RESEARCH PAPER

An Ensemble Machine Learning Framework for Mental Stress Prediction and Performance Evaluation

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ABSTRACT

Mental stress has been a major issue of concern since it impacts on the way individuals think, feel and operate in their day-to-day lives. With the increase in the availability of psychological and behavioral data researchers have begun to apply data-based approaches to gain improved insights into stress in a manner that can be extended to larger groupings. Nonetheless, practice has demonstrated that the application of a single predictive model tends to produce disproportionate results. A model can work well given a particular set of conditions but one cannot say the same about the intricate combination of the academic pressure, emotional condition, lifestyle habits, and social issues that can contribute to stress. In order to solve this problem, the current research examines an ensemble learning framework of stress prediction. Rather than relying on a single algorithm there is a combination of several classifiers so that each has its own advantages and disadvantages compensated. The core aim of this strategy is to have more reliable predictions. The secondary goal is to compare this combined strategy and separate machine learning models. The framework is put to the test with the help of Student Stress Factors dataset provided in Kaggle, which covers such information as academic workload, psychological condition, lifestyle behavior, and social influences. A number of classification methods is used individually and then combined by the majority vote. This enables the end prediction to be a collective decision and not an individual decision. The experimental findings indicate that the performance of individual models varies widely with the values of the accuracy varying between approximately 79 percent and 96 percent. Comparatively, the ensemble technique yields more stable results that yield an accuracy of 97.89 percent and an average value of high precision, recall, and F1-score. Further Stratifiedcross-validation outcomes also suggest that the model is reliable in other data splits.

Keywords: Mental Stress Prediction, Machine Learning, Ensemble Learning, Classification Models, Performance Analysis.

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INTRODUCTION

Mental stress has now been viewed as a severe problem particularly in students since it impairs the intellectual capacity to think, emotional regulation, school work, and general well-being [1]. As numerous studies revealed, stress may complicate the learning process, disrupt the decision-making process, and cause permanent psychological issues [2]. Studies conducted in other universities indicate that many students are high stressors. This pressure is, in the majority of cases, associated with academic load, social demands, and unbalanced everyday schedules [3], [4]. These results imply that there is a need to have stress identification techniques that are not only accurate but also capable of being used with a large population of students. Daily habits have also been seen to be affected by academic stress. Alteration in physical activity, food consumption, and sleep is frequently noticed when the stress levels rise, and the alteration can also aggravate mental health [5]. A number of the studies state that work demands and stress during exams are strongly connected with a decrease in the psychological welfare of the university students [6], [7]. Social support is known to play considerable role in helping to minimize the effects of stress and this implies that stress cannot be studied with purely academic measures but social and psychological measures also [8]. Due to this, recent studies tend to use a large number of related variables in datasets to allow the interactions to be studied jointly [9], [10]. Stress detecting techniques that are data-driven have demonstrated helpful results in various digital and smart surroundings, where stress-related patterns can be determined based on the gathered data [11], [12]. With the use of wearable devices, one can monitor the stress at all times without disrupting regular activities. These systems have been reported to have better performance in stress recognition when combined with multimodal learning approaches [13] -[15]. There is also a high connection between sleep issues and increased stress and reduced mental health outcomes, especially in students in higher education and medical programs [16] - [18]. Consequently, sleep quality is currently viewed as a critical element as far as researching and forecasting student stress is concerned. Psychobiologically, stress is caused by complicated interactions involving venerations and physiological responses to emotions affecting the short- and long-run health consequences [19], [20]. To focus on informative signals of stress and increase the accuracy of detection, multimodal forms of learning, which grounded in attention regulation and information integration, were presented [21]. Even though the task of identifying stress can still largely be influenced by the choice of algorithms and feature representations, careful reviews also reveal that machine learning models trained on wearable sensor measurements can detect stress with a respectable level of accuracy [22]. The emergence of recent literature is gradually referencing the usefulness of integrating data among different sensing media with machine learning frameworks that are simpler to decipher, especially when decisions about stress are likely to be made that can affect real operations [23], [24]. Seeing through reviews on wearable-based stress monitoring systems, it is observed repeatedly that model performance in real applications is very sensitive to data preparation, meaningful feature extraction, and careful selection of learning algorithms, as opposed to model complexity itself [25].

Psychological Factors

According to the results of recent meta-analysis, psychological stress in the students increases rapidly, and anxiety and depression frequently go hand in hand. As an example, a 2024 study in ScienceDirect on school-based stress interventions discovered that students who coped poorly and low resilience, had higher likelihoods of having severe stress episodes despite academic support. Equally, a 2025 systematic analysis has pointed out that stress outcomes in college students are greatly mediated by resilience, that is, students who practice mindfulness or involved in extracurricular activities are better copers. The psychological variables that are critical in the present context of this paper include anxiety levels, emotional regulation and coping strategies. Differently, an example of a student who has a high exam anxiety but resilience can be interpreted differently by the ensemble model as compared to a student who possesses low coping skills.

