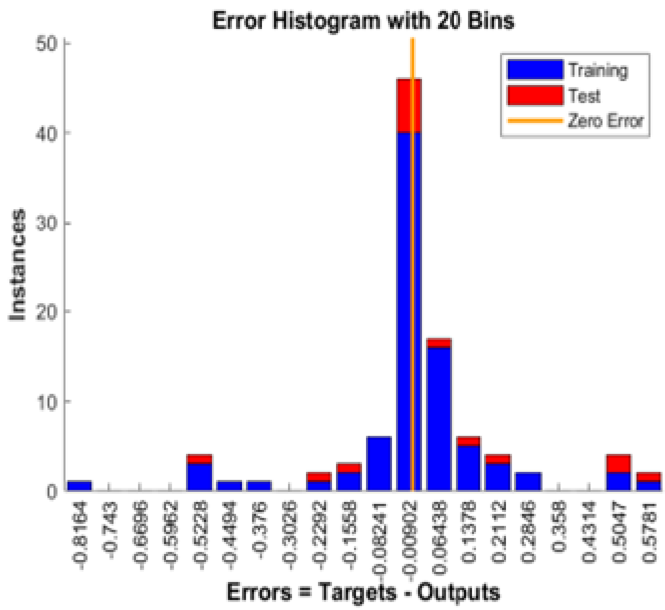


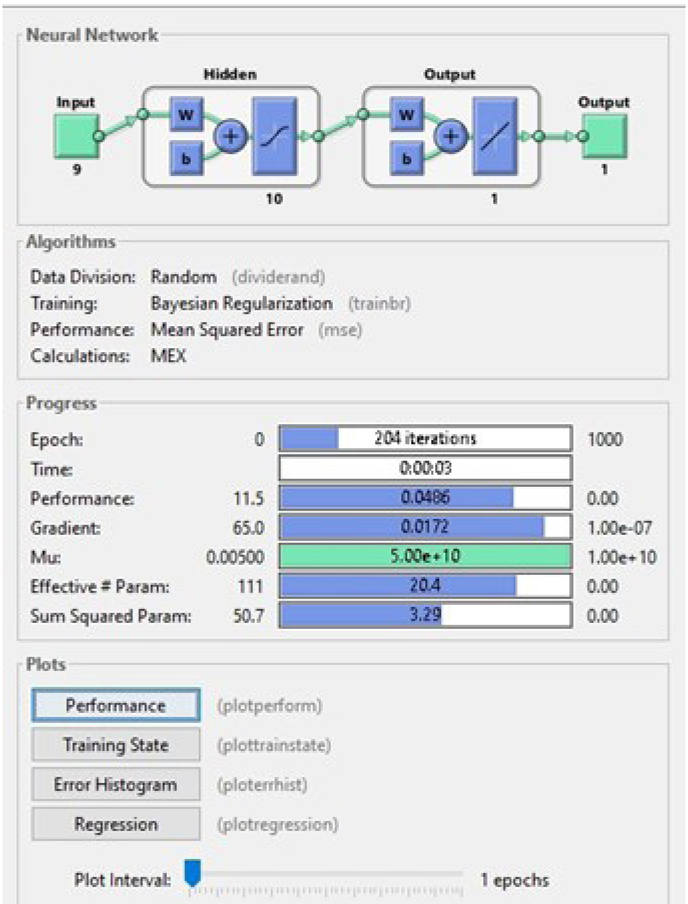
Figure 3. shows the neural network error histogram. It is a histogram of errors between target values and estimated values after training the neural network. As these error values show how the predicted values differ from the target values, these may be negative.

Drums are the number of vertical bars one can see on the graph. The total error rate is divided into 20 smaller bins here.

The Y-axis represents the number of samples from our database, located in a particular container. For example, an error range is from -0.87 to 0.5781 and the length of that training database bar is below but close to 120 and the validation and test database is between 130 and 180. The zero error line corresponds to the zero error value in the error axis (i.e. X-axis). In this case, the zero error point falls below the barrel with a center of .009.

Figure 4. Shows the neural network training parameters. The Bayesian Regularization algorithm is used to train the network. All parameters like mean square errors, gradient, performance, elapsed time, and epochs are given in Figure 4.

Figure 4
Neural Network Training Parameters



The verification of output values of the ANN model is based on the Square Error (MSE) and the Deviation R (regression) price.

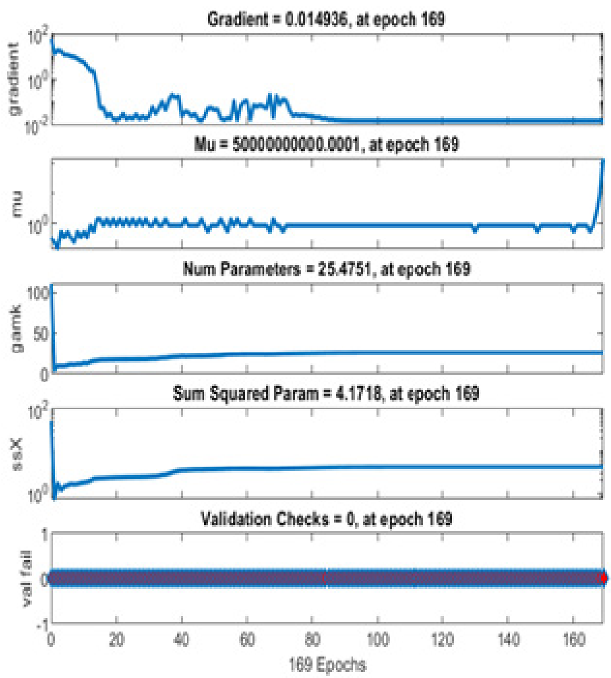
The Mean Square Error (MSE) is the square difference between the output and the target. Lower MSE values mean a better balance between actual and target output, and zero means no error.

