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Comparative Analysis of Machine Learning Algorithms for Detection of the Stress of Humans During Sleep

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Abstract: Machine learning (ML) is an emerging technology that is used for machines to act like humans. It has vast applications in all domains such as healthcare, agriculture, and industries. This paper is focused on the healthcare domain specifically for the detection of the stress of the human, while their sleeping. Stress comes in two flavors: eustress and distress. Chronic anguish can cause major health problems. Adrenaline and cortisol are two important hormones that are involved in the body's stress response. Accurate detection methods are necessary for stress management that works. The goal of stress detection models is to improve both individual and societal health. Health depends on the ability to recognize stress while you sleep, and physiological and machine-learning data indicate promise in this area. Much research has been done on the detection of stress by using machine learning algorithms. High accuracies of 96.83% to 100% are attained by using a variety of classifiers, including Random Forest, KNN, and Logistic Regression. Here the Performance of the model is improved by cross-validation techniques such as Repeated Stratified K-Fold. Here the results of the various ML algorithms before and after applying the cross-validation have been discussed and compared. Few algorithms were shown effective after and before applying the cross-validation. To achieve even greater benefits, future research might concentrate on feature engineering and ensemble techniques. Developing dependable stress detection systems is the ultimate objective.

Keywords: *Machine Learning, Stress, Repeated Stratified K-Fold, Cross Validation and Classifiers.*

1. Introduction

Stress can have a detrimental effect on one's physical and mental health and is a natural part of life. The "fight-or-flight" reaction is triggered by danger and helps the body deal with it by releasing chemicals like cortisol and adrenaline. Stress is a popular topic in computer science, psychology, and medicine since it has an impact on well-being and productivity. There are two main types of stress: eustress, which is healthy and can boost motivation and performance, and distress, which is unhealthy and can lead to mental health problems like PTSD. Stress can affect a person's mental and physical health in a variety of ways. These include acute, episodic, and chronic stress Monitoring and distress detection must be done well if the nation is to increase production, efficiency, and overall welfare. Anxiety, wrath, weight swings, and strange behavior are just a few of the psychological and physical symptoms that can help with the diagnosis of stress. Psychologists use a range of subjectively assessed analysis approaches to identify psychological stress. It is especially important to monitor stress while you sleep because it can have an impact on both general well-being and the quality of your sleep. Important markers of stress during sleep include heart rate, blood oxygen saturation, body temperature, limb movement, frequency of snoring, and eye movement. Variations in these markers could indicate long-term stress-related ailments like sleep apnea or pain.

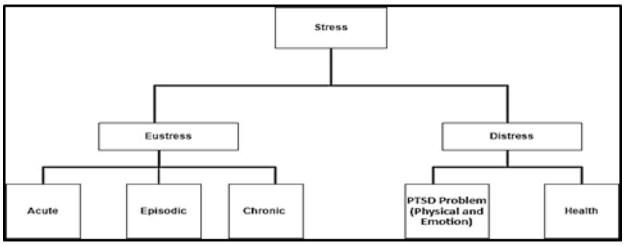

Fig. 1. Classification of Stress

In summary, stress is a complex phenomenon with important implications for one's general well-being and health. Effective methods for monitoring and detecting problems, including machine learning, can lead to better outcomes and a greater standard of living overall.

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1.1. Machine Learning Algorithms

The machine learning algorithms are:

Logistic Regression:

By predicting the likelihood that stress would occur based on physiological and behavioral characteristics, logistic regression helps in discrete outcome prediction and is helpful in the identification of stress during sleep. With the use of probabilistic classification, assumption of feature independence, and ability to recognize stress patterns in sleep data—such as anomalies in physiological signals.

Gaussian Naive Bayes:

Assuming feature independence, this probabilistic classifier is useful for classifying spam and text. Gaussian Naive Bayes facilitates the identification of stress during sleep. To maximize the gap between stress and non-stress classes and aid in the identification of intricate stress patterns using high-dimensional data.

