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Improving quality of life through brain-computer interfaces: an integrated stress prediction method using machine learning

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ABSTRACT

In recent days, people must deal with stress brought on by the demands of modern living, which constantly presents new obstacles. Stress, a state of mental tension triggered by challenging circumstances, has become a global risk factor impacting individual well-being. Understanding variations in stress resilience is crucial for tailoring treatment strategies. Previous studies have explored stress prediction using measures like electroencephalography (EEG), blood pressure (BP), heart rate (HR), and interventions such as Kriya Yoga and mindfulness meditation. The experimentation is done on the data collected from people who practice heartfulness meditation regularly. The research employs machine learning (ML) algorithms alongside physiological parameters such as EEG, BP, HR, and psychological parameters, perceived stress scale (PSS), to precisely classify, measure, and predict stress levels. The investigations are done using K-nearest neighbor (KNN), random forest (RF), and kernel-support vector machine (k-SVM). An accuracy of 98.27% accuracy was achieved with the RF algorithm in classifying stressed and non-stressed individuals.

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1. INTRODUCTION

In recent days, human beings have suffered from stress for many reasons such as financial stability, and work pressure, family responsibility. The growing prevalence of mental health disorders and the need for advanced technologies to assist in early detection and management. Mental health issues related to stress disorders have become a significant global concern affecting millions of individuals worldwide. As depicted in Figure 1, 34% of people across the world feel that they are stressed, and 31% of people feel stressed as they cannot deal with things [1]. Like the global scenario, in India also the fast-paced modern lifestyle, high work demands, academic pressures, and competitive environments often contribute to elevated stress levels among individuals. Additionally, factors such as socioeconomic challenges, urbanization, and digitalization have added complexity to the stress landscape in India. Stress is characterized as a condition of anxiety or mental tension brought on by a challenging circumstance. Stress is a normal human reaction that motivates us to deal with problems and dangers in our lives. Everyone goes through periods of stress [2]. As a complex relationship of physiological, cognitive, and emotional responses to external pressures, stress poses significant challenges to both individual well-being and public health systems [3]. Predicting stress levels in individuals is crucial for early intervention and prevention of stress-related health issues like anxiety, depression, and cardiovascular diseases. Identifying stress using various parameters involves assessing physiological, behavioral, and psychological indicators. Physiological parameters commonly used to identify stress are the electroencephalograph (EEG), a technique for capturing an electrogram of the brain's spontaneous electrical activity [4]. Blood pressure (BP), a measure of the degree to which the heart must pump to circulate blood throughout the body [5], the count of times a heart beats in a minute is known as heart rate (HR) [6]. Implementing personalized stress management strategies based on these predictions can significantly improve the mental and physical well-being of the population, leading to a healthier and more resilient society. The integration of brain-computer interfaces (BCIs) with machine learning (ML) algorithms offers a promising approach to predicting and managing stress levels, thereby improving the overall quality of life for individuals [7].

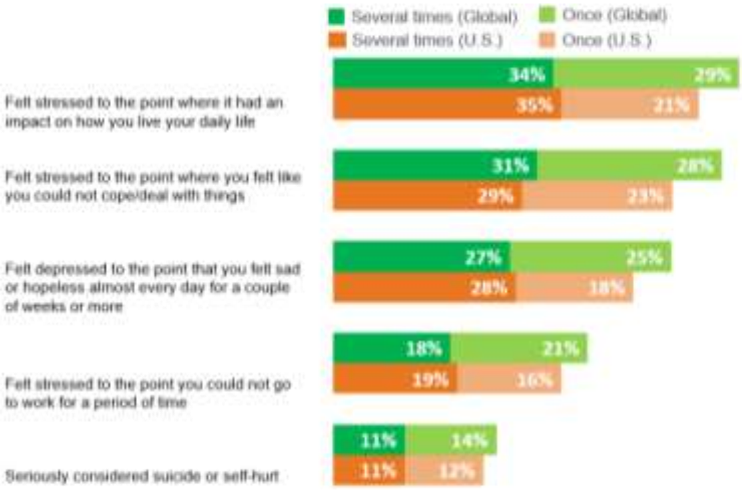


Figure 1. Percentage of people across the globe who experienced stress or stress related disorders in 2022 [1]

Psychological parameters along with physiological parameters are crucial to understand and analyze stress. These variables offer insightful information on the complex interplay of a person's cognitive, emotional, and physiological reactions to stressors. Additionally, these factors make it easier to identify groups at risk, evaluate the efficiency of stress therapies, and create customized stress management plans [8]. Fundamentally, the research of psychological variables in stress analysis is crucial for expanding our comprehension of this complicated phenomenon and as a result, for developing successful strategies to lessen its negative impact on people's well-being and quality of life.

Effective stress management requires using strategies to enhance both mental and physical health. By concentrating on breathing and attention, the potent practice of meditation promotes profound relaxation and mental clarity. Regular exercise releases endorphins, the body's natural stress relievers, such as aerobic exercises or yoga. Many researchers and healthcare professionals can use data analytics, ML, and wearable technology to develop predictive models and identify individuals at risk of high stress levels. Numerous studies have been carried out to evaluate or lessen stress by examining the signals associated with the heart and brain. Researchers have created the datasets by stimulating neurons to determine the predominant current flow captured in an EEG that mimics human comprehension. These studies gained strength after 1970. To facilitate communication, the Wadsworth Centre in New York [9] developed the BCI. It was very expensive, could only be used by specialists, and required invasive techniques. The electrodes are positioned beneath the scalp. Headsets, comparably less expensive and user-friendly, have been accessible since 2012 [10]. Alpha, beta, theta, gamma, and delta are only a few of the signals that the brain produces [11]-[15]. Conclusions regarding the brain are drawn from each of these signals.