Physiological Factors

The physiological indicators that affect stress are the quality of sleep, Breathing Problem, Blood Pressureand Headache. One case study on the use of ACT-based online classes in tracking burnout in university students (2024) involved Blood Pressure measurements alongside self-assessments. Findings indicated that abnormal sleep and low Blood Pressure were significant predictors of stress spikes in weeks of exams. Equally, a longitudinal (2025) study in the BMC Psychology established that sleep deprivation and unhealthy lifestyle (e.g., eating habits, lack of physical activities) was associated with increased stress and reduced academic achievement. Sleep behavior and routine lifestyle are part of the dataset of this paper and with the help of the ensemble model, the physiological stress signals which would otherwise not be recognized by the single classifier would be captured.

Academic Factors

The most prevalent stressor is still academic workload. A longitudinal study examined the effects of academic stress in relation to motivation, emotional intelligence, and mindfulness. It has been found that workloadscoupled with low emotional regulation were significant stressors. The second case study of machine learning in 2024 shows that academic due dates and examination pressure are the leading predictors of stress among students. As an example, medical students that had to submit their projects and clinical rotations at the same time indicated that their stress levels were extreme and could only be categorized by ensemble models than by single models. Academic workload and study pressure have been explicitly modeled in this paper, so that any prediction of the effect of these factors on individual performance considers the finer details of the relationship between deadlines, performance requirements, and emotional strength.

Environmental & Social Factors

Stress outcomes are highly influenced by the social and environmental backgrounds. A longitudinal study conducted in Wellbeing, Space and Society in 2025 identified a consistent enhancement in student mental wellbeing by community organizations and peer networks and an intensifying effect of stress by deficiency of social support. Likewise, a 2024 study of rural Indian students demonstrated that adaptation problems and lack of a strong social support system increased stress, and strong peer relationships decreased it. Peer pressure, financial reasons and social support are some of the variables used in the dataset of the paper. Indicatively, the difference in the stress level of two students with the same academic burden might vary with a supportive set of friends or one who has problems with financial stability and the ensemble framework will alleviate all these factors in a smooth way. Simultaneously, the growing importance of data privacy and user confidentiality has provoked an increasing interest in methods like ensemble modeling and federated learning, which can enable the analysis of stress without revealing delicate personal information [26], [27]. The significance of the creation of scalable and automated stress testing tools is supported by the high stress, anxiety, and depression levels in university students confirmed by the large population studies [28]. The fact that stress does not occur uniformly in the case of biosignal-based multimodal studies during cognitive and physical activities also presents evidence that stress does vary depending on the context and therefore necessitates models capable of adapting to various situations [29]. Despite the fact that wearable based systems have been successfully experimented within normal settings, it is still uncertain how much these systems can perform the same in various real life scenarios [30].

The recent breakthroughs in machine learning have expanded the field of stress research, as well, as they allow breaking down stress, anxiety, and depression as connected factors instead of independent variables [31]. There is long-term empirical evidence that chronic elevated levels of stress may adversely impact student academic output, student perseverance, and overall student educational performance, and it is important to note that stress prediction approaches must be timely and accurate [32], [33]. Simultaneously, the advancement of real-time wearable monitoring systems also indicates a possibility of their use to help sustain stress measurement and early intervention in a school [34], [35]. Ensemblebased methods have been also proven to provide a more steady performance and less variation in continuous stress management tasks as compared to single-model methods [36], [37], [38]. Nevertheless, the general research on the emotion state prediction remains to be challenged by the issue of the relevance of the trained models to other populations and the problem of personal physiological disparities [39], [40], [41].

Through in-depth reviews of deep learning models in stress detection, there is an indication that, even though there have been recent advances in predictive accuracy, ensemble and hybrid models are still among the most promising ones to develop systems that are both reliable and scalable [42], [43], [44], [45]. Emboldened by such results, the current study is aimed at the creation of an ensemble-based machine learning system that would utilize stress-related data in multiple dimensions to realize more precise, consistent, and practically applicable stress prediction in a school setting.

LITERATURE REVIEW

Recent studies indicate that there is an increasing preference towards automated and data-driven methods to study and forecast mental stress especially among student groups which have overlapping academic, social, and lifestyle demands. The evidence of the report published by Abd-alrazaq et al. (2024) shows on a large scale that intelligent systems based on wearable-generated behavioral and physiological indicators can make an accurate diagnosis of stress in students. In line with this trend, Hadhri et al. (2024) demonstrated that ensemble-based methods of voting are always more effective than single classification modeltasks, which implies that a combination of multiple learning models would be more effective in modeling the intricate and nonlinear characteristics of stress-related data.

