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A Machine Learning Framework for Automated Detection of Perceived Stress in Female Students

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Abstract: Stress is a mental state induced by difficult circumstances. COVID-19 has severely impacted the level of stress and mental health of individuals around the globe. Pharmaceutical treatment (hypnotic or sedative drugs) has shown its ineffectiveness with several unwanted side effects to reduce mental stress. Mindfulness practices have proven their potency to reduce perceived stress (PS) and enhance satisfaction with life (SWL) without any negative consequences. This study aims to detect PS in female students and study the impact of Heartfulness meditation in reducing it. In this work, statistical exploratory data analysis (EDA) is utilized to evaluate the effectiveness of Heartfulness meditation. PS and SWL scores of Week 0 and Week 20 data are recorded from two different age groups of female students and analyzed to detect stressed students using machine learning modules. The highest PS detection accuracy 66.88% and F1-score 65.30% for group-1 are obtained using the support vector machine classifier. EDA indicates that there is a significant decrease in the PS levels and an increase in the SWL after 20 weeks of Heartfulness meditation. The results of this study indicate that the practice of Heartfulness meditation offers significant advantages to female students, regardless of age. Moreover, it was found that the practice effectively reduces stress levels among the participants.

Keywords: machine learning, data analysis, Heartfulness meditation, stress, satisfaction with life

1. Introduction

Stress is a psychological and physiological reaction that arises when individuals perceive a situation as threatening, overwhelming, or beyond their ability to cope [1]. The COVID-19 pandemic has had a significant impact on stress levels and mental health worldwide [2]. Factors such as social isolation, fear, financial strain, grief, personal relationships, and health problems have contributed to increased stress after COVID-19 [3]. While everyone experiences some level of stress, excessive stress can lead to anxiety and have detrimental effects on the body [4]. This phenomenon is also common among college students who must adapt their academic lives to the highly competitive society in which they study. College students face the challenge of meeting rigorous standards necessary for success in the academic environment. They must possess the capacity to carry out tasks and perform under pressure to meet these requirements [5]. Academic workload, classroom dynamics, communication with instructors, illness, and emotional concerns outside of class are typical sources of stress. These demanding lives often result in heightened stress levels [6]. Additionally, college students undergo a challenging developmental transition from youth to adulthood, making them more susceptible to mental health problems. However, female students may experience higher levels of stress compared to males due to specific factors related to reproductive health, such as menstrual cycles, hormonal changes, contraception, and fertility concerns [7]. Moreover, body image and appearance pressures contribute to their emotional well-being and add a layer of stress. In a developing country like India, the literacy levels are low but slowly improving due to the steps taken by the Government of India. Especially for the female students, it has been a challenge with gender disparities in literacy levels [8]. Stress levels are high in students, more so during exam times. There is a growing concern regarding the increasing incidence of stress among female students, yet limited research has been conducted on practical self-care strategies for stress management outside of conventional therapeutic settings [9]. Also, there is limited evidence of any interventions to decrease stress and improve satisfaction with life (SWL) specifically for female students. Moreover, the existing body of research primarily concentrates on self-care strategies for stress management within the context of medical professionals, such as doctors, nurses, and students. However, effectively addressing stress in female students necessitates a comprehensive approach that encompasses multiple facets of their well-being. This approach entails the promotion of mental health awareness through practices such as Heartfulness meditation, yoga, and other mindfulness techniques. By engaging in these practices, individuals can cultivate self-awareness, induce relaxation, and foster emotional resilience.

Heartfulness meditation is a simple and heart-centric approach, facilitating people in connecting with their inner selves

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and cultivating a state of calm and tranquility [10]. Practitioners of Heartfulness meditation pay attention to their hearts, ignoring thoughts that arise and experiencing a state of deep relaxation. The practice promotes the development of self-awareness, emotional resilience, and compassion, all of which are important in stress management [11]. Heartfulness meditation has been found in studies to considerably reduce stress, anxiety, and sadness. It fosters inner calm and harmony by harmonizing the autonomic nerve system and controlling the body's stress response. Regular practice of Heartfulness meditation has also been shown to increase sleep quality, focus and concentration, and overall mental well-being [12]. Yoga, an ancient practice originating from India, combines physical postures (asanas), breathing exercises (pranayama), and meditation techniques to promote physical, mental, and spiritual well-being. It offers a holistic approach to stress reduction by integrating body, mind, and breath [13]. The physical aspect of yoga helps release tension and increase flexibility, while mindful breathing techniques calm the mind and activate the body's relaxation response. Yoga also enhances self-awareness and promotes present-moment awareness, allowing individuals to let go of stress-inducing thoughts and emotions. Contemplative practices focus on being fully present in the present moment, observing thoughts, feelings, and sensations without judgment. It involves paying attention to the present experience with openness and curiosity, allowing individuals to develop a greater understanding of their internal experiences and manage stress more effectively [14]. These practices help individuals shift their focus away from worries about the past or future, bringing their attention to the present moment. As a result, they can experience a greater sense of calmness, clarity, and resilience [15]. Studies have shown that mindfulness-based interventions can significantly reduce stress, anxiety, and depressive symptoms. Regular contemplative practice has been associated with improved emotional well-being, better cognitive function, and increased self-compassion [16, 17].

While all previous studies have either examined the stress reduction results of the mindfulness intervention or the stress detection results from the automated system without combining them, the present study combines assessment of stress in Heartfulness meditation with machine learning stress classification from psychological questionnaire responses. In addition, this research takes a close look at a group of female students specifically as they relate to perceived stress (PS), a group of students who are relatively under-researched and often heavily affected by stress. The proposed framework integrates exploratory data analysis (EDA) and machine learning approaches that assess the effectiveness of the intervention as well as automated stress screening.

