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Prediction and comparison of psychological health during COVID-19 among Indian population and Rajyoga meditators using machine learning algorithms

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Abstract

Issues of providing mental health support to people with emerging or current mental health disorders are becoming a significant concern throughout the world. One of the biggest effects of digital psychiatry during COVID-19 is its capacity for early identification and forecasting of a person's mental health decline resulting in chronic mental health issues. Therefore, through this study aims at addressing the hological problems by identifying people who are more likely to acquire mental health issues induced by COVID-19 epidemic. To achieve this goal, this study includes 1) Rajyoga practitioners' perceptions of psychological effects, levels of anxiety, stress, and depression are compared to those of the non practitioners 2) Predictions of mental health disorders such as stress, anxiety and depression using machine learning algorithms using the online survey data collected from Rajyoga meditators and general the population. Decision tree, randomforest, naive bayeBayespport vector machine and K nearest neighbor algorithms were used for the prediction as they have been shown to be more accurate for predicting psychological disorders. The support vector machine showed the highest accuracy among all otheralgorithms. The f1 score was also the highest for support vector machine.

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Keywords: *Machine learning algorithms; mental health; COVID-19; DASS*

1. Introduction

Mental illness is a form of sickness that affects a person's cognition, emotions, and behavior and is proven to have an impact on physical health. Depression, among other mental health difficulties, is extremely common nowadays, with an estimated 450 million individuals suffering from them [1]. Children and adolescents, like adults, are vulnerable to mental health problems. In addition, mental illnesses have long been one of the most significant and pervasive public health problems. One of the most prevalent causes of disability is depression. It may increase the risk of suicide thoughts and attempts [2].

The Corona virus pandemic has also resulted in a psychological crisis throughout the world. The people are suffering on emotional, financial, physical, and mental levels depending on the circumstances. The ongoing surge during the second wave is more rapid. Limited lockdowns have again been imposed in some areas and the threat of a more stringent lockdown looms large over the areas that are worst affected. The psychological effects of the pandemic are being ignored by the concerned health officials. Delivering psychologies therapies interventions to different societal groups, especially healthcare workers, is a must to curb the psychological crisis [3]. The National Health Commission of

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China released recommendations on emergency psychological crisis intervention on January 27, 2020 [4], for the provision of trained professionals' mental health support services to patients and healthcare personnel. For individuals to have access to free mental health treatments across many platforms during this mental health crisis, there has to be a digital mental health revolution [5]. Thus, resilience to stress is must for facing the crisispost COVID-19 pandemic and the strategies to enhance resilience among all sections of society is the need of the hourtoday [6]. To manage distress and cultivate resilience in the prevailing crisis, coping strategies such as meditation interventions should be provided [7]. These strategies help build tolerance, increase social support, develop human interconnectedness, and help redefining goals and actions.

Fears and anxiety can be reduced with mindfulness and meditation [8]. Rajyoga meditation is a universal and unique meditation technique, that can be practiced by anyone and anywhere. This practice is taught without any cost by Rajyoga meditation centers spread throughout the world. This meditation has been demonstrated to lower diastolic blood pressure in hypertensive individuals [9]. Rajyoga meditation calms the mind and body while balancing energy. As a result, a person's cardiorespiratory endurance is improved. One of the metrics used to assess a person's aerobic and physical fitness is their maximal rate of oxygen consumption during exercise (VO2 max). Rajyoga practitioners showed an increase in VO2 max [10]. When heart patients undergo coronary artery bypass surgery, regular Rajyoga meditation practice helps to control anxiety and cortisol levels [11]. It is believed that meditation can help people manage their stress and improve their cardio-respiratory health After six weeks of participation, even a short-term Rajyoga meditation intervention decreased anxiety and depression in the patients who were experiencing these conditions [12]. Rajyoga meditation interventions are proved to have neural benefits also Rajyoga meditators demonstrated high powers in the alpha band and theta band range [13]. Rajyoga meditation significantly improved the frontal and parietal regions of the brain that process emotions and thought. Early diagnosis of mental health disorders is critical for better understanding mental health conditions and providing better patient care. Unlike the diagnosis of other chronic illnesses, which is based on laboratory tests and measurements, an individual's self-report to particular questionnaires designed to detect specific patterns of sensationsor social interactions is often used to diagnose mental diseases. Because data about an individual's mental health state is becoming more widely available, artificial intelligence and machine learning technologies can be utilized to providebetter services for mental health care and assist mental health practitioners in making better clinical decisions [14].