Traditional approaches to stress assessment, often struggle to capture the complicated and dynamic nature of stress experiences. The use of ML techniques in this context has become a promising avenue for advancing stress prediction and management [16]. ML, a subcategory of artificial intelligence, empowers researchers and practitioners to extract meaningful insights from intricate and diverse datasets. Potential usage of algorithmic models on several data sources including physiological signals, behavioral patterns, social interactions, and contextual information, unveils hidden patterns and correlations that rise above human perception [17]. Including ML techniques in stress prediction models holds the promise of enhancing accuracy, objectivity, and early detection, thereby transforming the field of mental health assessment [18]. This research seeks to comprehensively explore the landscape of ML applications in stress prediction among humans. Previous researchers have worked on stress prediction using either of the indicators such as EEG, BP, HR, and therapies like transcendental meditation and mindfulness meditation. The proposed work is based on data acquired from individuals who frequently practice heartfulness meditation. The subjects were made to undergo tasks that artificially induced stress. The data was collected before the task, after the task, and after the relaxation meditation which lasted for 15 minutes. To correctly categorize, measure, and predict stress levels, the study uses ML algorithms in conjunction with physiological measures such as EEG, BP, and HR, as well as a psychological component known as the perceived stress scale (PSS). The investigations employ K-nearest neighbor (KNN), random forest (RF), and kernel-support vector machine (k-SVM). The paper is split into 4 sections. The focus of section 2 is on the work's approach and the ML methods employed. The work's results and discussions are reported in section 3. In section 4 concludes the paper.

In the rapidly evolving landscape of technological innovation, the synergy between ML and the complicated world of human emotions has led to a paradigm shift in the study of stress prediction, fostering new avenues for enhancing well-being and quality of life. The literature survey provides a comprehensive overview of research studies examining the impacts of different ML techniques on various aspects of mental well-being. Beck *et al.* [19] focus on the development and validation of an instrument, the depression inventory, to measure the behavioral manifestations of depression. The study involved two patient samples: an original group of 226 patients and a replication group of 183 patients. The instrument was administered after collecting background data, conducting intelligence tests, and eliciting relevant ideational material. They used statistical analyses, including the Kruskal-Wallis test and Mann-Whitney U test to evaluate the instrument's effectiveness in discriminating between different levels of depression. Differences in depression severity categories were found to be significant, except for one category, indicating the instrument's ability to discriminate between levels of depression effectively. The work in [20] explores the structure of coping strategies using a hierarchical factor analysis approach. The study aims to identify primary, secondary, and tertiary factors within coping strategies to provide a comprehensive understanding of how individuals cope with stress. The study utilized the coping strategies inventory (CSI) to assess coping strategies. A total of 88 items were selected for the initial study. The hierarchical factor analysis method by Wherry was employed to analyze the data. The study conducted three separate studies to explore the coping structure. The hierarchical factor analysis involved a rotational procedure to examine complex theoretical constructs. Factor extractions were performed using a varimax rotation to identify primary, secondary, and tertiary factors. The study also assessed factor invariance and reliability of the hypothesized subscales across different samples. The study identified a hierarchical factor structure with three levels for the coping strategies inventory. At the primary level, eight coping strategies were identified, including problem-solving, cognitive restructuring, social support, express emotions, problem avoidance, wishful thinking, social withdrawal, and self-criticism. These primary factors were organized into problem-focused and emotion-focused coping activities at the secondary level. At the tertiary level, coping strategies were categorized into engagement and disengagement approaches for managing stressful situations. The findings supported the theoretical hypotheses about the hierarchical structure of coping and provided empirical evidence for the relationships among coping constructs.

Brantley *et al.* [21] focuses on the creation and validation of the daily stress inventory (DSI), a self-report measure designed to assess daily stressors and their impact on individuals. The study utilized a sample of undergraduate college students and nonstudent adults to develop and validate the DSI. The DSI consists of 58 items where individuals report events experienced in the past 24 hours and rate their stressfulness on a Likert scale. Three daily scores such as number of events (FREQ), total impact rating (SUM), and average impact rating (AIR) are derived. Normative data was collected from nonstudent adults in Baton Rouge, Louisiana. Participants completed daily measures of stress, anxiety, and global stress ratings over 28 days. The DSI demonstrated reliability and validity in assessing daily stress levels. The SUM score showed consistent relationships with concurrent measures of stress and anxiety. The AIR score was related to concurrent stress measures and daily anxiety. The FREQ score was least predictive of anxiety but related to some concurrent stress measures. Divergent validity was supported as DSI scores did not correlate with state measures of uplifts and hostility. The study highlighted the need for further exploration of the factor structure of the DSI and the development of norms for long-term use.

Folkman [22] discusses stress, appraisal, and coping within the framework of behavioral medicine research. It explores how individuals perceive and respond to stressors, emphasizing the importance of appraisal and coping strategies in influencing health outcomes. The study highlights Richard Lazarus' stress and coping theory, which defines stress as a relationship between the person and the environment that exceeds coping resources. Methodologically, the paper suggests that understanding stress, appraisal, and coping involves assessing individuals' perceptions of stressors, their appraisal of the situation, and the coping strategies they employ. Researchers can use various measures to evaluate stress levels, appraisal processes, and coping mechanisms, such as self-report questionnaires, interviews, and behavioral observations.