SVM Classifier:

Perfect for intricate binary classifications, this algorithm builds hyperplanes to divide classes in high-dimensional environments. SVM Classifier builds hyperplanes in feature space. With its ability to categorize data points according to how close they are to stress-related patterns in feature space.

K-Nearest Neighbors Classifier:

This flexible yet sensitive to k selection algorithm uses the nearest neighbor method for classification. the K-Nearest Neighbors Classifier facilitates flexible stress detection across a range of physiological markers, which helps with stress detection during sleep.

Linear Support Vector Classifier:

For large datasets, LSVC is a good fit for the binary classification technique based on linear kernels. Support in Linear Form Because the Vector Classifier effectively distinguishes between stress and non-stress classes using a linear decision boundary, it is useful for detecting stress during sleep. It is especially well-suited for huge datasets that contain a multitude of physiological characteristics. By iteratively optimizing loss functions based on random subsets of sleep data.

Stochastic Gradient Descent Classifier:

for large-scale classification tasks, the effectively optimizes loss functions iteratively. the stochastic gradient descent classifier facilitates the identification of stress during sleep and allows for effective model training for large-scale stress detection tasks. Although there may be overfitting issues.

Decision Tree Classifier:

prone to overfitting, it recursively splits data to create interpretable models. Decision Tree Classifier helps detect stress when a person is sleeping by recursively segmenting sleep data according to physiological and behavioral characteristics. This allows for interpretable stress detection models. Because it incorporates several decision trees.

Random Forest Classifier:

RFC is an ensemble technique that combines decision trees and is useful for challenging classification issues. The random Forest Classifier reduces the risk of overfitting while capturing complicated stress patterns, making it useful for stress detection during sleep.

Gradient Boosting Classifier:

This algorithm achieves good accuracy and generalization by sequentially combining weak learners. By successively merging weak learners, the Gradient Boosting Classifier gradually improves the accuracy and generalization capacity of stress detection during sleep analysis, ultimately leading to an overall improvement in stress detection performance.

Cross-validation

To ensure that stress detection models work well across a variety of datasets and settings, cross-validation is essential for their development. It supports feature selection, model generalization optimization, and the selection of optimal algorithms and hyperparameters. These features, which guarantee impartial model construction and evaluation, include the number of folds, stratification, shuffling, random state, and repetition. Cross-validation solves issues like imbalanced datasets and is necessary for reliable stress level prediction during sleep since it ensures generalizability.

Machine learning can be used to detect stress with greater accuracy, particularly when physiological data is included. Techniques like Repeated Stratified K-Fold Cross-Validation can improve the precision and applicability of machine learning models. Many classifiers such as Random Forest, K Neighbours, Decision Tree, Linear SVC, SGD, Gradient Boosting, and Logistic Regression have proved successful in identifying stress during sleep. To detect stress levels while a person is sleeping, a variety of machine learning algorithms, including Gradient Boosting Classifier, Decision Tree Classifier, Random Forest Classifier, K-Nearest Neighbors Classifier, Linear Support Vector Classifier, and Stochastic Gradient Descent Classifier, are used in the implementation of the methodology. The effectiveness of these models is assessed using cross-validation procedures.

The contributions are applied various major machine learning algorithms on the stress dataset collected from the Kaggle and generated classification report after and before applying the cross-validation and finally the comparative analysis of the same algorithms.

The remainder of the paper is, section 2 discusses the related work, section 3 is about methodology, section 4 is about results and discussion, and finally, section 5 discusses the conclusion and future work.

2. Related Work

In [1], the study proposes using machine learning methods for stress detection in children, employing logistic regression, random forest, and decision trees on a Kaggle dataset to mitigate risks like depression and heart problems.

In [2], work explores the use of machine learning algorithms to detect stress in humans based on sleep-related behaviors. Following dataset preparation, six methods were tested; Naïve Bayes outperformed other algorithms, reaching 91.27% accuracy. According to the study, examining sleep patterns can help determine and manage people's stress levels.