2. Machine learning based prediction systems

This section shows how the systems proposed previously use artificial intelligence's machine learningtechniques in health systems. It comprises prediction systems created for disease and mental health prediction.

2.1 Disease prediction

Using the revised fusion node and deep learning algorithms, Zhong and Xiao [15] created a system to improve health prediction. A fusion node is a paradigm for combining information in order to build prediction systems. Deep learning may be used in conjunction with fusion nodes to give reliable predictions from large amounts of health data. An experimental system is constructed as an illustration for the framework implementation based on the given framework. The suggested fused model has 73.21 % accuracy in detecting various health concerns based on the model's results.

Ambiga et al. [16] created the Smart Health Prediction system that addressed the prior systems' flaws. The system performs a basic examination of a patient and suggests diseases that may be present. It starts by asking about the patient's symptoms. If the system can identify the correct disease, it then suggests a doctor in the patient's nearby area. If the system is unclear, it will ask the patient a series of questions and recommend testing. Based on the available cumulative data, the system will give the result. The Smart Health Prediction system is based on a database of multiple patients' medical records. Dahiwade et al. [17] presented a technique for forecasting illness based upon the symptoms of the patient. They employed K-Nearest Neighbor and Convolutional Neural Network machine learning algorithms to forecast illness accurately. This disease prediction tool took into account the living habits and check-up information of an individualfor precise prediction. In general illness prediction, the CNN algorithm showed an accuracy of 84.5 percent, which isgreater than the KNN technique. In addition, KNN had a higher time and memory demand than CNN. Jamgade and Zade [18] presented a disease prediction system based on the K-mean algorithm. To estimate health risk, they integrated structured and unstructured data from the healthcare domains. The method of the latent component model was used for reconstructing missing data in hospital medical records. They also used statistical information to discover the most common chronic illnesses in a certain region and population. Then they consulted hospital professionals to learn about valuable characteristics for structured data, and used K-Mean to automatically extract features from unstructured data. The accuracy of the algorithm was 95% for both structured and unstructured data. Because machine learning algorithms produce excellent results for disease prediction, Joshi et al. [19] suggested anew method. They utilized symptoms as characteristics and created a chatbot that takes the symptoms and uses a decision tree algorithm to anticipate the disease. This method makes it simple to establish real-time communication by utilizing contemporary and updated technology, and it is more accurate than the others. Furthermore, Ali and Divya [20] suggested a smart health care system for disease prediction. They used data mining with machine learning techniques to improve the performance of the systems. The researchers compared the performance of several algorithms for diseases such as heart, kidney, liver, diabetes, and cancer and discovered that neural networks had the best performance for predicting heart and kidney disorders. Singh et al. [21] proposed another smart health-care system based on a machine-learning algorithm. They developed a predictive modelling-based application that predicted illness in patients depending upon the symptoms supplied by the user as input. To develop smart health predictions, they utilized the Nave Bayes Classifier, which used all of the features learned throughout the training to compute the chance of an illness. After the prediction, the patient can visit a specialized doctor via a chat consultation window. The AdaBoost method was used to enhance a Random Forest model [22]. The model was used to predict the mental disorders based upon the demographics, location, travel history and health data. The model had an F1 Score of 0.86 and a 94 percent accuracy on the dataset provided. The patients were mostly aged between 20 and 70. The data analysis demonstrated a link between gender of the patient and death.