By examining these parameters, researchers can gain insights into how individuals interpret and manage stress in their daily lives. In terms of results, the paper underscores the dynamic nature of stress, appraisal, and coping processes. It highlights the variability in individuals' responses to stressors based on their appraisal and coping strategies. The study emphasizes the importance of considering individual differences in resources, experiences, and coping skills when examining the impact of stress on health outcomes. Overall, the paper emphasizes the significance of stress and coping theory in understanding the complex interplay between stress, appraisal, coping, and health. Thieme *et al.* [23] focus on the application of ML in mental health. The study analyzed 54 papers published between 2000 and 2019 to understand the trends, gaps, and challenges in this field. The review corpus included papers on ML applications in mental health. Publications were analyzed based on their main research contributions, ML techniques used, evaluation approaches, data sources, target mental health behaviors, and target users. The study considered the types of ML algorithms applied, data processing steps, data access, data subjects, data scale, and ethical considerations. A systematic review approach was employed to analyze the selected papers. Data extraction was conducted using a structured data extraction sheet, which included information on authors, affiliations, publication type, ML applications, motivations, data sources, target users, data challenges, ML algorithms, evaluation approaches, research insights, and ethical issues.

Tindle *et al.* [24] pilot-tested the data extraction sheet on a subset of papers to ensure consistency and accuracy in data extraction. The analysis focused on identifying trends in ML applications for mental health, highlighting the main contributions of the reviewed papers, and discussing challenges and ethical considerations in this domain. The review identified an increasing trend in the number of ML mental health publications over time. Most papers primarily described the development of ML models based on specific data as their main research contribution. Common ML techniques used included supervised learning (SL) algorithms such as SVM, RF, decision trees (DT), and logistic regression (LR). Evaluation of developed ML models often relied on aggregate metrics like accuracy, AUC, and mean square error, with limited exploration of model performance across different population groups. The study emphasized the importance of ensuring that ML models capture the complexity of the real world and avoid under-representing certain groups to enhance generalizability and effectiveness in real-world applications. Wang *et al.* [25] utilized smartphone sensor data to assess the impact of workload on stress, sleep, activity, mood, and academic performance among college students. The methodology involved collecting data through the StudentLife app, administering surveys, and analyzing smartphone sensor data to correlate with mental health and academic outcomes. Results showed significant correlations between smartphone sensor data, such as conversation duration and indoor mobility, and academic performance metrics like GPA. The study identified a term lifecycle reflecting changes in student behavior throughout the academic term. However, the research acknowledged limitations in determining causality and addressing potential confounding factors such as campus adjustment or health issues, indicating a need for further investigation into the complex interplay between workload, stress, and academic success.

Vividha *et al.* [26] utilized physical activity tracker device data, cardiac rate, and electrocardiogram (ECG) data as criteria for stress detection. The techniques used a ML approach to identify stress levels, evaluate stressors individually using ML models, build a NN model, and assess using ordinal LR models such as logit, probit, and complementary log-log. ML models were utilized to identify stress levels based on real-time data from an internet of things (IoT) device (sensor). IoT was also utilized to notify or alert people about their state of stress. The findings showed how to predict stress levels based on cardiac rate and ECG data, and how to identify cognitive stress levels using data from physical activity trackers. Real-time identification of stress levels using an IoT device was also achieved. Gonzalez-Carabarin *et al.* [27] conducted experiments on 24 healthy bachelor students to evaluate acute stress responses using EEG and ECG signals. The methodology involved inducing stress through various tests and analyzing the signals to assess individual stress levels. EEG and ECG data were processed using unsupervised clustering and SL techniques to classify stress and non-stress periods. Results showed variability in stress responses among subjects, with the potential for personalized stress detection. However, the study lacked a comparison with existing stress assessment methods and did not explore the long-term implications of chronic stress. Further research could focus on validating the proposed metrics and integrating them into real-time monitoring systems for preventive healthcare interventions.

Sharma *et al.* [28] conducted a review on SL and soft computing (SC) techniques for stress diagnosis in humans encompassing various parameters such as EEG signals, HR, skin temperature, and galvanic skin response for stress diagnosis. The methodology involved a three-tier approach of manuscript selection, data synthesis, and analysis, leading to the extraction of 168 peer-reviewed articles on stress diagnosis using SL and SC techniques. The results highlighted the prevalence of stress globally, the impact of stress on various bodily systems, and the effectiveness of SL and SC techniques in stress diagnosis. However, gaps in the research were identified, including the subjective nature of stress diagnosis, challenges in designing person-specific diagnostic models, and the need for further exploration of hybrid nature-inspired computing techniques and feature selection methods for precise stress diagnosis. Agrawal *et al.* [29] on early stress detection using EEG signals incorporate various parameters such as accuracy, precision, sensitivity, and specificity to evaluate the performance of different ML algorithms. The methodology involves placing electrodes on the scalp to capture EEG signals, preprocessing the data to remove artefacts, and extracting features using fractal analysis techniques like Higuchi, Katz, and Permutation Entropy. The study compares classic ML algorithms like SVM, NB, and KNN with neural network algorithms, highlighting the superior performance of neural networks in stress detection. Results show that neural network algorithms achieve higher accuracy and precision compared to classic ML algorithms. However, gaps in the research include the need for further exploration of feature extraction methods and the optimization of classification algorithms for more accurate stress detection and analysis. Priya *et al.* [30] focused on predicting anxiety, depression, and stress using ML algorithms. The study involved 348 participants aged between 20 and 60, who completed the Depression, Anxiety, and Stress Scale questionnaire. Five ML algorithms: DT, RF tree, Naïve Bayes (NB), SVM, and KNN were applied to classify the data. The results indicated that NB had the highest accuracy, while RF was identified as the best model overall. Important variables such as 'Scared_without_any_good_reason', 'Life_was_meaningless', and 'Difficult_to_relax' were highlighted for detecting psychological disorders. However, the research did not delve into the specific reasons behind the effectiveness of these variables or explore potential biases in the data collection process, suggesting a gap in the study that could be addressed in future research.