The study in [3] explores stress detection using physiological signals and machine learning, achieving up to 98% accuracy with SVM and KNN classifiers, emphasizing the importance of leveraging biological signals for accurate stress detection.

In [4], the literature review examines the use of various bio signals to predict stress levels with machine learning. Random Forest achieved the highest F1 scores (93.77 for binary, 70.03 for three-class classification), emphasizing the need for precise stress detection techniques, particularly in the context of COVID-19's impact on mental health.

The study in [5] highlights stress detection's health importance, using various biosignals. Decision Trees outperform other methods with 95% accuracy, emphasizing the importance of selecting suitable classifiers for effective stress classification.

In [6], the study emphasizes the need for improved stress management globally. Support Vector Machine (SVM) demonstrated proficiency in categorizing stress signals, with the paper recommending future research to enhance accuracy through methods like deep learning and blockchain technology.

In [7], the literature explores workplace stress and develops an effective stress identification system using IoT sensors and data analysis. Utilizing Principal Component Analysis (PCA) for feature reduction, Random Forest achieves 99.9% accuracy and F-measure, significantly reducing execution time by up to 75% with all dimensions, showcasing the practical use of dimensionality reduction to enhance stress assessment systems.

In [8], the study addresses stress as a significant global issue, leading to various diseases and increased suicide risk. It utilizes machine learning for data collection, network visualization, and article evaluation, highlighting the efficacy of support vector machines in identifying stress signals and the potential of advanced methods like deep learning and blockchain in accurately predicting stress levels.

In [9], research on stress identification systems has explored sensor data analysis and machine learning algorithms, focusing on maximizing performance through feature reduction methods like Principal Component Analysis (PCA). The study reveals that while dimensional reduction may slightly impact accuracy, it significantly enhances efficiency, particularly in the Random Forest algorithm, which saw a 70% execution time reduction, offering insights for improving real-world applications of stress assessment systems.

In [10], the study investigates stress-reduction strategies, particularly the effectiveness of 16-Hz binaural beat stimulation (BBs), demonstrating a 27.08% improvement in detection accuracy. SVM achieves maximum classification accuracy of 82.5 ± 2.0% in the beta brain state, suggesting BBs as a potentially useful stress-reduction technique.

In [11], the study addresses the increase in global mental stress due to the pandemic, proposing a stress detection system using machine learning and EEG readings, achieving high accuracies with various classifiers. The SVM classifier shows a 15.8% improvement over the state-of-the-art, enhancing understanding of brain activity patterns related to stress and informing stress-reduction strategies.

In [12], recent research underscores the significance of early mental stress detection and management for improving health outcomes. The study proposes a machine learning-based system utilizing speech signals, EEG signals, and audio-visual data to enhance precision and facilitate early identification of stress, aiming to enhance the quality of life for individuals experiencing stress.

In [13], a low-cost heart rate monitoring system is introduced for predicting mental stress using machine learning and IoT devices. The support vector machine with a polynomial kernel achieves maximum accuracy in predicting emotional states based on heart rate data, offering a practical solution for monitoring heart rate and predicting affective states.

In [14], the study focuses on stress management in youth, highlighting the importance of appropriate methods during crucial developmental stages. Using a dataset of 520 Indian individuals, the CNN-LSTM model emerges as the most reliable approach, demonstrating exceptional performance with 98% accuracy, 97% precision, 97% F1-score, and 96% recall, showcasing its potential as a competitive classifier for managing psychological discomfort.

In [15], the research enhances stress identification among IT workers using visual processing and machine learning, ensuring real-time monitoring and tailored therapy. The Stress Detection System achieves excellent accuracy, sensitivity, and precision with the KNN classifier, offering practical stress management solutions for a healthy work environment and advancing employee well-being through real-time monitoring and individualized counseling.