This study has as its objective the effectiveness of Heartfulness meditation on reducing PS and increasing SWL in female students, and its feasibility for automated measurement of stress using machine learning models based on psychological questionnaire responses.

The main contributions of this study are listed below.

1) This research explores the potential of Heartfulness meditation as a means of stress reduction specifically for female students.
2) In this work, for the first time, machine learning modules are used to categorize Week 0 and Week 20 practitioners and detect stressed females.

The rest of this paper is organized as follows: Section 2 presents previous studies on stress; Section 3 gives the preliminaries of this work; Section 4 presents the experimental findings and discussion of this work; and Section 5 presents the conclusion of this study.

2. Previous Studies

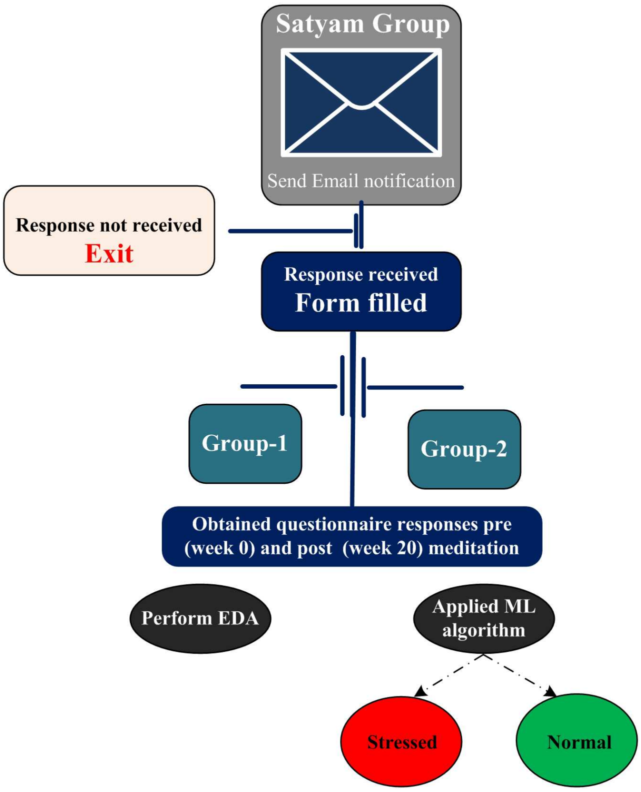
Numerous methods for evaluating, detecting, and managing the level of stress using different procedures have been presented in the literature. Amanvermez et al. [18] presented a comprehensive research review and meta-analysis aimed at investigating the efficacy of treatments in reducing stress among university students. A review report on stress in dental students has been presented by Smolana et al. [19]. The authors demonstrated that dentistry students face significant stress during their training. Pascoe et al. [20] conducted a review on the impact of stress on secondary and higher education students. Rahman et al. [21] conducted an exploratory analysis on the application of linguistic and keystroke features for automatic stress detection. Their study reveals the potential for classifying physical and cognitive stress through the utilization of these features. Bari et al. [22] proposed a methodology for identifying stressful conversations by employing wearable physiological and inertial sensors. Their developed system successfully recognized specific hand gestures associated with stress in conversations and obtained an impressive F1-score of 0.83. Graves et al. [23] conducted a study focusing on stress-coping methods and gender differences among undergraduate students during the final stages of the semester. The researchers identified a higher level of stress among female students in comparison to their male counterparts. Masri et al. [24] have presented a case study focused on the detection of mental and physical stress during work. Their study aimed to validate methods for identifying and assessing stress levels in the workplace.

Existing literature has already demonstrated the efficacy of both physical and virtual attendance in the Heartfulness meditation program, providing evidence of its positive impact on the physical and mental well-being of individuals. Amarnath et al. [25] conducted a prospective observational study to evaluate the effectiveness of Heartfulness meditation in reducing stress among nursing students. The results of their study demonstrated that Heartfulness meditation served as a valuable mental and emotional support mechanism in coping with and alleviating stress. Arya et al. [26] examined the effectiveness of Heartfulness cleaning and meditation on blood pressure, heart rate variability, and heart rate. The authors concluded that the practice of Heartfulness cleaning and meditation led to an enhancement in the sympathovagal balance, indicating a positive impact on the autonomic nervous system. Thimmapuram et al. [27] conducted a study investigating the effectiveness of combining Heartfulness meditation with sleep hygiene techniques for treating chronic insomnia. Their findings suggested that Heartfulness meditation played a beneficial role in gradually reducing and ultimately discontinuing the use of sedative-hypnotics among patients with chronic insomnia. Gurram et al. [28] investigated the impact of Heartfulness meditation on intraoperative anxiety levels during impacted third molar surgery. The researchers concluded that a single session of Heartfulness meditation proved to be effective in reducing anxiety levels during the surgical procedure for impacted third molars. Desai et al. [29] conducted a mixed-method study to explore the impact of the virtual Heartfulness meditation program and investigated the efficacy of participating in the virtual program in reducing stress levels and enhancing sleep quality.

In the literature, there are some studies that focused on the development of stress management interventions and some that focused on automated stress detection, but limited research has integrated both mindfulness-based intervention analysis and machine learning-based stress classification based on the subjective psychological responses to stress. Furthermore, the existing studies tend to examine physiological measures or mixed populations of girls/boys, and fewer studies specifically explore the female population with longitudinal measures of PS and SWL.

This study includes a 20-week prospective cohort analysis comparing PS and SWL outcomes given by female students. Recorded outcomes are utilized to detect the stressed participants using a machine learning classifier and also used to evaluate the effectiveness of the Heartfulness meditation practice. Figure 1 shows the schematic illustration of this study.