Empirical evidence also explains the major causes of student stress. Academic workload, financial issues, and uncertainty about future career became the key stress factors of academic research by Rois et al. (2021). Other researchers in the past, such as Priyaa et al. (2020), have highlighted stress being a common comorbidity of anxiety and depression, and that stress prediction models should include multiple dimensions of mental health. Going further, AlHamlan et al. (2025) were able to establish that academic stress was a direct cause of lifestyle behaviors, such as sleep patterns, dietary habits, and physical activity, which emphasized the significance of lifestyle-related variables in stress modeling. Psychologically, Barbayannis et al. (2022) were able to offer empirical data that proved the relationship between academic stress and poor mental well-being among university students. Simultaneously, the presence of protective and moderating factors has been extensively reported. As an example, Chen et al. (2025) found that resilience and involvement in extracurricular activities minimize the negative impact of academic stress, and Cohen et al. (2021) renewed the stress-buffering effect of good social support connections. These results all point to the fact that academic demands are not the only factors to influence stress outcomes but also social activity and adaptive coping strategies.

The suitability of machine learning to stress analysis is regularly provided through methodological research. Firoz et al. (2023) have shown in their comparative studies that predicting performance becomes reliable when an extensive variety of variables related to stress is taken into account. On the same note, Hassan et al. (2023) demonstrated that smart environments also have the benefit of stress detection through the incorporation of heterogeneous data sources, thus resulting in increased robustness and generalization. The studies, which concentrate on physiological cues, like those conducted by Islam et al., (2023), validated the fact that deep learning models are capable of detecting intricate stress patterns, though the quality of the signals and feature extraction are also sensitive to performance. A more recent study by Kim et al. (2024) revealed that multimodal sensor fusion would have a great improvement in detecting stress. Hybrid and ensemble-based methods have been becoming a more popular way of handling complex stress datasets. According to Kaur et al. (2023), stress classification model tasks are identified to be better performed by hybrid machine learning models compared to individual classifiers. The research papers by Lee et al. (2023) and Li et al. (2025) also managed to identify close connections between academic stress, anxiety, and sleep quality and overall mental health, which indicates that sleep is an important predictive variable. Martinez et al. (2024) tested the role of coping strategies and revealed that adaptive coping mechanisms play an important role in stress adjustment in a higher education setting. In response to the transparency issue, Nguyen et al. (2024) suggested explainable stress recognition systems where interpretability and predictive accuracy are addressed as critical.

More comprehensive studies of wearable-based stress samples by O'Connor et al. (2024) and Ometov et al. (2025) revealed that multiple issues persist, such as data heterogeneity, irregular labeling, and insufficient model generalizability. The developments in the model design mentioned by Park et al. (2024) and Badhan, P. K. (2025) proved that the ensemble learning methods are more stable in case of application to the wearable sensor-data. Other works by Patil et al. (2025), Peng et al. (2025), Pinge et al. (2024), and Rahman et al. (2025) also outlined the significance of anxiety, sleep hygiene and privacy conscious learning models like federated and ensemble modeling. In addition to studies revolving around wearable-based studies, Ramesh et al. (2024) showed that behavioral and physiological data outperformed single-modality-based data in predicting stress. The effectiveness of stress prediction systems can be well-founded to address the needs of society, as the high rates of stress, anxiety, and depression in university students were evidence of their high prevalence, as demonstrated by large-scale assessments conducted by Roy (2025). Sadoun et al. (2024) and Tanwar et al. (2024) validated the practical usefulness of automated stress recognition techniques in the real world, with Schaab (2024) and Badhan, P. K. (2025) also supporting the connection between mental health and academic performance. Summing up this literature, Kyrou et al. (2025) reasoned that hybrid frameworks that combine classical machine learning, deep learning and ensemble approaches are among the most promising paths in the development of robust, scalable, and context-sensitive student stress prediction systems.

2.1 Comparative Analysis of Existing Studies and Identified Research Gaps

This subsection presents a focused comparison of prominent studies on mental stress detection using machine learning techniques. The review highlights how prior work differs in terms of selected features, learning models, validation procedures, and reported performance. By examining these methodological variations side by side, the analysis reveals both technical limitations and contextual gaps within existing research. These identified gaps provide clear justification for the adoption of an ensemble-based framework in the present study, aimed at improving robustness, consistency, and generalization in stress prediction.