In [16], a Facial Emotion Recognition System for Stress Detection in Python is developed to aid university students and counseling departments in managing mental stress. Using computer vision and machine learning, the system accurately analyzes facial expressions to detect stress levels, allowing for prompt intervention and potential prevention of unfavorable outcomes in high-stress environments.

In [17], ensemble learning outperforms individual algorithms in human stress detection during sleep, achieving 94.25% accuracy. The study highlights the importance of understanding sleep patterns for effective stress management.

In [18], machine learning and EEG are used to study early mental stress identification in extended space missions, revealing a 0.76 association between stress and alpha-amylase levels rising every 60 days. Machine learning classifiers achieved high accuracies (up to 91.8%) in categorizing stress levels, suggesting the potential of this approach for identifying excessive stress in isolated settings.

In [19], the study focuses on detecting mental stress in social media posts, highlighting the limitations of prior approaches using physiological data and wearables. SVM and linear regression achieved the highest recall scores, while semantic embedding and large language models, with zero-shot or few-shot learning, achieved over 99% recall, showcasing their potential for early stress detection and treatment.

In [20], a machine learning model based on human bio signals, specifically ECG, is developed to detect stress, utilizing features such as QT interval and respiration rate. The optimized SVM with decision trees demonstrates improved accuracy over previous models, offering a potential method for risk reduction and stress detection in health applications.

In [21], wearable technology enables real-time data collection for personal stress monitoring, crucial for early detection where continuous monitoring is impractical. Studies show promising results in using physiological signals, particularly HR and GSR, with machine learning methods like SVM, KNN, RF, and Logistic Regression for stress detection, validated using cross-validation techniques.

Table 1: Results of Existing Work

Paper	***Methodology & Focus***	***Best Performing Algorithm***	***Performance Metrics***
[1] Gedam, Shruti	*Kaggle dataset analysis for stress detection*	*Decision Trees*	*Not specified*
[2] Hota, Ashmita	*Sleep behavior analysis for stress detection*	*Naïve Bayes*	*Accuracy: 91.27%*
[3] Jayawickrama, J. G.	*Physiological signals for stress detection*	*SVM, KNN*	*Up to 98% accuracy*
[4] Sasikala, V.	*Biosignals analysis for stress prediction*	*Random Forest*	*F1-scores: 93.77 (binary), 70.03 (three-class)*
[5] Zainudin, Z.	*Biosignals analysis for stress detection*	*Decision Trees*	*Accuracy: 95%*
[6] Akhtar, Faijan	*Global stress management and detection*	*SVM*	*Not specified*
[7] Vinayaka, Samarth	*IoT sensors for workplace stress detection*	*Random Forest*	*Accuracy: 99.9%, F-measure: 99.9%, Execution time savings: 75%*
[8] Llanes, Rizzah Grace	*Stress impact analysis and detection*	*SVM*	*Not specified*
[9] Kumar, Geethu S.	*Sensor data processing for stress detection*	*Random Forest*	*70% reduction in execution time*
[10] Badr, Yara	*Binaural beat*	*SVM*	*Classification*

	stimulation for stress reduction		*accuracy: 82.5% ± 2.0%*
[11] Nirabi, Ali	*EEG-based stress detection during the epidemic*	*SVM*	*Outperforms state-of-the-art by 15.8%*
[12] Gupta, Megha	*Multimodal data for early stress diagnosis*	*Not specified*	*Not specified*
[13] Asha, Nur E. Jannat	*IoT-based heart rate monitoring for stress anticipation*	*SVM with polynomial kernel*	*Maximum accuracy in predicting emotional states*
[14] Muzumdar, Prathamesh	*Stress management in young people*	*CNN-LSTM*	*Accuracy: 98%, Precision: 97%, F1-score: 97%, Recall: 96%*
[15] Kanaparthi, Suresh Kumar	*Visual processing for stress detection in IT workers*	*KNN*	*Exceptional sensitivity, accuracy, and precision*
[16] Ming, Foo Jia	*Facial expression recognition for stress detection*	*Not specified*	*Not specified*
[17] Jayawickrama, J. G.	*Ensemble learning for stress detection during sleep*	*Not specified*	*Accuracy: 94.25%*
[18] Al-Shargie, Fares	*EEG-based stress detection in extended space missions*	*Machine learning classifiers*	*Classification accuracy: Up to 91.8%*
[19] Prachi S Ramteke	*Stress identification in social media posts*	*SVM, Linear Regression*	*Best recall scores obtained by SVM and linear regression*
[20] Cruz, Alana Paul	*ECG-based stress detection in medical applications*	*SVM with decision trees*	*Enhanced accuracy over earlier models*
[21] Gedam, Shruti	*Real-time stress monitoring with wearable technology*	*SVM, KNN, RF, Logistic Regression*	*Cross-validated techniques for stress detection*