Figure 1
Schematic illustration of the study



3. Preliminaries

3.1. Participants and data collection

This study involves the female students of the Satyam group of institutions who voluntarily participated in the Heartfulness meditation program. E-mail communications from the institution to all students are utilized to find volunteers. A direct web link is provided to evaluate the study's concept in depth, give their consent voluntarily, and self-register. Any student 18 years and above is eligible to participate in the study. The study was a prospective cohort analysis comparing PS and SWL outcomes among female students who self-selected to participate in the Heartfulness meditation program as an intervention. Students were divided into two groups; the first group underwent intervention from Week 0 until Week 12 and continued their practice on their own till Week 20. The second group joined the intervention at Week 7 until Week 12 and continued their practice on their own till Week 20. With all other factors being similar, the main difference between the two groups was that the first group had a 12-week exposure to the guided meditation with a certified Heartfulness trainer compared to the second group, which had only 6 weeks of exposure. Data on PS and SWL were collected at Week 0 and Week 20 for both groups. The analysis included only students who finished both the Week 0 and Week 20 assessments from the students who registered initially. In the intervention period, those who had partial data or who dropped out of the study were not included. This study targeted female students because previous literature reports higher susceptibility to stress because of academic pressure, psychosocial challenges, hormonal changes, and emotional issues in female students compared to males. The responses at Week 0 were classified in the "stressed" class, while the responses at Week 20 after meditation practice were classified in the "normal" class for classification purposes.

3.2. Statistical exploratory data analysis

Statistical EDA constitutes a crucial phase in data analysis, wherein the assessment and summarization of fundamental characteristics of a dataset take place. Its purpose is to acquire valuable insights, identify patterns, and detect potential correlations or anomalies within the data [30]. Throughout the process of statistical EDA, diverse statistical techniques and visual representations are employed to investigate the data. Summary statistics, encompassing measures of central tendency and variability, offer a comprehensive overview of the overall distribution of the dataset. In our study, data visualization tools such as line plots and violin plots are utilized to visually depict the structure of the recorded data.

3.3. Data preprocessing and feature representation

Preprocessing of the collected dataset was carefully carried out to ensure consistency and reliability of the analysis before applying the machine learning classifiers. All the data collected from the participants at the two time points (Week 0 and Week 20) were initially checked for completeness and validity. Avoiding bias and maintaining data quality, responses with missing, inconsistent, and incomplete information were not included in the final analysis. The participants who had passed the baseline (Week 0) and the post-intervention (Week 20) tests were included in the study. The responses to the PS and SWL questionnaires were directly used as features for classification. The PS and SWL questionnaires were answered by each participant, and their answers were used as a feature vector to represent the psychological state of each participant. The data collected were simple numerical responses to structured questionnaires, and the dimensionality was not large, so no additional complex feature extraction techniques were needed. Feature normalization was done prior to the training of classifiers to enhance the stability and performance of the machine learning models. By normalizing all the features in the questionnaire, it ensured that each feature had an equal contribution in learning and not the features with bigger numerical ranges having a dominating role in classification. For classification, the responses taken at Week 0 were taken as representative of the "stressed" class, and responses taken after meditation intervention at Week 20 were considered as representative of the "normal" class. Processed feature vectors were then fed into the chosen machine learning classifiers to detect and classify the stress automatically.

3.4. Machine learning modules

Machine learning classifiers are algorithms or models that have undergone training to categorize or classify data into pre-determined classes or categories [31]. They acquire knowledge from labeled training data, wherein each data point is associated with a known class label. By examining patterns and relationships within the training data, classifiers can generate predictions or assign class labels to new, unidentified instances.

There exist several types of classifiers, each possessing its unique algorithmic approach and distinct characteristics. This study compares the classification performance of five distinct classifiers: Naive Bayes (NB), support vector machines (SVM), k-Nearest Neighbors (KNN), wide neural network (WNN), and decision tree (DT). These classifiers are assessed based on their ability to classify responses from female participants into either the normal (Week 20) or stressed (Week 0) category.

NB classifiers are founded upon Bayes' theorem and assume independence among features. They demonstrate computational efficiency and perform well with high-dimensional data [32].

SVM classifiers determine an optimal hyperplane to segregate data points into different classes. They exhibit effectiveness with both linearly separable and nonlinearly separable data [33].

KNN classifiers assign a class label to an instance by considering the class labels of its KNN within the feature space. They are characterized by simplicity and ease of understanding, albeit computational expenses may arise when handling large datasets [34].

WNNs encompass multiple layers of interconnected artificial neurons and can learn intricate patterns from data [35].

DT classifiers establish a hierarchical decision-making structure based on features to classify data. They possess intuitiveness and ease of interpretation, thereby aiding in understanding the decision-making process [36].

These traditional classifiers were chosen due to their effectiveness in structured tabular datasets with lesser sample sizes: NB, SVM, KNN, WNN, and DT. In general, deep learning techniques need significantly larger datasets to prevent overfitting and to obtain good generalization. For this reason, classical machine learning methods were used in the present study.

3.5. Statistical validation and performance evaluation

A 10-fold cross-validation methodology was used to validate the proposed machine learning framework to ensure the reliability and robustness of the proposed framework. In the latter, the entire dataset was randomly split into 10 equally sized datasets. For every iteration, nine subsets were employed to train the classifier, and the other subset was used to test the classifier. This process was replicated 10 times, where each set was tested 10 times. The average of all iterations was used for the final performance. To prevent overfitting and to get a more general approximation for the potential performance of the classifiers, 10-fold cross-validation was used. In this study, eight performance parameters are employed to evaluate the effectiveness of the utilized machine learning modules in detecting stressed female participants. These parameters include sensitivity (S_{EN}), specificity (S_{PE}), positive predicted value (P_{PV}), negative predicted value (N_{PV}), false negative rate (F_{NR}), accuracy (A_{CC}), F-1 score, and area under the curve (AUC). These metrics present an in-depth evaluation of the classification performance of the proposed framework in various aspects. The mathematical equations for each of these measures are presented below:

$$S_{EN}(\%) = \frac{T_{Pos}}{T_{Pos} + F_{Neg}} \times 100 \tag{1}$$

$$S_{PE}(\%) = \frac{T_{Neg}}{T_{Neg} + F_{Pos}} \times 100 \tag{2}$$

$$P_{PV}(\%) = \frac{T_{Pos}}{T_{Pos} + F_{Pos}} \times 100 \tag{3}$$

$$N_{PV} = \frac{T_{Neg}}{T_{Neg} + F_{Neg}} \tag{4}$$

$$F_{NR} = \frac{F_{Neg}}{T_{Pos} + F_{Neg}} \tag{5}$$

$$A_{CC}(\%) = \frac{T_{Pos} + T_{Neg}}{T_{Pos} + F_{Neg} + T_{Neg} + F_{Pos}} \times 100 \tag{6}$$

$$F-1\ score = \frac{2 \times T_{Pos}}{2 \times T_{Pos} + F_{Pos} + F_{Neg}} \tag{7}$$

Where:

(T_{Pos}): True positives, which are the number of positive instances correctly predicted as positive.

(F_{Pos}): False positives, which are the number of negative instances incorrectly predicted as positive.

(T_{Neg}): True negatives, which are the number of negative instances correctly predicted as negative.

(F_{Neg}): False negatives, which are the number of positive instances incorrectly predicted as negative.

Sensitivity indicates the classifier's ability to correctly classify stressed participants, while specificity indicates the ability of the classifier to correctly classify normal participants. The accuracy value is the overall classification accuracy, while the F1-score is a balance between the precision and recall. Furthermore, receiver operating characteristic (ROC) analysis was carried out to evaluate the discriminative power of the classifiers at different decision thresholds. The results of the AUC obtained show the strength of the proposed model in discriminating between stressed and normal participant responses. Employing several evaluation metrics in addition to classification accuracy enhances the statistical significance and interpretability of the results, especially in psychological and behavioral datasets where there is naturally a lot of inter-individual variability.

4. Results and Discussion

A total of 240 female students initially registered for this study. However, after applying the inclusion criteria, 187 students were deemed eligible and included in the analysis. The participants' ages ranged from 18 to 33 years, with a mean age of 21.98 (SD = 4.33). Throughout the study, participants were asked to respond to 10 questions related to PS and 5 questions related to SWL at two time points: Week 0 (beginning) and Week 20 (end). The mean values indicated a decrease in the PS and an increase in the SWL scores for both groups. However, p-values from paired t-tests indicated a statistically significant decrease in PS and a significant increase in SWL for the second group. ANOVA analysis of intercept and age indicated that age had no impact on the results of the intervention for both PS and SWL. The study of the Pearson correlation coefficient indicated that there is a weak positive correlation between pre- and post-scores for both groups for both PS and SWL.

The responses provided by the participants are utilized as features for the classification task. To assess the performance of the classifiers, a 10-fold cross-validation method was employed, which involved training and testing the classifiers on different subsets of the data. In Batch I, a total of 104 students joined the study at Week 0, and 114 students enrolled in the 20-week meditation program. For Batch II, 111 students initially joined the study at Week 0, but only 89 of them completed the full 20-week meditation program. Ultimately, 77 students from Batch I and 83 students from Batch II completed the entire 20-week meditation program and were included in the final analysis.

Figure 2(a) and (b) represent the line and violin plots of the mean value of recorded SWL responses of Batch-I female students at Week 0 and Week 20, respectively. It can be noted from Figure 2 that the mean values of SWL responses of Batch-I female students at Week 20 are higher compared to Week 0. Additionally, there is a very small variation in the responses for Week 20 compared to Week 0. Response R3 was chosen by the maximum number of participants, and the median value shifted from 4.4 to 4.8 after the completion of the program. Figure 3(a) and (b) represent the line and violin plots of the mean value of recorded SWL responses of Batch-II female students at Week 0 and Week 20, respectively.

It can be understood from Figure 3 that there is a very small variation in the responses of Batch-II female students at Week 20 compared to Week 0. Before entering the program, Response R4 was chosen by the maximum number of participants, whereas after the program, Response R3 was opted. Additionally, there is very little shifting observed in the median value. Figure 4(a) and (b) represent the line and violin plots of the mean value of recorded PS responses of Batch-I female students at Week 0 and Week 20, respectively.

It can be noted from Figure 4 that the mean values of PS responses of Batch-I female students at Week 20 are higher compared to Week 0. Response R4 was chosen by the maximum number of participants, and no change is observed in the median value. Figure 5(a) and (b) represent the line and violin plots of the mean value of recorded PS responses of Batch-II female students at Week 0 and Week 20, respectively.

It can be observed from Figure 5 that the mean values of PS responses of Batch-II female students at Week 20 are higher compared to Week 0. Response R4 was chosen by the maximum

Figure 2
Mean value of recorded SWL responses of Batch-I female students at Week 0 and Week 20: (a) line plot, (b) box plot