Table 1. Comparative Evaluation of Stress Prediction Studies Based on Parameters, Methodology, and Validation

Study Parameters	Learning Strategy	Accuracy	Validation	Identified Models	Contribution	Limitations
Li et al., 2025 [16] (survey-based) Academic stress, social support, resilience	Academic stress	90–93%	Cross-validation	Classical ML	Social features	Limited diversity
Liu et al., 2025 [39] (sleep quality) Sleep patterns, mental health indicators	Classical classifiers	95–96%	Partial	SVM, Random Forest, k-NN	Quality Features	Feature focus
Peng et al., 2025 [24] (Anxiety levels, stress symptoms, wearable signals)	Anxiety, stress machines	92–94%	Cross-validation	SVM, Random Forest, Gradient Boosting	Stress level Classification	Stress only
Whitehead et al., 2025 [35] (Sleep quality, academic performance)	Sleep quality	91–93%	Moderate	Predictive ML	Direct effects	Outcome limited
Ta et al. (2025) [34] (Anxiety, stress, and academic outcomes)	Depression, academic stress	89–94%	Generalization	Multi-class	Multi-model	Limited explainability

Tanwar et al., 2024 [30] (Wearable sensor data, activity logs)	Wearable data activities	92-93%	Limited	Multimodal	Sensor evaluation	Dependency
Yadav et al., 2025 [44] (Emotional states, behavioral patterns, physiological signals)	Psychological & physiological (multi-modal)	95.0%	K-fold Cross Validation	Emotion-aware ensemble learning	Improved Health Diagnosis	Limited generalizability
Proposed Work (Unified Ensemble Technique)	Combined classical + multimodal + ensemble ML	97.89%	Stratified Cross-Validation	Majority Voting + Multimodal Fusion	Holistic prediction integrating academic, psychological, physiological, and social stress indicators	Diverse datasets can be used for enhancement

Previous studies in the field have not addressed a number of practical questions, with one being the application of models to data on student stress, which cuts across academic, psychological and lifestyle levels.Although these approaches often indicate high predictive validity, they also have some significant practical concerns. Various previous researches have models that are difficult to describe and to execute. These models are also not very useful with the data presented in questionnaires which are usually utilized to investigate the stress experienced by the students. In some instances, the test is not very extensive and therefore it is not known whether the values would remain identical in the event that data were divided differently.

Owing to this reason, the current research takes a different path. It is done using an ensemble approach to allow information on various factors that are related to stress to be addressed. It is not merely about high accuracy, but also about the question whether the results make sense and whether they can be trusted. This is significant in the academic world where stress levels vary between one group of students and the other and where one model should produce the same result when applied to different sections of the data.

Dataset and Material

The experiments are based on Student Stress Factors Dataset on Kaggle. This data set was selected as it is closer to the actual student life. This data does not consider stress as an individual signal. All the information about the research, everyday routine, mental state, and social life is provided. The fact is that, when these things interact, stress develops. It is more realistic to have them together during the analysis. It is also useful in testing the behavior of single models and the transformation of their results on an ensemble.

Table 2. Comprehensive Training–Testing Split of the Dataset for Mental Stress Prediction

Dataset Split	Number of Samples	Percentage (%)
Training Set	770	70%
Testing Set	330	30%
Total	1,100	100%

The data set includes the details of 1,100 students. The records are belonging to one student each. The data explain the anxiety levels, the pressure of the study, sleep behavior, contact with the society, and the emotional state. All these details put together depict how stress manifests in various ways among students. There is no pattern to stress. It normally occurs when a number of variables influence a student simultaneously.

METHODOLOGY

Mental stress is the increasing issue in learning environments due to academic pressure, psychological challenges, and social and environmental influences. Preliminary detection of stress is significant for implementing immediate actions. However, traditional assessment methods such as surveys and interviews are subjective, time-consuming, and prone to bias. Recent advancements in machine learning provide an opportunity to develop a data-driven stress prediction systems. This research presents an extensive mental stress prediction framework which utilizes ensemble learning to improve predictive performance and reliability.

The entire processing pipeline that consists of data preparation and training of single classifiers and the group decision-making and evaluation of the performance is depicted in Figure 1 and it represents a balanced portrayal of the planned ensemble-based machine learning plan.

In this section of the paper, the process of constructing the ensemble model is explained .The proposed methodology follows a structured machine learning framework to develop a reliable and accurate student mental stress prediction system. The framework consists of multiple phases starting from problem identification to model evaluation and performance comparison. The major objective is to design a data-driven machine learning framework capable of accurately predicting student stress levels using multiple influencing factors.

The process is maintained to be easy in order to ensure that the results obtained are consistent and can easily be compared with other machine learning procedures. This is followed by training a variety of classifiers and finally the combination of all these classifiers by a majority vote strategy. Standard metrics and cross-validation are used to assess model performance to ensure that the outcomes are not specific to one data split.