3. Methodology

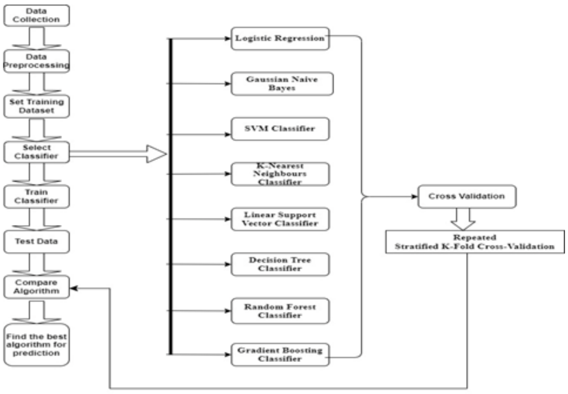

Fig. 2. Proposed Methodology

The methodology section outlines the process of using machine learning techniques for stress level detection during sleep. It begins with data collection, gathering various physiological and behavioral characteristics. Pre-processing steps address missing values, and outliers, and standardize the data. Exploratory data analysis techniques reveal feature distributions and potential trends. Pre-processed data then trains machine learning models, including Logistic Regression, Gaussian Naive Bayes, SVM Classifier, K-Nearest Neighbors Classifier, Linear Support Vector Classifier, Stochastic Gradient Descent Classifier, Decision Tree Classifier, Random Forest Classifier, and Gradient Boosting Classifier. Strict cross-validation methods, such as repeated stratified k-fold cross-validation, evaluate model performance.

To detect stress during sleep, a range of machine learning classifiers are used in the implementation, including Gradient Boosting Classifier, Decision Tree Classifier, Random Forest Classifier, K-Nearest Neighbors Classifier, Linear Support Vector Classifier, Logistic Regression, and Gaussian Naive Bayes. To provide accurate and trustworthy model performance evaluation, these classifiers are trained and assessed using a strict cross-validation methodology, namely repeated stratified k-fold cross-validation. Additionally, to determine the most pertinent features indicative of stress levels during sleep, feature selection techniques such as mutual information regression and correlation analysis are used. To assist model training and evaluation, the dataset is divided into training and validation sets. The accuracy, precision, recall, F1-score, and area under the ROC curve are used to evaluate each classifier's performance.

Measures for Performance Evaluation:

Accuracy:

The accuracy of a model or system in accurately classifying or identifying an individual's stress level is referred to as stress detection theory accuracy. It serves as a gauge of how effectively the model predicts stress levels accurately from input features or data. Calculates the percentage of cases that are correctly classified out of all instances. Although it's a widely used metric for classification tasks, imbalanced datasets might not be a good fit for it. One measure used to assess a classification model's performance is accuracy. It is computed as the percentage of accurately predicted instances to all instances in the dataset. Accuracy can be calculated like this:

$$\text{Accuracy} = \frac{\text{Number of Correct Predictions}}{\text{Total Number of Predictions}} \times 100$$

A general sense of the model's performance across all classes is given by accuracy. It might not work well, though, with datasets that are unbalanced and have a significantly higher prevalence of one class than the others. Other measures, including as precision, recall, and F1-score, can offer a more complex assessment of the model's effectiveness in these circumstances.