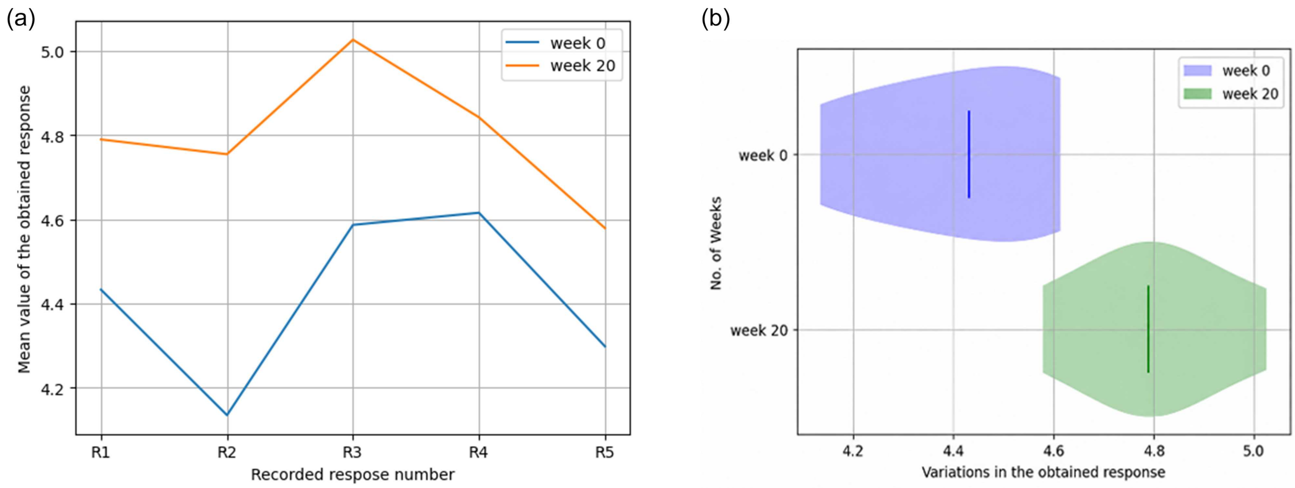


Figure 3
Mean value of recorded SWL responses of Batch-II female students at Week 0 and Week 20: (a) line plot, (b) box plot

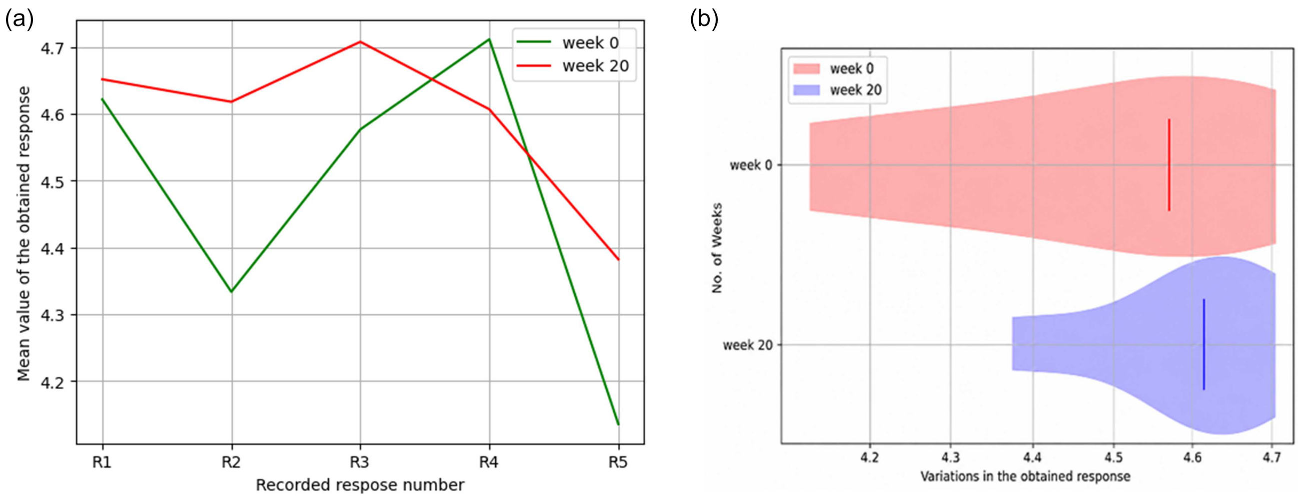


Figure 4
Mean value of recorded PS responses of Batch-I female students at Week 0 and Week 20: (a) line plot, (b) box plot

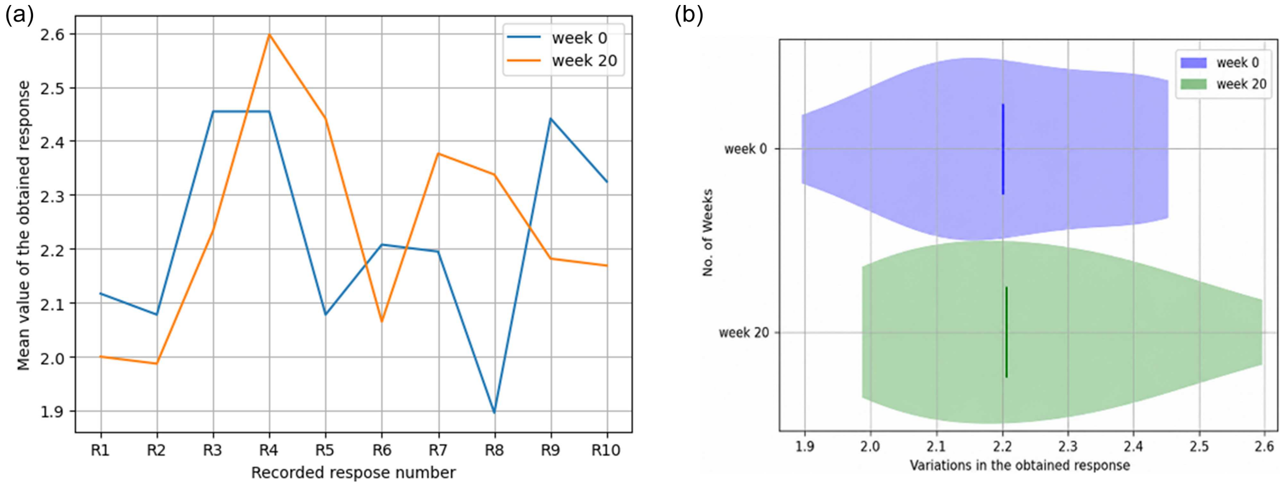
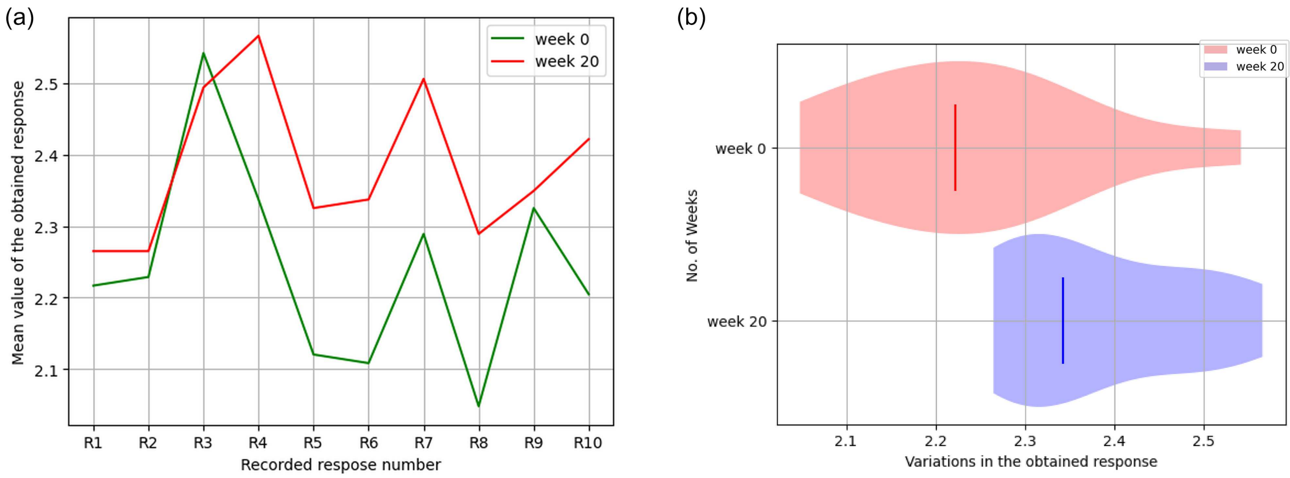