2.2 Mental health prediction

Table 1 summarizes the studies on existing machine learning-based mental health prediction systems. Features are extracted from the available dataset and machine learning algorithms are then applied depending upon the type of data.

Table 1 machine learning-based mental health prediction system

Reference	Data source	Subjects	Feature extracted	ML algorithms	Results
[27]	Survey data collected from U.S. adult household population	17764 adults in USA	Physical health, mental health, economic factors and social factors	Random-Forest, Naive-Bayes, Support vector machine, logistic.	Accuracy of about 80 percent was achieved in predicting mentally vulnerable people.
[28]	EEG signal analysis of stressed participants	42 healthy subjects (19-25 years of age).	Electroencephalogram (EEG) signal	Logistic regression, Support vector machine and Naïve Bayes classifiers	Accuracy of about 94.6 percent could be achieved for prediction of stress.
[19]	Twitter API	A set of 166 Twitter users	Structural features and behavioral features	K-neighbors, Random Forest. Ada Boosting Gradient Boosting	The best accuracy received by this model is 89%.
[29]	Jerusalem Trauma Outreach and Prevention Study	957 trauma survivors	Predictive features for PSTD	Support Vector Machines	Predicting non-remitting PTSD from that group was no more accurate than predicting from all available data.
[24]	Open Sourcing Mental Illness Survey	Working individuals	Labels	Decision Tree, Naïve Bayes Random Forest,	Better Performance by Decision Tree (82.2%)
[25]	DASS Questionnaire	348 respondents	Depression, Anxiety and Stress levels	Decision Tree, SVM, RF, K- neighbors, and Naïve Bayes	Naive Bayes was the most accurate
[26]	Strengths and Difficulties Questionnaire (SDQ)	474 Twins	A binary variable based on a combination of the parent reported subscales	RF algorithms, SVM, Neural Network, and XG Boost	The performance of the model was evaluated using the area under the receiver operating characteristic curve.
[23]	Clinical psychologist	Ten children	Using Feature Selection methods, 25 attributes were minimized.	AODE, Radial basis function network, K Star, Multi-Class Classifier, FT, LAD tree	MLP, MCC, and LAD Tree showed more accuracy.

3. Methodology

A google form was prepared that included the demographic data of the participants, medical history, COVID related history and a questionnaire to determine the mental health status of the respondents. To measure mental health, the DASS questionnaire was utilized. DASS-21 comprises three sub scales depression, anxiety and stress.

Each subscale has seven products, each of which is rated on a four-point scale. The scores of the sub scales subscales range from normal, to extremely severe. The link of the online survey was shared to SpARC (Spiritual Applications Research Centre) research wing of Brahma Kumaris World Spiritual University, which passed it on to the Rajyoga meditators. The non-meditators were recruited through snowball sampling. Data was collected from Rajyoga meditators over 15 days (16 January- 31 January,2021) and from non-meditators over 23 days (5 February – 28 March ,2021). The depression, stress and anxiety levels of both the groups were compared. SPSS Statistic 26.0 was used to conduct the statistical analysis All tests of associations were carried with a significance level of $p < 0.05$. The predictors of stress were then formulated and applied to different machine learning algorithms.

4. Results

The analysis of the data produced the following results.

4.1 Demographic characteristics of Rajyoga meditators

Table 2 shows the demographic characteristics of the Rajyoga meditators. In total, 801 responses were received. Most of the meditators were female (59.6%), aged between 30-50 years (47.5%), married (61.2%) and employed (61.7%). Out of them, 15.2% of the respondents suffered from covid symptoms. About 34.6% meditators had 1 to 4 years of Rajyoga meditation experience, and about 31% had 5 to 10 years of Rajyoga meditation experience, while rest of them being long term meditators.