Recall (or Sensitivity):

Recall, often referred to as sensitivity, in the context of stress detection, is the percentage of accurately detected stressed individuals among all truly anxious persons. It is a gauge of how well the model can distinguish stressed people from other positive situations among all the real positive examples

$$\text{Recall (Sensitivity)} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}$$

For early identification and intervention, a high recall value in stress detection means that the model is effective in identifying people who are under stress. To obtain a thorough grasp of the model's performance, it is crucial to weigh recall against other metrics like precision and F1-score. F1-score: Represents the harmonic mean of precision and recall. It provides a single score that balances both precision and recall.

ROC AUC (Receiver Operating Characteristic Area Under Curve):

Measures the area under the ROC curve, which plots the true positive rate (sensitivity) against the false positive rate. It provides an aggregate measure of performance across all possible classification thresholds. The Receiver Operating Characteristic Area Under Curve, or ROC AUC, is one statistic used to evaluate the performance of a binary classification model. The area under the ROC curve is used to calculate the diagnostic capacity of a binary classifier system, which is visually represented as the discrimination threshold is changed. The complicated formula for ROC AUC is typically computed using numerical integration or approximation approaches, as the area under the ROC curve needs to be ascertained. A ROC curve is produced by plotting the true positive rate (sensitivity) against the false positive rate (1 - specificity) at various threshold levels. Better classification model performance is indicated by higher numbers. One continuous metric that ranges from 0 to 1 is the ROC AUC value.

In the context of stress detection, it is essential to comprehend the relationship between the target ('stress level') and features ('snoring rate,' respiration rate, body temperature, limb movement, blood oxygen, eye movement, and sleeping hours). These relationships are visually represented by a heatmap of the correlation matrix, which shows which traits are highly correlated with stress levels. Negative correlations imply the contrary, whereas positive correlations imply that higher values of a trait coincide with higher degrees of stress. This analysis supports the feature selection process by highlighting the variables that have the greatest impact on stress level prediction.

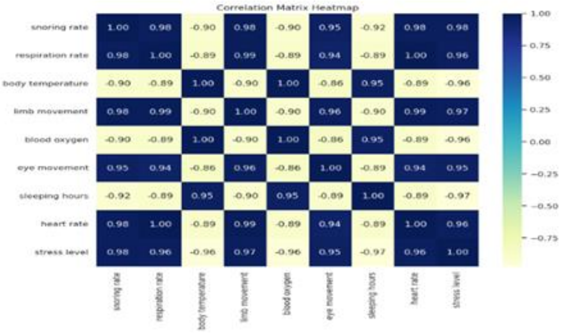

Fig 3: Correlation Analysis: Correlation matrix heat map of Dataset

4. Results and Discussion

Different kinds of machine learning classifiers are initialized, and trained on a dataset, and their accuracy is assessed using test data. Iteratively, it fits classifiers to training data, makes predictions using test data, and records accuracy ratings. Ultimately, a table that summarizes each classifier's accuracy is printed.