2. METHOD

Evaluation of stress in human beings can be predicted using a combination of physiological and psychological measures such as BP, HR, PSS, and EEG. The process involved in the work undertaken is as follows.

2.1. Data collection process

130 regular meditators were involved in the experimentation. The process of data collection is shown in Figure 2. Vital parameters such as HR, BP, and EEG readings were acquired with wearable devices. The device Open BCI is employed in the work to capture the brain signals in real-time. The open BCI boards use ordinary EEG electrodes to record and process electrical signals from the brain, muscles, and heart [31]-[33]. These boards include integrated circuits (ICs) for bio-potential measurements, such as Texas Instruments' ADS1299 [34]. The architecture of Open BCI is shown in Figure 3. An 8-channel open BCI device was used to record the EEG.

Figure 2. Data collection procedure

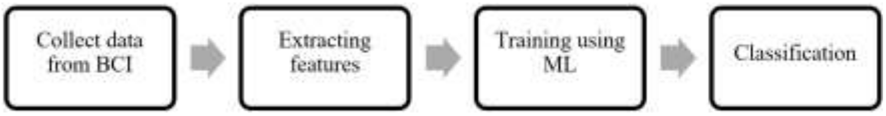
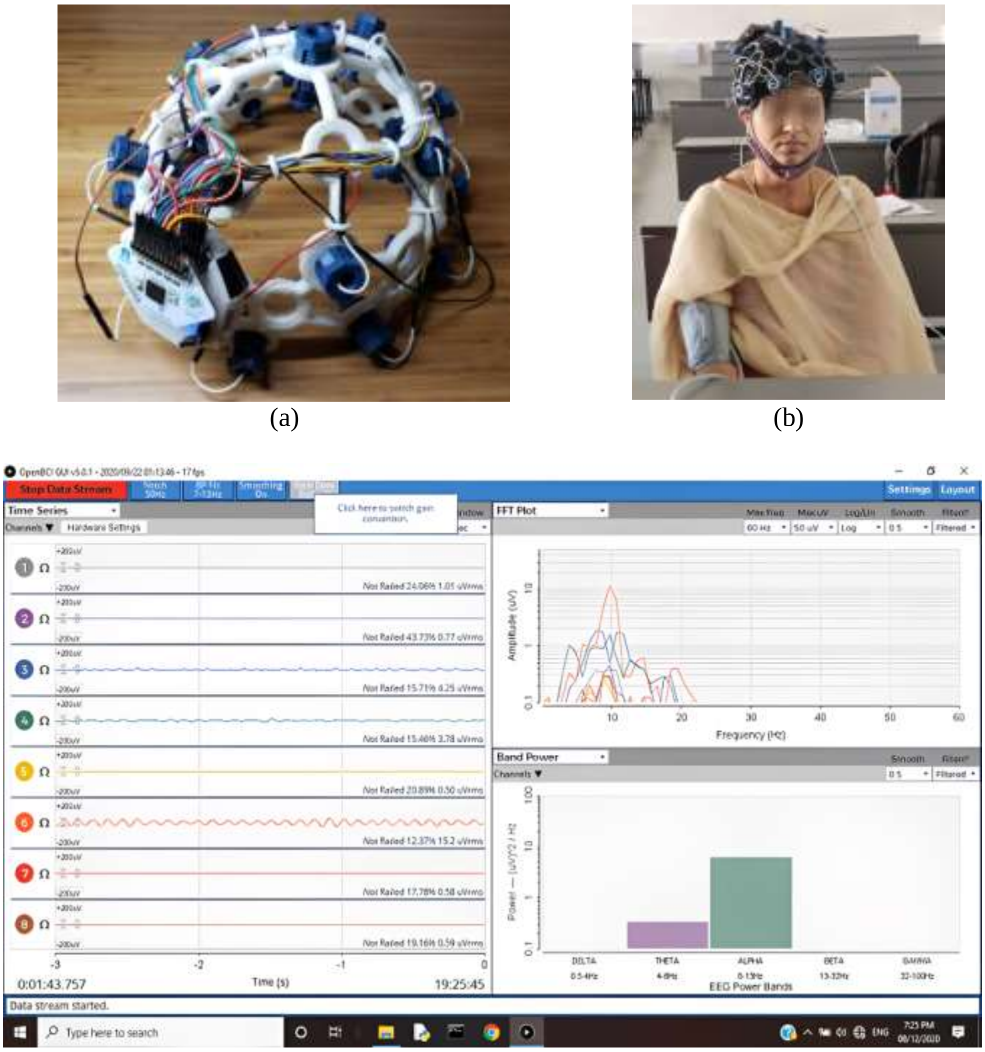