4.2 Demographic characteristics of non-meditators

Table 3 shows the demographic characteristics of the non-meditators. In total, 361 responses were received. The incomplete entries were removed and 309 entries were selected for the analysis. In this data, around half of the non-meditators were male (50.8%), most of them were aged between 30- 50 years (47.6%), married (58.3%) and employed (55.3%). Maximum of the respondents were not actively engaged in any exercise/yoga or meditation activities.

Table 2 Demographic characteristics of Rajyoga meditators

Variables	N (%)
Gender	
Male	321(40.1%)
Female	478(59.7%)
Others	2(0.2%)
Marital Status	
Married	490(61.2%)
Unmarried	232(29%)
Widow/widower	55(6.9%)
Divorced	12(1.5%)
Separated	12(1.5%)
Employment	
Employed	296(37%)
Self Employed	210(26.2%)
Not Employed	295(36.8%)
Suffered Covid Symptoms	
Yes	121(15.1%)
No	680(84.9%)
Contact with Covid person	
Yes	173(21.6%)
No	466(58.2%)
Not Sure	162(20.2%)
Travel History	
Yes	14(1.7%)
No	787(98.3%)
Age	
18-30 years	115(14.2%)
30-50 years	381(47.6%)
>50 years	305(38.1%)
Experience of Meditation	
1-4 years	184(23%)
5-10 years	248(31.0%)
11-20 years	158(19.7%)
21-30 years	76(9.5%)
>30 years	42(5.2%)
Not given	93(11.6%)

Table 3 Demographic characteristics of non-meditators

Variables	N (%)
Gender	
Male	157(50.8%)
Female	152(49.2%)
Marital Status	
Married	180(58.3%)
Unmarried	125(40.5%)
Widow/widower	2(0.6%)
Divorced	2(0.6%)
Employment	
Employed	171(55.3%)
Self Employed	34(11.0%)
Not Employed	104(33.7%)
Suffered Covid Symptoms	
Yes	52(16.8%)
No	257(83.2%)
Contact with Covid person	
Yes	55(17.8%)
No	184(59.5%)
Not Sure	70(22.7%)
Travel History	
Yes	6(1.9%)
No	303(98.1%)
Age	
18-30 years	127(41.1%)
30-50 years	147(47.6%)
>50 years	35(11.3%)

4.3 Comparison of psychological well-being of Rajyoga meditators and general population

Fig. 1 shows the comparison between depression, stress and anxiety levels of meditation practitioners and non-practitioners. In comparison to Rajyoga meditators, non-practitioners had higher DASS scores.

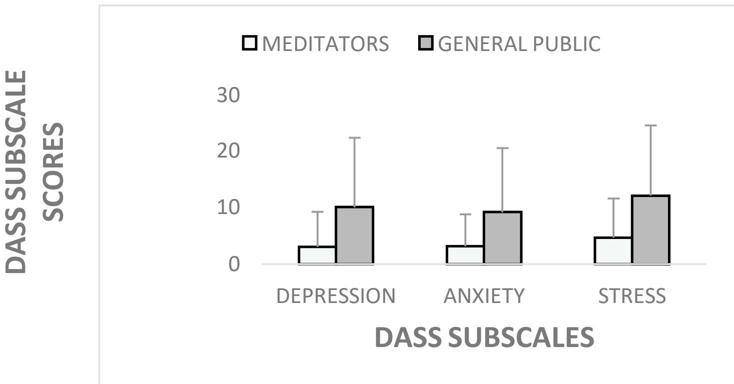

Figure 1 DASS scores of Rajyoga meditators and general public

4.4 Comparison with previous studies

DASS has also been used in several previous studies to assess the mental well-being of general public of different countries. Figures 2, 3 and 4 show that as compared to the outcomes of previous studies, the Rajyoga meditators exhibited very low levels of stress, anxiety and depression.