Figure 5
Mean value of recorded PS responses of Batch-II female students at Week 0 and Week 20: (a) line plot, (b) box plot



number of participants, and there is little variation found in the median value of the Week 20 responses.

Table 1 indicates the performance metrics (%) on classifying Week 0 and Week 20 PS responses of Batch-I subjects using different classifiers (keeping the same subjects).

From Table 1, it is evident that the SVM classifier achieved the highest values for various performance metrics when classifying the PS responses of participants at Week 0 and Week 20. The highest SEN of 68.57%, SEP of 65.48%, PPV of 62.34%, NPV of 71.43%, ACC of 66.88%, F1-score of 0.65, and minimum FNR of 31.42% are yielded using an SVM classifier.

Table 2 indicates the performance metrics (%) on classifying Week 0 and Week 20 SWL responses of Batch-I subjects using different classifiers (keeping the same subjects).

It can be understood from Table 2 that the DT classifier achieved the highest values for various performance metrics when classifying the SWL responses of participants at Week 0 and Week 20. The highest SEN of 67.80%, SEP of 61.05%, PPV of 51.95%, NPV of 75.32%, ACC of 63.64%, F1-score of 0.58, and minimum FNR of 32.20% are obtained using the DT classifier.

Table 3 indicates the performance metrics (%) on classifying Week 0 and Week 20 PS responses of Batch-II subjects using different classifiers (keeping the same subjects).

It can be noted from Table 3 that the SVM classifier achieved the highest values for various performance metrics when classifying the PS responses of Batch-II participants at Week 0 and Week 20. The highest SEN of 59.09%, SEP of 56.00%, PPV of 46.99%, NPV of 67.47%, ACC of 57.23%, F1-score of 0.52, and minimum FNR of 40.91% are obtained using the DT classifier.

Table 4 indicates the performance metrics (%) on classifying Week 0 and Week 20 SWL responses of Batch-II subjects using different classifiers (keeping the same subjects).

It can be noted from Table 4 that the DT classifier achieved the highest values for various performance metrics when classifying the SWL responses of Batch-II participants at Week 0 and Week 20. The highest SEN of 59.68%, SEP of 55.77%, PPV of 44.58%, NPV of 69.88%, ACC of 57.23%, F1-score of 0.51, and minimum FNR of 40.32% are obtained using the DT classifier.

Table 5 indicates the performance metrics (%) on classifying Week 0 and Week 20 PS responses of Batch-I subjects using different classifiers (with different subjects).

Table 1
Performance metrics (%) on classifying Week 0 and Week 20 PS responses of Batch-I subjects using different classifiers (keeping same subjects)

Classifier	SEN	SEP	PPV	NPV	FNR	ACC	F1-score
NB	68.75	63.33	57.14	74.03	31.25	65.58	0.62
SVM	68.57	65.48	62.34	71.43	31.43	66.88	0.65
KNN	60.78	55.34	40.26	74.03	39.22	57.14	0.48
WNN	65.71	63.10	59.74	68.83	34.29	64.29	0.63
DT	65.22	62.35	58.44	68.83	34.78	63.64	0.62

Table 2
Performance metrics (%) on classifying Week 0 and Week 20 SWL responses of Batch-I subjects using different classifiers (keeping same subjects)

Classifier	SEN	SEP	PPV	NPV	FNR	ACC	F1-score
NB	61.22	55.24	38.96	75.32	38.78	57.14	0.48
SVM	63.64	57.58	45.45	74.03	36.36	59.74	0.53
KNN	59.62	54.90	40.26	72.73	40.38	56.49	0.48
WNN	60.00	60.81	62.34	58.44	40.00	60.39	0.61
DT	67.80	61.05	51.95	75.32	32.20	63.64	0.59