Figure 3. Open BCI architecture

Individuals were stimulated with tasks that induced stress. The techniques used to induce stress were, solving mathematical problems, identification of differences, and participating in memory-based activities. Firstly, participants were presented with four to five arithmetic questions. The allotted time for individuals was two minutes, to find solutions to the problems. A stopwatch was positioned before them to induce anxiety. Secondly, a grid-formatted display of ten to fifteen images was displayed to the participants. The participants had thirty seconds to memorize the pictures. A random image from the grid was shown after 30 seconds, and participants had 15 seconds to determine the position of the image in the grid. Lastly, Participants were presented with two photos with four slight variations. In thirty seconds, they had to name every difference. A time shout-out was used to divert the participants every ten seconds. In this manner, the subjects were made to feel stressed, and information was gathered. Participants engaged in a 15-minute heartfulness relaxation exercise after completion of aforesaid tasks and the vital parameter measurements were taken.

The PSS is a widely used self-report survey that assesses individuals' perceptions of stress. The PSS assesses how much people think their life circumstances are stressful as well as how well they believe they can handle these stressors [35]. The PSS is made up of multiple items that ask participants to rate how often and how intensely they experienced stress-related thoughts and feelings over the previous month. PSS-10 questionnaire consisting of predefined questions about how individuals felt about a particular circumstance [36] is used for the work. Table 1 depicts the data of BP, HR, and PSS. The data is obtained thrice during the experiment: before the task, after the task, and after meditation. Table 2 shows a sample EEG dataset collected. Figure 4 shows the device, experimental setup and a view of GUI used in the study. The EEG data is gathered from an 8-channel noninvasive open-source headset called open BCI ultra cortex Mark IV as shown in Figure 4(a). Figure 4(b) shows the experimental setup and the Figure 4(c) depicts the Open BCI GUI which was used for the collection and simulation of the EEG data. The device which used a fixed sample rate of 250 Hz [37]. The column 2-8 is the EEG values obtained from the electrodes placed at 8 different spots on the scalp. The placement of the electrodes was made in a standard 10-20 electrode placement system [38].



(a) (b)

(c)

Figure 4. Devices and experimental setup used in the study; (a) open BCI ultra cortex mark IV, (b) experimental setup, and (c) open BCI GUI

Table 1. Sample data set of vital parameters

Age	Gender	Before task Systolic BP (mmHg)	Before task Diastolic BP (mmHg)	Before task Heart rate (bpm)	After task Systolic BP (mmHg)	After task Diastolic BP (mmHg)	After task Heart rate (bpm)	After relaxation meditation Systolic BP (mmHg)	After relaxation meditation Diastolic BP (mmHg)	After relaxation meditation Heart rate (bpm)	PSS
17	M	123	71	75	143	89	92	134	86	85	14
17	F	145	79	72	133	88	98	135	81	74	5
36	M	154	98	81	131	100	90	136	83	70	25
37	F	137	85	88	141	88	86	137	82	83	23
59	M	157	77	85	142	97	93	123	82	83	17
59	M	136	100	80	138	97	102	120	82	82	27

Table 2. Sample EEG data collected

Time	EXG Channel 0	EXG Channel 1	EXG Channel 2	EXG Channel 3	EXG Channel 4	EXG Channel 5	EXG Channel 6	EXG Channel 7
15:52.2	7250.449695	7279.466455	7285.360403	7339.457797	-18382.56263	7350.959481	-21301.4653	-28511.46832
15:52.8	6912.754875	6941.661837	6947.458915	7001.394263	-16261.36139	7013.994283	-23990.32422	-27578.3411
15:53.3	6929.447343	6958.352039	6964.132975	7018.067542	-16305.65024	7030.698682	-23986.53734	-27526.09388
15:53.8	6933.191026	6962.124734	6967.86387	7021.763155	-16338.43099	7034.462201	-23986.23733	-27486.90815
15:53.8	6940.990112	6969.978581	6975.667509	7029.587261	-16358.11623	7042.213867	-23983.38353	-27461.85137

2.2. Stress level indicator algorithm (SLI algorithm)

a) The work records EEG, BP, HR, and PSS from 130 subjects before the tasks, after the tasks, and after meditation.
b) With the use of the 10-fold cross-validation technique, statistical characteristics are retrieved and used to train the RF, SVM, and KNN algorithms to categorize stress levels.
c) Categorization of stress is based on the threshold values of parameters as shown in Table 3 [39], [40].
d) Less stressed, moderately stressed, and extremely stressed stress levels are defined in the research based on the HR, BP, EEG, and PSS score values.
e) A confusion matrix is obtained, which aids in the analysis and evaluation of performance metrics including sensitivity, precision, accuracy, and specificity. The performance metrics are computed utilizing (1) to (4)

$$\text{Sensitivity} = \frac{TP}{TP+FN} \tag{1}$$

$$\text{Specificity} = \frac{TN}{TN+FP} \tag{2}$$

$$\text{Precision} = \frac{TP}{TP+FP} \tag{3}$$

$$\text{Accuracy} = \frac{(TP+TN)}{(TP+TN+FP+FN)} \tag{4}$$

Where TP is (true positive), TN is (true negative), FP is (false positive), and FN is (false negative).