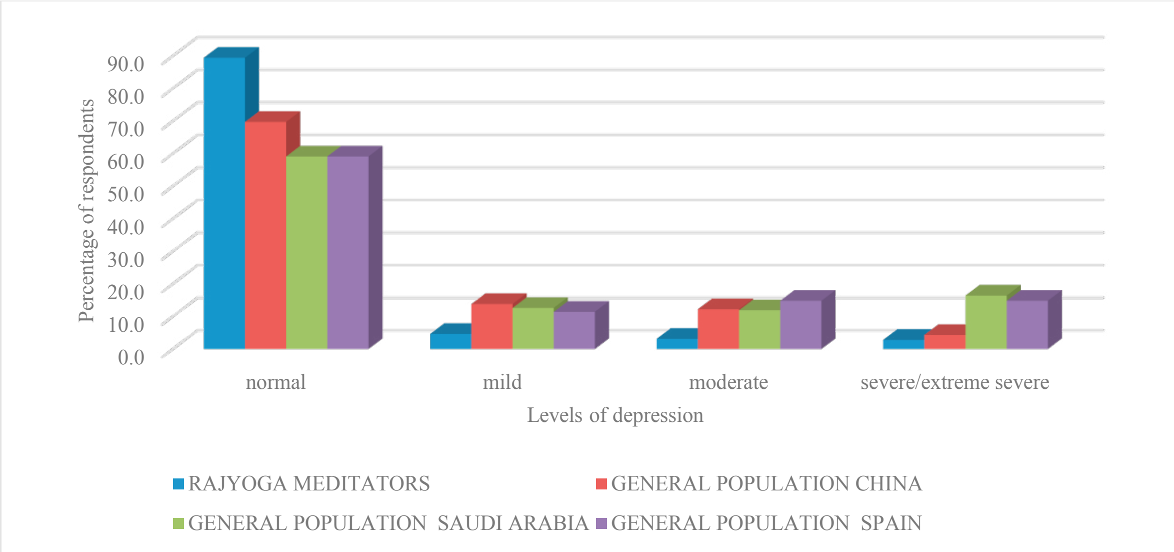

Fig 2 Comparison of levels of depression among Rajyoga meditators and general population in previous studies

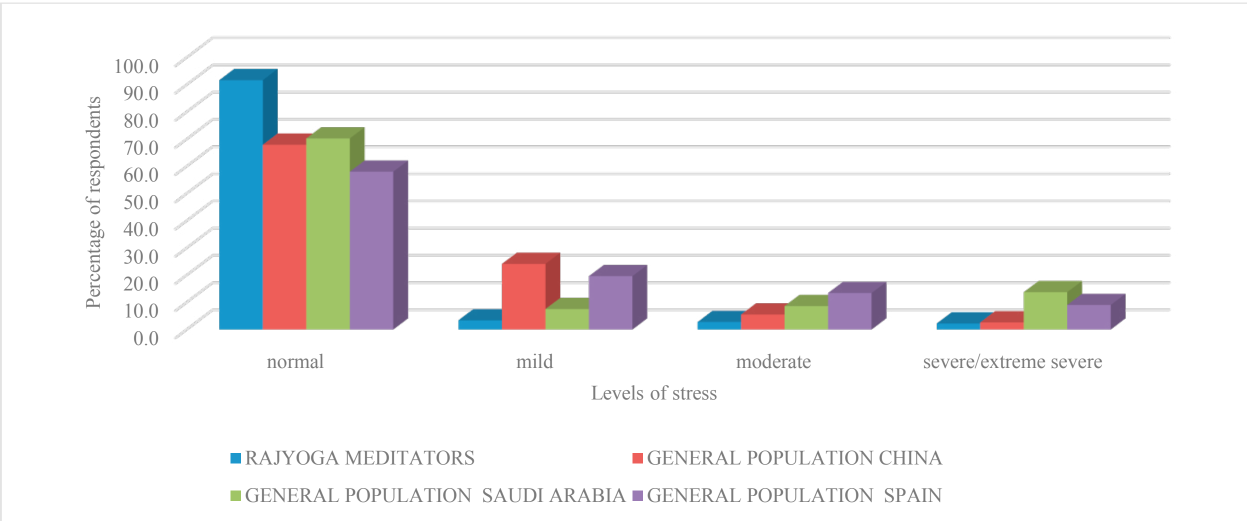

Fig 3 Comparison of levels of stress among Rajyoga meditators and general population in previous studies