Table 3
Performance metrics (%) on classifying Week 0 and Week 20 PS responses of Batch-II subjects using different classifiers (keeping same subjects)

Classifier	SEN	SEP	PPV	NPV	FNR	ACC	F1-score
NB	54.69	52.94	42.17	65.06	45.31	53.61	0.48
SVM	59.09	56.00	46.99	67.47	40.91	57.23	0.52
KNN	55.41	54.35	49.40	60.24	44.59	54.82	0.52
WNN	50.59	50.62	51.81	49.40	49.41	50.60	0.51
DT	57.14	57.32	57.83	56.63	42.86	57.23	0.57

Table 4
Performance metrics (%) on classifying Week 0 and Week 20 SWL responses of Batch-II subjects using different classifiers (keeping same subjects)

Classifier	SEN	SEP	PPV	NPV	FNR	ACC	F1-score
NB	57.35	55.10	46.99	65.06	42.65	56.02	0.52
SVM	54.29	57.38	68.67	42.17	45.71	55.42	0.61
KNN	55.74	53.33	40.96	67.47	44.26	54.22	0.47
WNN	50.56	50.65	54.22	46.99	49.44	50.60	0.52
DT	59.68	55.77	44.58	69.88	40.32	57.23	0.51

Table 5
Performance metrics (%) on classifying Week 0 and Week 20 PS responses of Batch-I subjects using different classifiers (with different subjects)

Classifier	SEN	SEP	PPV	NPV	FNR	ACC	F1-score
NB	65.33	61.54	47.12	77.19	34.67	62.84	0.55
SVM	62.03	60.43	47.12	73.68	37.97	61.01	0.54
KNN	71.19	61.01	40.38	85.09	28.81	63.76	0.52
WNN	60.17	67.00	68.27	58.77	39.83	63.30	0.64
DT	62.11	63.41	56.73	68.42	37.89	62.84	0.59

It can be evident from Table 5 that the KNN classifier achieved the highest values for various performance metrics when classifying the PS responses of Batch-I participants at Week 0 and Week 20. The highest SEN of 71.19%, SEP of 61.01%, PPV of 40.38%, NPV of 85.09%, ACC of 63.76 %, F1-score of 0.51, and minimum FNR of 28.81% are obtained using a KNN classifier.

Table 6 indicates the performance metrics (%) on classifying Week 0 and Week 20 SWL responses of Batch-I subjects using different classifiers (with different subjects).

It can be noted from Table 6 that the SVM classifier obtained the highest values for various performance metrics when classifying the SWL scores of Batch-I participants at Week 0 and Week 20. The highest SEN of 64.20%, SEP of 61.76%, PPV of 50.00%, NPV of 74.34%, ACC of 62.67%, F1-score of 0.56, and minimum FNR of 35.80% are obtained using a KNN classifier.

Table 7 indicates the performance metrics (%) on classifying Week 0 and Week 20 PS responses of Batch-II subjects using different classifiers (with different subjects).

From Table 7, it is clear that the SVM classifier achieved the highest values for various performance metrics when classifying the PS responses of Batch-II participants at Week 0 and Week 20. The highest SEN of 66.07%, SEP of 57.47%, PPV of 66.67%, NPV of 56.82%, ACC of 62.31%, F1-score of 0.66, and minimum FNR of 33.93% are yielded using an SVM classifier.

Table 8 indicates the performance metrics (%) on classifying Week 0 and Week 20 SWL responses of Batch-II subjects using different classifiers (with different subjects).

It can be noted from Table 8 that the NB and DT classifiers obtained the same highest values for various performance metrics when classifying the SWL scores of Batch-I participants at Week 0 and Week 20. The highest SEN of 61.16%, SEP of 52.56%, PPV of 66.67%, NPV of 46.59%, ACC of 57.79%, F1-score of 0.63, and minimum FNR of 38.84% are obtained using both NB and DT classifiers.

Besides the classification accuracy, the discriminative power of the proposed method was also investigated using ROC analysis. The area under the curve (AUC) value obtained was 0.70, which was found as acceptable separability of stressed and normal participant responses. Figure 6 shows the receiver operating characteristic (ROC) curve obtained for the SVM classifier on classifying the PS responses of Batch I for the same subjects. An AUC value of 0.70 is obtained for the SVM classifier.

The self-reported questionnaire-based approach for psychological stress detection is a very complex process, as there is a significant inter-individual variability, emotional overlapping of self-reported stress factors, differences in subjective perception of the stress, and environmental influences. So, it might be expected that a dataset of such behaviors will have moderate classification performance. An important observation that has emerged from this study is the strong correlation between PS and SWL. The study revealed a noteworthy trend where a decrease in PS levels corresponded to an increase in subjective well-being levels. This suggests that as participants reported lower levels of PS, they also reported higher levels of subjective well-being. This finding

Table 6
Performance metrics (%) on classifying Week 0 and Week 20 SWL responses of Batch-I subjects using different classifiers (with different subjects)

Classifier	SEN	SEP	PPV	NPV	FNR	ACC	F1-score
NB	60.27	58.62	42.31	74.56	39.73	59.17	0.50
SVM	64.20	61.76	50.00	74.34	35.80	62.67	0.56
KNN	56.67	55.70	32.69	77.19	43.33	55.96	0.41
WNN	54.64	57.85	50.96	61.40	45.36	56.42	0.53
DT	57.89	60.16	52.88	64.91	42.11	59.17	0.55