Table 3. Threshold values of parameters

Categorization	Threshold
Less stressed	Systolic BP: 120-129 mmHg Diastolic BP: <80 mmHg HR: 70-90 bpm PSS: 0-13
Moderately stressed	Systolic BP: 130-139 mmHg Diastolic BP: 80-89 mmHg HR: 90-100 bpm PSS: 14-26
Highly stressed	Systolic BP: >140 mmHg Diastolic BP: >90 mmHg HR: >100 bpm PSS: >26

2.3. Machine learning algorithms

The work utilizes the application of ML algorithms, specifically SVM, RF, and KNN, in predicting stress levels using EEG, BP, HR, and PSS data sets. SVM is utilized for stress classification by training a model with the data and employing various kernel functions such as RBF. RF combines DT to create a forest for stress prediction [25], [41], while KNN assigns data to groups based on nearest neighbors [42]. The algorithms are evaluated based on performance metrics like precision, recall, specificity, and accuracy to assess their effectiveness in classifying individuals into different stress categories. The study highlights the significance of using RF in predicting stress levels due to its ability to handle complex data sets effectively and provide reliable predictions [28]. Additionally, the SVM algorithm leverages EEG, BP, HR, and PSS data to classify stress levels by training a model on the input data sets and utilizing different kernel functions. The RF algorithm is significant in predicting stress levels due to its ability to handle complex and high-dimensional data sets effectively. RF is a powerful ensemble learning method that combines multiple DT to create a robust predictive model. By aggregating the predictions of individual DT, RF can capture intricate relationships and interactions within the data, making it well-suited for tasks like stress classification where multiple variables (such as EEG, BP, HR, and PSS data) may influence the outcome. Additionally, RF is less prone to overfitting compared to a single DT, providing more reliable and generalizable predictions. Its flexibility in handling various types of data and its capability to handle missing values make RF a valuable tool in predicting stress levels accurately and efficiently.

3. RESULTS AND DISCUSSIONS

The study explores the use of psychological and physiological markers to predict human stress levels. It discovered that the accuracy of predicting stress levels using a combination of EEG, BP, HR, and PSS is higher than that of prior research. With an accuracy rate of up to 98%, the suggested approach is more advanced than previous studies. The application of ML techniques for stress prediction was also investigated in this work. However, additional research may be required to consider additional factors such as body temperature, respiration rate, and galvanic skin response (GSR). Subsequent studies could investigate the utilisation of a group of ML algorithms or deep learning methods to forecast stress levels instantaneously. According to recent discoveries, ML algorithms such as SVM, KNN and RF can be used to predict the stress levels of humans with a higher accuracy.

3.1. Scenario 1: experimentation before tasks

The performance metrics such as specificity, sensitivity, precision, and accuracy are measured for the data collected in three phases: before the tasks, after the tasks, and after heartfulness relaxation meditation. Figure 5 represents the performance of the algorithms and ROC curve of algorithms in dataset collected before task. Figure 5(a) represents the performance of the algorithms on the data set before tasks. It is observed that the classifier is useful since the specificity and precision are high and sensitivity is lesser. Changing the size of test data has no considerable increase in the sensitivity value which means the algorithm is working well with the data set. The average accuracy of the SVM algorithm before tasks is 96%. The performance of the RF algorithm on the dataset collected before tasks in terms of specificity, sensitivity, and precision values are high indicating the algorithm is best suited for the application. The mean accuracy of the algorithm is observed to be 97.63%. The KNN algorithm performs considerably well with the test percentage being 10% and 20%. With the increase in the percentage of test data to 30%, there is a decrease in the sensitivity of the algorithm. The mean accuracy of the KNN algorithm is observed to be 96.8% in this case. The area under the curve (AUC) of RF is 0.99, KNN is 0.96 and SVM is 0.96 as shown in Figure 5(b). This indicates the RF algorithm classifies the data more efficiently when compared with SVM and KNN.