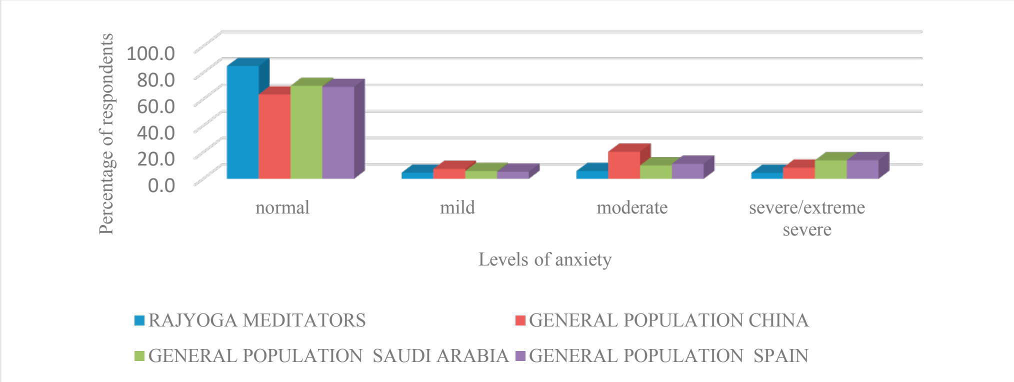

Fig 4 Comparison of levels of anxiety among Rajyoga meditators and general population in previous studies

4.5 Application of machine learning algorithms

The Python language was used to implement the machine learning techniques to the survey form data collected from DASS-21 described in the previous section. Using five separate machine learning methods, this algorithm forecasts the responders having symptoms of depression, stress and anxiety on five different levels of severity. The training and test sets were split in a 70:30 ratio. The confusion matrices presented in Table 4 were created by applying all five approaches, Decision Tree, Random Forest Tree, Nave Bayes, Support Vector Machine, and K-Nearest Neighbor, to the sub scales, Stress, Anxiety, and Depression. The actual classes are shown in the rows of the table, while predicted ones are shown in the columns. In the rows and columns, the numbers 1, 2, 3, 4, and 5 denote the levels of severity of depression, stress and anxiety. The class parameters achieved by machine learning algorithms are shown in Table 5. The maximum accuracy for all three measures was reached by the support vector machine, as shown in the table. The f1 score was also highest for support vector machine. For our model, SVM is most efficient because it works effectively when there is a clear line of demarcation between classes.