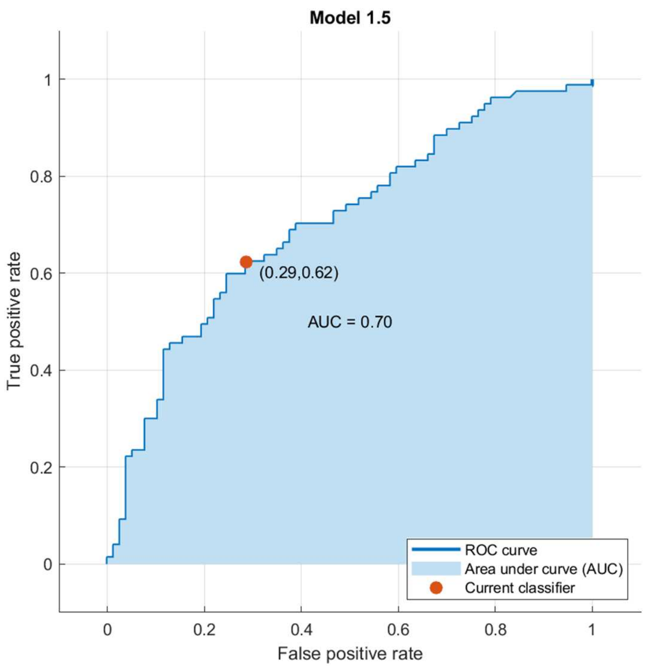
Table 7
Performance metrics (%) on classifying Week 0 and Week 20 PS responses of Batch-II subjects using different classifiers (with different subjects)

Classifier	SEN	SEP	PPV	NPV	FNR	ACC	F1-score
NB	67.78	54.13	54.95	67.05	32.22	60.30	0.61
SVM	66.07	57.47	66.67	56.82	33.93	62.31	0.66
KNN	60.34	50.60	63.06	47.73	39.66	56.28	0.62
WNN	57.63	46.91	61.26	43.18	42.37	53.27	0.59
DT	65.59	52.83	54.95	63.64	34.41	58.79	0.60

Table 8
Performance metrics (%) on classifying Week 0 and Week 20 SWL responses of Batch-II subjects using different classifiers (with different subjects)

Classifier	SEN	SEP	PPV	NPV	FNR	ACC	F1-score
NB	61.16	52.56	66.67	46.59	38.84	57.79	0.64
SVM	62.50	51.58	58.56	55.68	37.50	57.29	0.60
KNN	57.69	46.32	54.05	50.00	42.31	52.26	0.56
WNN	60.68	51.22	63.96	47.73	39.32	56.78	0.62
DT	61.16	52.56	66.67	46.59	38.84	57.79	0.64

Figure 6
ROC curve yielded for SVM classifier on classifying the PS responses of Batch-I subjects



highlights the interconnectedness between stress and well-being and emphasizes the potential benefits of stress reduction interventions on overall well-being.

4.1. Limitations of the study

The results of the present study should be interpreted with some limitations in mind. The study was conducted during the pandemic of COVID-19, which could have had a direct impact on the level of PS and SWL in the participants. The psychological responses during the study period could be influenced by the external factors related to the pandemic such as social isolation, uncertainty, and academic disruptions. Second, the study did not account for the differences between academic and nonacademic institutions, meaning that the results may not be applicable to nonacademic institutions in general or to students across a wider demographic in terms of their academic backgrounds, cultural and linguistic diversity, or geographical location. Additionally, the selection of participants was voluntary and not randomized, which might have resulted in self-selection bias and other factors potentially affecting the results. Further, the academic stress and subjective well-being of the participants may have been influenced by other academic factors, such as examinations, assignments, and the announcement of academic results, during the intervention period. The observed responses could have been affected by these unplanned external academic pressures. The study has also not quantified participants' use of meditation after the end of the guided online sessions. Hence, the sustainability and consistency of the meditation intervention could not be evaluated completely. In addition, no attempt has been made to fully assess or control for individual differences in psychology, lifestyle, emotions, and personal circumstances, which may have led to some variation in response from participants. The study has employed a relatively small dataset of questionnaires (subjective psychological responses), introducing inter-individual variability that may hamper classification performance from the machine learning perspective. While promising feasibility for the automated stress detection was shown in the proposed framework, the moderate degree of accuracy obtained in the classification should be regarded as exploratory and not as clinically definitive. Future research should consider larger multicenter datasets, randomized controlled study designs, more diverse participant populations, longer follow-up periods for adherence monitoring, and the incorporation of physiological signals and more sophisticated explainable artificial intelligence (AI) frameworks to enhance the robustness, interpretability, and generalizability of automated systems for the detection of stress.

5. Conclusion

Stress is a psychological condition that arises from challenging situations, and the global impact of COVID-19 has significantly affected stress levels and mental well-being worldwide. Traditional pharmaceutical interventions have demonstrated limited effectiveness, whereas Heartfulness practices have shown better results in reducing stress levels and enhancing overall SWL. Consequently, this study aimed to demonstrate the impact of Heartfulness meditation practices through EDA plots. To automatically detect stress in female students, PS and SWL scores were recorded at Week 0 and Week 20 of meditation. Machine learning classifiers with a 10-fold validation scheme were employed for detection. The study achieved the highest PS detection accuracy of 66.88% and an F1-score of 0.65 using the SVM classifier. These results indicate the potential of Heartfulness meditation practices in effectively reducing PS and improving SWL without any adverse consequences. Future research involves expansion to larger multicenter datasets, incorporating male participants, deep learning, and explainable AI models for stress prediction, and integration of physiological signals.

Ethical Statement

The study involving human participants was reviewed by the Satyam Group of Institutions' institutional review board and is associated with SNDT Women's University in Mumbai (ID 0508/Research/SGI-HFN). All procedures were conducted in accordance with relevant ethical guidelines and regulations. Where applicable, informed consent was obtained from all human participants.

Conflicts of Interest

The author declares that he has no conflicts of interest to this work.

Data Availability Statement

Data are available from the corresponding author upon reasonable request.

Author Contribution Statement

Kapil Gupta: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Writing – original draft, Writing – review & editing, Visualization.

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