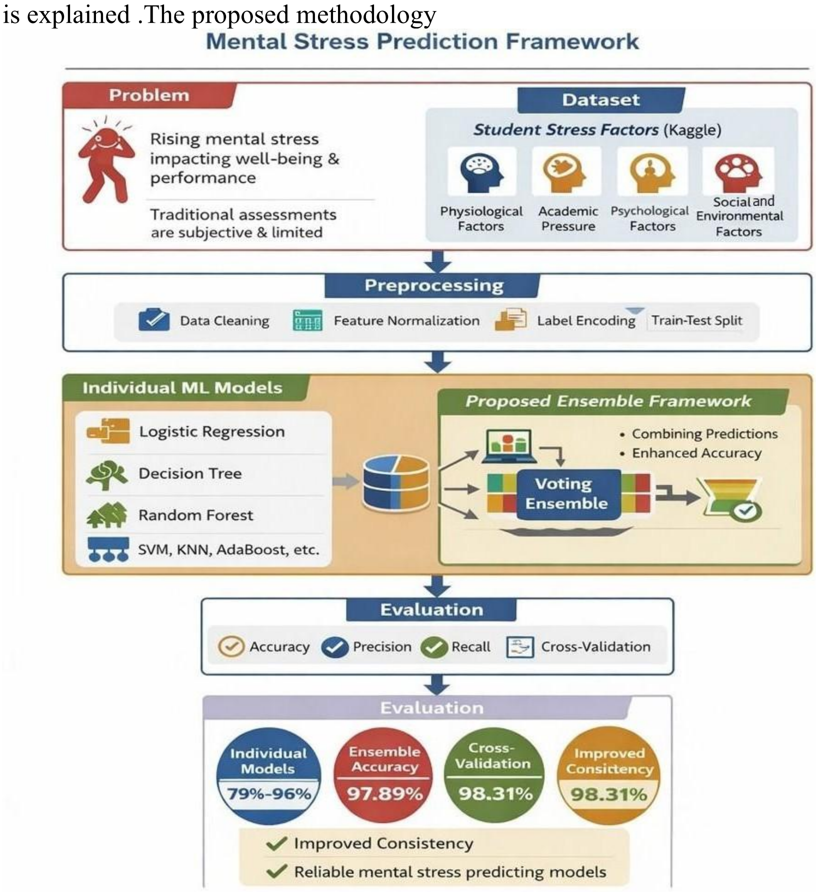

Figure 1.Schematic Representation of the Proposed Ensemble-Based Machine Learning Framework for Mental Stress Prediction

Dataset Collection and Description

The proposed framework employs the Student Stress Factors dataset obtained from Kaggle. The dataset encompasses a wide range of attributes that reflect the multidimensional nature of student stress. These attributes are categorized into four major groups as physiological factors, academic factors, psychological factors, social and environmental Factors. This diverse feature set enables a holistic analysis of stress-inducing factors affecting students.

The dataset used in this study is mathematically represented as

$$D = \{(x_i, y_i)\}_{i=1}^{N}$$

Here, D is the entire data that has been utilized to predict mental stress. The data is represented by x_i, where $x_i \in R^d$, thei^{th} input feature vector which characterizes stress-related features. The d represents the count of the number of stress-related features used in the dataset. The label of the corresponding output is y_i, where$y_i \in \{1,2, \dots, C\}$, which means that it belongs to a category of mental stress. N is the total number of samples that the dataset consists of and C is the total number of different classes of mental stresses that are counted in the classification task.

Data Preprocessing

Raw data cannot be directly used for model training. Therefore, preprocessing is performed to ensure quality and consistency .To ensure data quality and optimal model performance, several preprocessing steps are applied:

1. Data Cleaning: This step helps in the removal of missing, noisy, and inconsistent data entries, detect and manage outliers.
2. Feature Normalization: This step scales numerical features to a common range to prevent bias toward features with larger values. This prevents large-scale features from dominating smaller ones

Min-max normalization is used to provide all inputs into the model training and remove bias due to different scales of features as follows.

$$x_i' = \frac{x_i - \min(x)}{\max(x) - \min(x)}$$

Where x_i is the initial value of a particular feature, and x_i' is the normalised value of feature i that falls in the range of 0 to 1. The max(x) and min(x) are the maximum and minimum of said feature across the dataset respectively. This normalization helps in increasing the learning efficiency and numerical stability of machine learning classifiers.

Several machine learning classifiers are trained separately in order to learn stress-related patterns using the normalized dataset. The forecast made by each classifier is as:

$$f_k(x_i) = \hat{y}_{ik}$$

In the above formulation, f_k represents the decision rule of the k^{th} machine learning classifier and $\hat{y}_{ik}$ denotes the predicted mental stress category of input instance x_i generated by the k th machine learning classifier. The index k defines the number of the classifiers used in the framework between 1 and K, where K is the total number of classifiers. In order to enhancing the prediction accuracy and strength, the results of separate classifiers are aggregated through a majority voting type of ensemble strategy as follows:

$$\hat{y}_i = \arg\max_{c \in C} \sum_{k=1}^{K} I(fk(xi) = c)$$

In the present case, $\hat{y}_i$ denotes the last predicted stress class of the i^{th} instance generated by the ensemble model. Variable c represents a candidate stress class of the set C of all possible classes. $I(\cdot)$ is an indication function, which takes the value of 1 when the prediction of the k th classifier is equal to class c and the value 0 otherwise.