The setback *R* measures the correlation between the output and the target. *R* values of 1 mean intimate relationships, and 0 means random relationships.

Analyzing the Artificial Neural Network after training is a very special decision, where the performance of the network model is analyzed and determined what changes need to be made to the training process, network architecture, or database. In this case, the parameters to be tested can be determined using the following charts: Network performance, retrieval structure, error histogram, and training conditions.

Network performance is shown in Figure 5. It is a plot of MSE vs epochs. Network performance reflects the ethical standards of training, verification, and testing. This structure helps determine what changes need to be made to the training process, network construction, or database. In Figure 5, a circle in a network operating structure indicates the number of repetitions when the validation function reaches a minimum; training continued 1000 times before the training stopped. For example, the structure shown in Figure 5 does not indicate major problems with training; validation and test curves are very similar.

Figure 5
Neural Network Training State

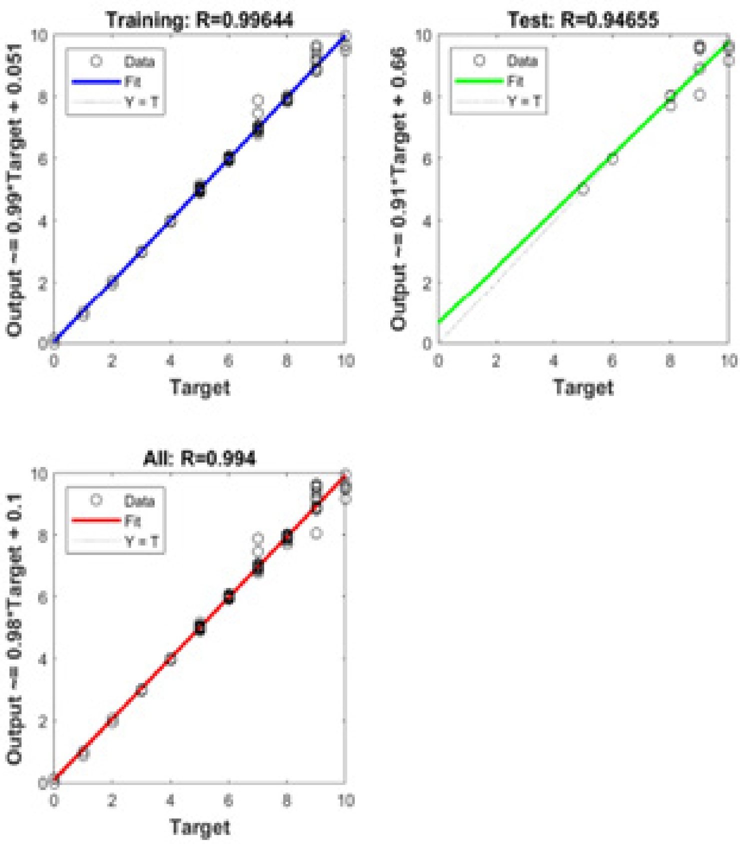


The training states are a series of training district plots ranging from a trained gradient record, mu, and indicators of validation failure compared to epochs. In Figure 5, the mu structure against Epochs shows very low values of mu, while the gradient structure against the periods shows that each time the gradient is small, and the verification structure shows that after epoch 1000, validation fails to begin to increase; this is in line with the circle indicator of verification efficiency shown in Figure 5.

Briefly with the data used again, based on the episodes of Figure 5, this ANN model is acceptable at R = .99644, indicating a retrospective calculation as this is shown in the y-axis of Figure 5. The error histogram shows the smallest error in almost all cases, and epoch 1000 with validation performance does not show major problems with training; validation and test curves are very similar.

Regression plots are shown in Figure 6. These plots show the relationship between network output and target. If the training were complete, the network results and objectives would be the same. As shown in Figure 6. the value of R = 0.9964 indicates the closest relationship.

Figure 6
Neural Network Training Regression



Conclusions

The method presented for assessing the spirituality index after the pandemic COVID-19. It can be extended to any country or group of countries under the rather obvious condition of data availability. The possibility, noted by us, of objectively assessing the positive effects of a pandemic on a common person. It can be concluded from the simulated results that the sprituality index has been improved for the considered data set after COVID-19.

One can, of course, consider other examples, other countries or groups of countries, or entire continents. We believe that this is a very interesting guideline for research, especially regarding the variability of these indicators over time. Moreover, it has been observed that the Bayesian algorithm performs better than all other considered ML algorithms.

It has been observed from the analysis that there is a significant relationship between the increase in spirituality and the COVID-19 pandemic.

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