Table 4 Confusion matrices table

		Depression					Stress					Anxiety				
Decision tree		**1**	**2**	**3**	**4**	**5**	**1**	**2**	**3**	**4**	**5**	**1**	**2**	**3**	**4**	**5**
	1	23	0	1	0	5	35	0	3	0	3	22	1	0	0	3
	2	0	12	1	0	0	0	17	0	0	0	0	8	1	7	0
	3	1	4	10	0	2	0	0	22	0	0	2	1	11	1	1
	4	0	0	0	168	0	0	0	0	148	0	0	2	0	161	0
	5	1	1	2	0	2	0	0	0	0	5	2	1	4	0	5
Random forest		**1**	**2**	**3**	**4**	**5**	**1**	**2**	**3**	**4**	**5**	**1**	**2**	**3**	**4**	**5**
	1	24	0	1	0	0	36	0	0	0	1	28	0	1	0	2
	2	36	0	0	0	1	0	32	0	2	0	0	4	0	5	0
	3	0	32	0	2	0	0	3	17	0	1	0	5	12	1	1
	4	0	0	0	135	0	0	0	0	135	0	0	2	0	166	0
	5	0	0	1	0	5	0	0	1	0	5	2	0	2	0	2
Naïve Bayes		**1**	**2**	**3**	**4**	**5**	**1**	**2**	**3**	**4**	**5**	**1**	**2**	**3**	**4**	**5**
	1	22	0	0	6	0	27	0	0	11	0	8	0	0	25	0
	2	1	0	0	16	0	2	0	0	25	0	0	0	0	11	0
	3	4	0	0	15	0	3	0	0	14	0	0	0	0	17	0
	4	1	0	0	158	0	0	0	0	138	0	0	0	0	157	0
	5	4	0	0	6	0	2	0	0	11	0	0	0	0	15	0
Support Vector Machine		**1**	**2**	**3**	**4**	**5**	**1**	**2**	**3**	**4**	**5**	**1**	**2**	**3**	**4**	**5**
	1	29	0	0	0	1	38	0	0	0	4	38	0	0	0	1
	2	0	13	2	1	0	0	21	0	0	0	0	6	0	1	0
	3	0	1	12	0	1	0	0	10	0	0	0	0	13	0	1
	4	0	1	0	165	0	0	0	0	151	0	0	0	0	165	0
	5	3	0	0	0	4	0	0	0	0	9	2	0	1	0	5
kNN		**1**	**2**	**3**	**4**	**5**	**1**	**2**	**3**	**4**	**5**	**1**	**2**	**3**	**4**	**5**
	1	24	0	2	0	2	36	1	2	0	6	29	0	0	0	4
	2	0	12	1	3	0	0	12	0	0	0	0	2	1	8	0
	3	0	5	7	0	3	0	5	13	0	1	0	4	7	4	2
	4	0	1	0	170	0	0	0	0	150	0	0	3	0	159	0
	5	0	0	1	0	2	2	2	2	0	1	1	0	4	0	5

Table 5 Parameters of machine learning algorithms applied to DASS data

	Accuracy	Error Rate	Precision	Recall	F1 Score
		Decision Tree			
Depression	0.923	0.077	0.945	0.921	0.932
Anxiety	0.936	0.074	0.942	0.941	0.943
Stress	0.946	0.064	0.943	0.943	0.944
		K Nearest Neighbor			
Depression	0.911	0.089	0.914	0.924	0.912
Anxiety	0.940	0.060	0.932	0.943	0.936
Stress	0.954	0.046	0.961	0.957	0.951
		Naïve Bayes			
Depression	0.824	0.176	0.727	0.823	0.776
Anxiety	0.819	0.181	0.741	0.822	0.762
Stress	0.892	0.108	0.803	0.894	0.846
		Support Vector Machine			
Depression	0.949	0.051	0.949	0.947	0.948
Anxiety	0.978	0.022	0.986	0.984	0.988
Stress	0.974	0.026	0.994	0.978	0.982
		Random Forest			
Depression	0.939	0.061	0.941	0.943	0.942
Anxiety	0.927	0.073	0.931	0.934	0.926
Stress	0.914	0.086	0.923	0.916	0.911

5. Conclusion

Given that the majority of the worldly population is exhibiting stress-related symptoms post COVID-19, the suggested approach for predicting and preventing mental health issues is crucial. Health officials can identify patients more promptly and correctly if they have the necessary conditions for early prediction and prevention of mental health issues. In this paper, psychological health of Rajyoga meditators was compared with that of non-meditators. As seen in the study, the Rajyoga meditation intervention proved to be a promising tool to make the meditators more resilient towards the pandemic as compared to the non-meditators. Five separate severity degrees of mental health disorders were determined with the use of machine learning algorithms to devise the prediction of early warning indicators and risk factors for prevention of mental health issues of global population. The future studies may include the acquisition of more trustworthy objective predictors for analyzing early warning risks in vulnerable population.

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