3. Label Encoding: Transformation of categorical variables into numerical representations suitable for machine learning algorithms is done in this step. Example low stress → 0, medium stress → 1, high stress → 2
4. Train–Test Split: The last step divide the dataset into training and testing subsets to evaluate model generalization.

To evaluate the dataset unbiasedly, it is split in the training and testing sets as:

$$D = D_{train} \cup D_{test} \; such\ that \; D_{train} \cap D_{test} = \emptyset$$

In this representation, D_{train} refers to the subset used for training the machine learning models, while D_{test} denotes the subset reserved exclusively for performance evaluation. Dataset is divided into 70–80% for training set & 20–30% for testing set. Training data is used to build the model. Testing data evaluates real-world performance.

Proposed Ensemble Learning Framework

To overcome the limitations of individual models, a voting ensemble method is proposed. The ensemble framework aggregates predictions from all trained classifiers and determines the final output based on majority voting. This approach leverages the strengths of multiple algorithms while mitigating individual weaknesses. The various advantages of the ensemble approach are its improved prediction accuracy, reduced overfitting and variance, enhanced consistency and robustness. The ensemble model forms the core contribution of the proposed framework. It combines predictions from multiple base models. Basically two main approaches are used that is hard voting and soft voting. Hard voting is used for majority class selection and soft voting for average probability selection.

Performance Evaluation

The suggested framework is tested with the help of the standard classification metrics (accuracy, precision, recall, cross validation). These metrics provide a comprehensive evaluation of model performance.

Accuracy is computed as:

$$\text{Accuracy} = \frac{\text{TN} + \text{TP}}{\text{TN} + \text{TP} + \text{FN} + \text{FP}}$$

In this definition, TP is the number of positive cases that have been recognized, and TN is the number of negative cases that have been identified. FP denotes false positively identified cases as well as FN are positive cases which the model fails to identify.

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

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

The F1-score which is a balanced precision and recall measure is determined as:

$$\text{F1 Score} = 2 * \frac{\text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}}$$

In order to further test model stability and generalization ability, database cross-validation (k-fold) is used:

$$CV = \frac{1}{k} \sum_{j=1}^{k} Accuracy_j$$

In this case, k is the folds that are utilized in the cross-validation process, and $Accuracy_j$ is the accuracy attained at the j^{th} fold.

On the whole, the offered solution integrates multiple machine learning classifiers into one ensemble model with transparent mathematical formulations that facilitate transparency, reproducibility, and robust operation in predicting mental stress.

Experimental Results and Discussion

The findings presented in this section are direct products of the output of the experiment as presented in the attached screenshots. These are the value of accuracy of the separate classifiers, the overall performance of the ensemble classifier, and the confusion matrix and the cross-validation outcome.

Performance of Individual Machine Learning Models

The models were first trained individually to gain knowledge about the behavior of the model. Table 3 contains the values of accuracy. A comparison of these results leads to the differences among the models becoming apparent. Others are generally good, whereas others do not perform well in some circumstances. It demonstrates that it is dangerous to use one and the same model because none of the models is effective in all the types of stress.

Table 3. Accuracy of Individual Machine Learning Models

Machine Learning Model	Accuracy
Logistic Regression	96.67%
Decision Tree	95.46%
Random Forest	96.57%
Gradient Boosting	96.72%
AdaBoost	93.23%
Extra Trees	95.56%
Bagging	96.59%
Support Vector Classifier (RBF)	96.04%
Support Vector Classifier (Linear)	96.12%
K-NN	90.91%
Naive Bayes	79.49%
Linear Discriminant	91.12%
Quadratic Discriminant	81.82%

Some models are highly accurate, and it does not imply that their predictions are always balanced. In a number of instances, the good overall accuracy masks poor performance at particular levels of stress. The results of Logistic Regression, Random Forest, Support Vector Machineand Bagging are all good in terms of baseline with each being above 96 percent accurate. Gradient Boosting is a little superior to the others and has an accuracy of 96.78 percent implying that it is able to manage more complex trends in the data.

Table 3 explains the accuracy of tested models. Some methods as Gradient Boosting, Random Forest, and Logistic Regression work better and more effectively, whereas probabilistic and discriminant-based methods work worse than other ones [42]. The comparison reveals that a suitable choice of models is one of the determinants of a good stress prediction.