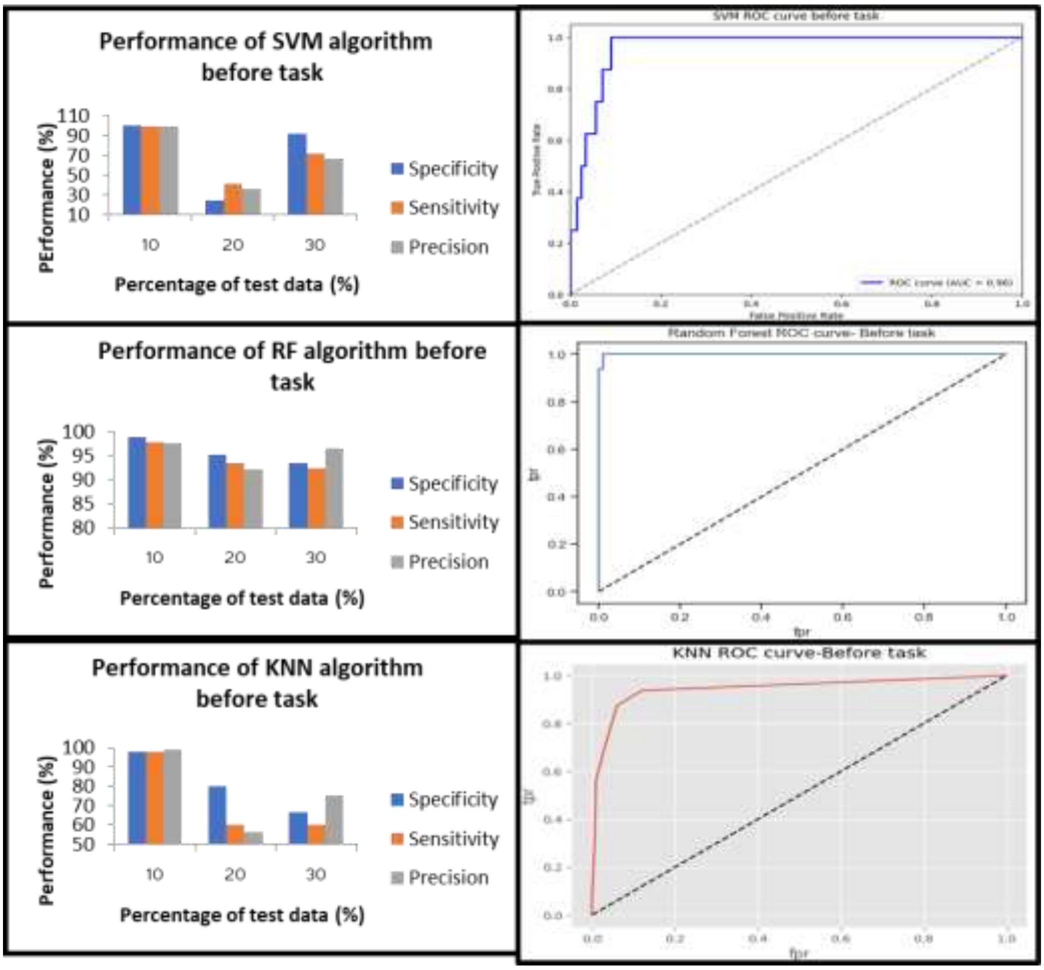
3.2. Scenario 2: experimentation after the tasks

The values in Figure 6 represents the performance of the algorithms and ROC curve of algorithms in dataset collected after task. Figure 6(a) represent the performance of the algorithms on the data set after the tasks. It is observed that SVM classifier is useful since the specificity and precision is high and sensitivity is lesser. There is no considerable increase in the sensitivity value on change in the size of test data which means the algorithm is working well with the data set. The average accuracy of the SVM algorithm before tasks is 81.81%. The specificity, sensitivity and precision values of RF are high indicating the algorithm is best suited for the application. The mean accuracy of the RF algorithm is measured to be 98.59%. The KNN algorithm performs considerably well with the dataset. With the increase in percentage of test data, there is a slight increase in the sensitivity and specificity of the algorithm and the value for precision decreases with increase in the percentage of test data. The accuracy of KNN algorithm is observed to be 92.56% in this case. AUC of RF is 0.99, KNN is 0.95 and SVM is 0.88 as shown in Figure 6(b). This indicates the RF algorithm classifies the data more efficiently when compared with SVM and KNN.

3.3. Scenario 3: experimentation after the heartfulness relaxation meditation

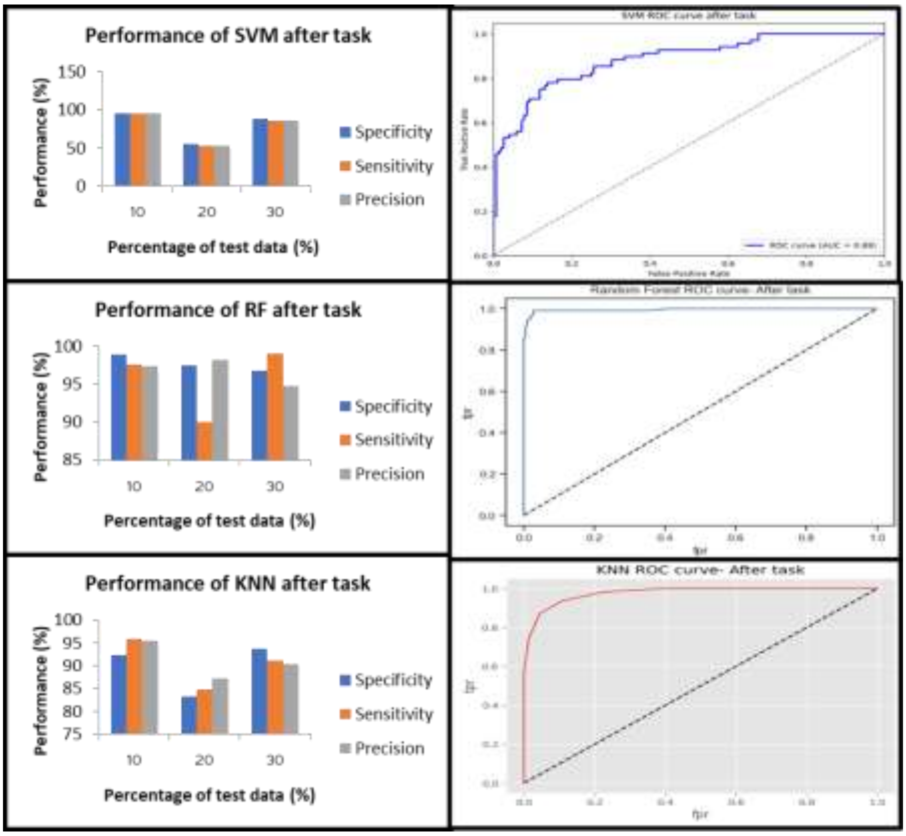
The values in Figure 7 represents the performance of the algorithms and ROC curve of algorithms in dataset collected after meditation. Figure 7(a) represent the performance of the algorithms on the data set after the meditation. The SVM classifier is not useful since the specificity is high and precision and sensitivity are lesser. The average accuracy of the SVM algorithm after the tasks is 92.27%. The specificity, sensitivity, and precision values of RF algorithm is high indicating the algorithm is best suited for the application. The mean accuracy of the algorithm is measured to be 98.59%. The KNN algorithm performs considerably well with the dataset. With the increase in the percentage of test data, there is a slight increase in the sensitivity and specificity of the algorithm and the value for precision decreases with the increase in the percentage of test data. The accuracy of the KNN algorithm is observed to be 92.56% in this case. The AUC of RF is 0.99, KNN is 0.96 and SVM is 0.96 as shown in Figure 7(b). This indicates the RF algorithm classifies the data more efficiently when compared with SVM and KNN. Considering all the average performance of the SVM, RF, and KNN algorithms in the different scenarios, it is observed that the SVM has an average accuracy of 90.02%. The RF algorithm shows an accuracy of 98.27% while KNN has an accuracy of 93.97%. This shows that the RF algorithm outperforms with a mean accuracy of 98.27% and classifies the data as stressed or not stressed efficiently.