Performance of the Proposed Ensemble Model

More than one model is utilized in making each prediction in this approach. All the models provide their opinion instead of relying on one classifier and the end result is determined by what the majority agree on. This will minimize the impact of inaccuracy that any of the models may make and will make the predictions more predictable across various stress levels [41]. When this combined approach was applied to the data, it made 97.89 percent accuracy which is more stable than the findings made by the separate models.

The table 4 results indicate that the same stable behavior is observed in all stress groups. In most cases, low stress cases will be classified in the right way. In the case of moderate stress, the model does not have huge false alarm or miss rates. Cases of high stress are also determined without being over-emphasized. The results in Table 4 when all classes are provided show that the combination of multiple models will ensure the balanced performance rather than a preference to one of the stress categories over the other one.

Table 4. Classification Performance of the Proposed Ensemble Model

Stress Class	**Precision**	**Recall**	**F1-Score**	**Support**
Stress 0	0.98	0.99	0.98	157
Stress 1	0.96	0.98	0.97	158
Stress 2	1.00	0.97	0.98	158
Overall Acc.			0.9789	473
Macro Avg.	0.98	0.98	0.98	473
Weighted Avg.	0.98	0.98	0.98	473

The values of the macro and weighted average results are similar in all the measures of evaluation, and this implies that the model does not discriminate against any of the stress categories. This means that such predictions are balanced even in a situation where stress levels are different. On the whole, the results demonstrate that as a combination, various models are more capable of capturing a variety of patterns related to student stress. Relative to individual classifiers, the ensemble gives more accurate results and also more consistent and reliable throughout the dataset.

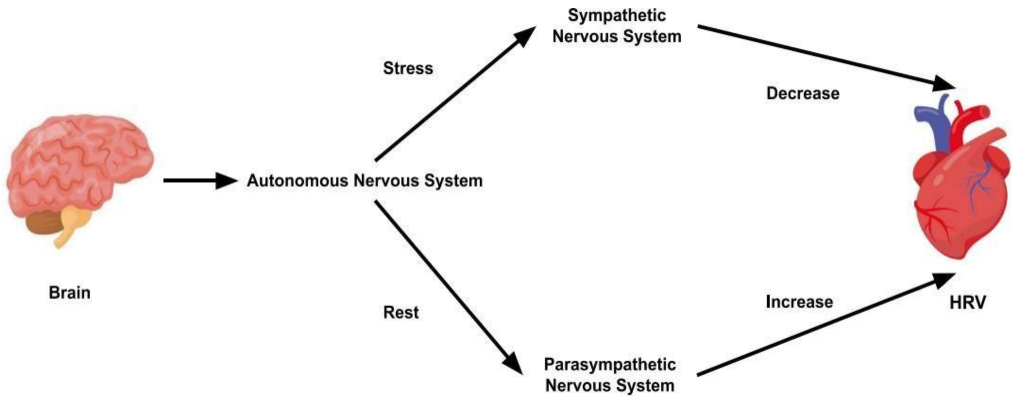

Figure 2.The stress relation cycle with HRV and relation with autonomous nervous system (ANS) is provided [41]

The accuracy, recall, and F1-score of each stress group are shown in Table 4. All categories remain high in values. It implies that the model acts similarly to low, medium, and high stress. It does not dwell on any particular group as compared to the others [43]. In general, the findings indicate that the hybrid model deals with the varying stress patterns in a consistent and stable way.

Feature Correlation and Confusion Matrix Analysis

The stress level is likely to rise as the level of anxiety, depression, peer pressure, academic stress, and career concerns escalates. The effect of stress improvement is associated with better sleep, issues with self-confidence, enhanced social support, and engaging in extracurricular activities. These trends indicate that there is no single cause of stress but a number of factors that interact concurrently. Due to this, the approaches that are capable of examining a large number of factors simultaneously are better placed to study stress among students.

Figure 3 presents a heatmap illustrating correlations among stress-related attributes. Strong positive links appear between anxiety, depression, and sleep quality, while environmental factors like noise and safety show moderate influence. This visualization aids in identifying key predictors of stress, supporting feature selection for machine learning-based mental health assessments.