Table 4 represents a comparative analysis of the proposed method and other existing techniques for the classification of stress levels. Most researchers have worked using either physiological or psychological parameters. The proposed method considers both physiological and psychological parameters to classify stress levels and is found to be a better classification model.



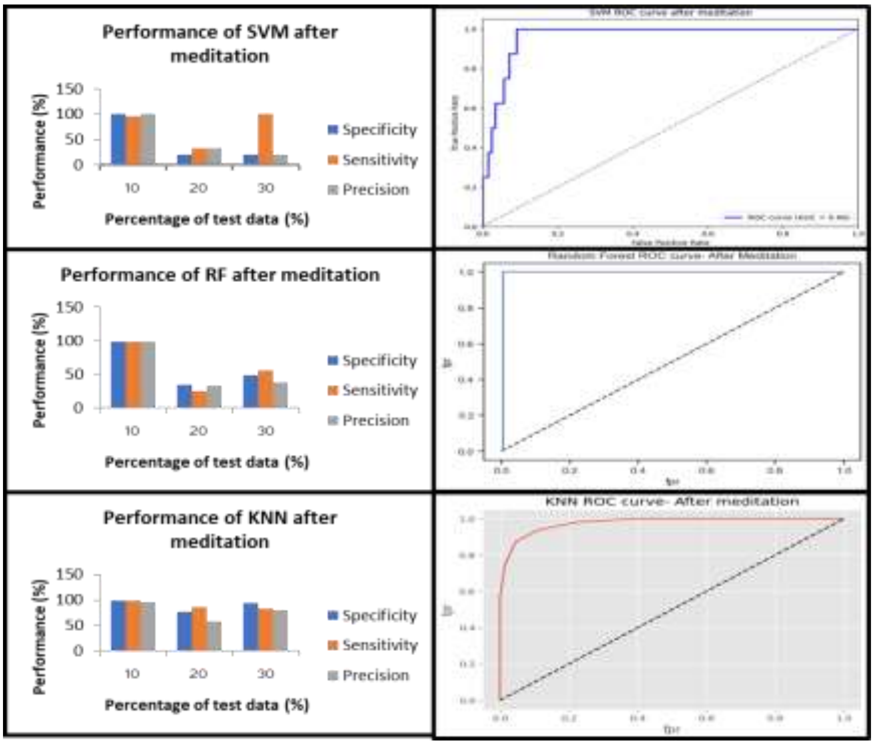
(a) (b)

Figure 5. Performance results of (a) algorithms before task and (b) ROC curve of algorithms before task



(a) (b)

Figure 6. Performance results of (a) algorithms after tasks and (b) ROC curve of algorithms after task



(a) (b)

Figure 7. Performance results of (a) algorithms after meditation and (b) ROC curve of algorithms after meditation

Table 4. Comparison of stress classification results of existing techniques with the proposed method

Authors	Parameters used	Classifier employed	Accuracy (%)
Mazlan *et al.* [43]	EEG	KNN, NB, multilayer perceptron (MLP)	99
Rao *et al.* [44]	PSS	SVM, KNN, NB	95.32
Nirabi *et al.* [45]	EEG	SVM, KNN, NB, linear discriminant analysis (LDA)	86.3
Rastgoo *et al.* [46]	ECG signals,	Convolution neural network (CNN), long short-term memory (LSTM)	92.8
SLI algorithm (proposed method)	EEG, BP, HR, PSS	SVM, RF, KNN	98

4. CONCLUSION

An individual's perceived inability to cope with demands from the outside world causes stress, which appears as a variety of physical, emotional, and behavioral symptoms. The results of this research highlight the significance of proactive stress identification and management. The identification of psychological concerns like stress is made possible by deploying ML algorithms for the precise assessment and prediction of stress levels. The proposed SLI algorithm utilizes most of the psychological parameters like PSS and physiological parameters such as EEG, BP, and HR to classify stress levels. The work considers ML techniques like KNN, RF, and k-SVM algorithm to indicate the stress levels. SVM, RF, and KNN have demonstrated accuracy values as high as 90.02%, 98.27%, and 93.97%, respectively, highlighting their ability in the domain of stress analysis. It is observed that the RF algorithm performs better and is reliable for the prediction of stress levels in an individual.

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