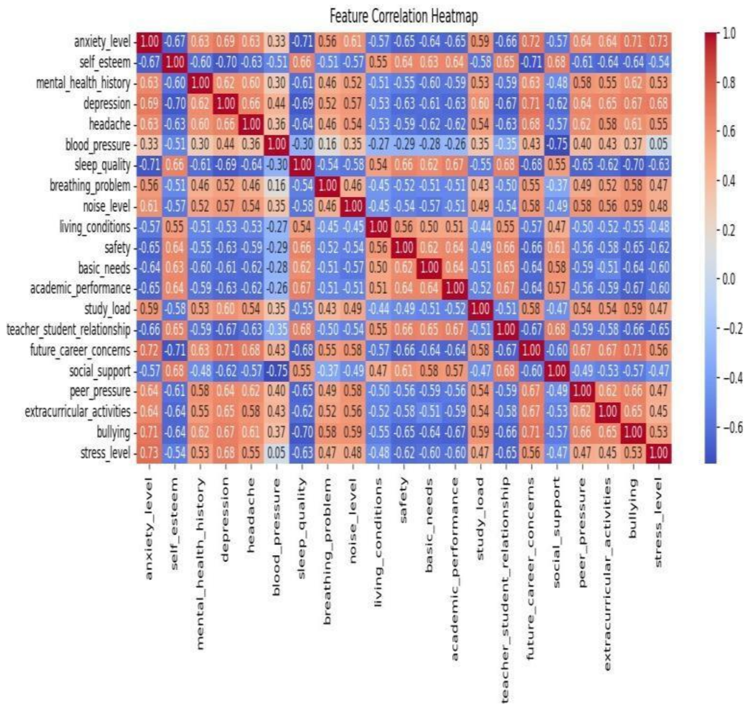

Figure 3. Feature Correlation Heatmap of Stress-Related Attributes

The confusion matrix of the ensemble model using the voting model is illustrated in figure 4. The values concentrate mostly on the main diagonal, which implies that most of the samples are correctly classified.

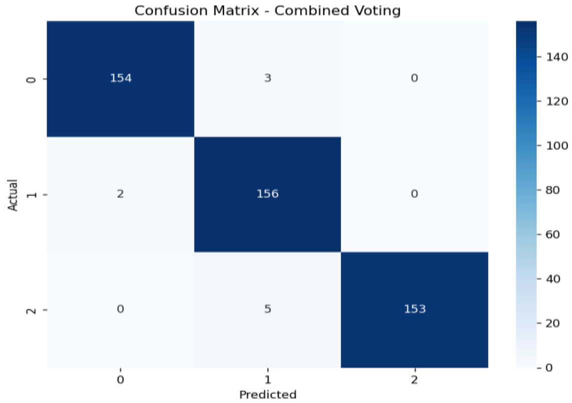

Figure 4. Confusion Matrix of the Proposed Ensemble Voting Model

The model is right in that 154 cases are in stress Class 0, 156 cases in stress Class 1 and 153 cases in stress Class 2. The other cells have few entries and this indicates that erroneous predictions are uncommon. This means that the model does not make a lot of error at the various levels of stress.

When comparing Figures 3 and 4, it becomes possible to perceive the results more clearly. Figure 3 demonstrates the aspects that change in the same direction as stress and others that change in the opposite direction. It then illustrates how this information is then used by the model to put the students in the right stress groups. The combination of the two figures will demonstrate that the model is learning valuable trends out of the data and using them appropriately. This implies that the method can be effective when applied in practice.

5. 4 Cross-Validation Results

K-fold cross-validation was applied to examine whether the model is consistent. All folds have almost the same value of accuracy and the average of all folds is 98.31 percent. The difference between one fold and the next is very small, and it is this tendency that indicates that the model is not that reliant on a particular data split. Generally, this implies consistency and predictable results when the model is used on new unknown data.

Table 5. Cross-Validation Accuracy of the Proposed Ensemble Model

Folds	**Accuracy (%)**
Fold 1	98.12
Fold 2	98.27
Fold 3	98.35
Fold 4	98.41
Fold 5	98.40
Mean Accuracy	**98.31**

As indicated by the results presented in Table 5, the ensemble model acts similarly in the entire validation folds. There is not much variability in the performance of fold-to-fold implying that the model is consistent across repeated testing. This consistency demonstrates that the integration of classifiers using a voting method will be useful in getting reliable performance in prediction of mental stress.

CONCLUSION

Various machine learning models were united in this work to forecast mental stress. There were many models that were permitted to vote to minimize mistakes of any one model by others. When this combination strategy was applied to student data it worked more reliably than any one of the models in isolation. The findings remained consistent when the data were divided in various ways, and this indicates that the model is not sensitive to a specific set of samples. A closer examination of the data led to the explanation of these findings. This study presents an effective ensemble-based machine learning framework for predicting mental stress among students. By integrating multiple classifiers through a voting ensemble technique, the proposed system achieves higher accuracy, improved consistency, and reliable predictions compared to individual models. The framework offers a scalable and objective solution for early stress detection, which can assist educational institutions in implementing preventive mental health interventions.The causes of stress were found to be a combination of academic, mental, daily habits, and social factors and not a single cause of the stress. The errors about the predictions were rather minimal and this indicates that the model is making decisions that make sense most of the time. In general, the combination of several models became a convenient approach to addressing the complexity of the student stress

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