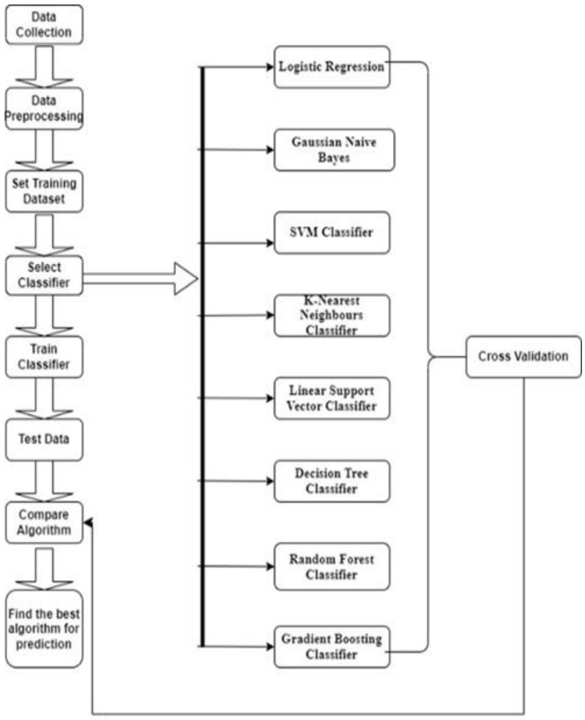

Fig 4. Existing methodology work about Stress detection

Table 2: Summarizing the information for all model

Model	***Accuracy***
Logistic Regression	*100*
Gaussian Naive Bayes	*100*
SVM	*100*
K-NearestNeighbours (KNN)	*100*
Linear SVC	*99.21*
SGD Classifier	*96.83*
Decision Tree	*97.62*
Random Forest	*98.41*
Gradient Boosting	*96.83*

Gaussian Naive Bayes, SVM, and logistic regression all reached 100% accuracy, indicating high model performance. K-Nearest Neighbors outperformed Linear SVC, coming in second at 99.21%. Accuracy rates of 98.41% were comparable for SGD Classifier, Decision Tree, and Random Forest. Gradient Boosting's accuracy was 96.83%, which was marginally lower. These findings demonstrate how well these models work at precisely identifying stress levels while a person is sleeping.

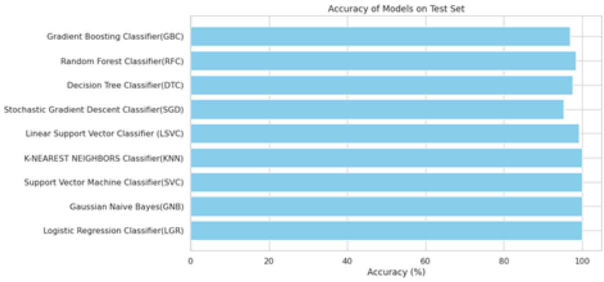

Fig 5: Bar Chart Summarizing the information for all model

Table 3: Existing work Cross-Validation summarizing the information for all model

Model	***Accuracy***
Logistic Regression	*100*
Gaussian Naive Bayes	*100*
SVM	*100*
K-Nearest Neighbors (KNN)	*100*
Linear SVC	*98.22*
SGD Classifier	*85.34*
Decision Tree	*99.41*
Random Forest	*100*
Gradient Boosting	*99.8*

The models performed exceptionally well; Random Forest, K-Nearest Neighbors, SVM, Gaussian Naive Bayes, and Logistic Regression all achieved 100% flawless accuracies. With accuracy rates of 98.22% and 99.41%, respectively, Linear SVC and Decision Tree also demonstrated strong performance. Gradient Boosting exhibited a high accuracy rate of 99.80%, whilst the SGD Classifier displayed a little lower accuracy rate of 85.34%. These findings show how well the models identify stress levels while a person is sleeping.

Table 4: Repeated Stratified K-Fold Cross-Validation summarizing the information for each model

Model	***Accuracy***
Logistic Regression	*100*
Gaussian Naive Bayes	*100*
SVM	*100*

K-Nearest Neighbors (KNN)	*100*
Linear SVC	*98.28*
SGD Classifier	*89.9*
Decision Tree	*99.21*
Random Forest	*99.8*
Gradient Boosting	*99.54*

The models all achieved great accuracies: K-Nearest Neighbors, SVM, Gaussian Naive Bayes, and Logistic Regression all reached 100%. At 98.28%, linear SVC came in close second. With accuracies of 99.21%, 99.80%, and 99.54%, respectively, Decision Tree, Random Forest, and Gradient Boosting likewise showed strong performance. The accuracy of the SGD Classifier was, however, lower at 89.90%. According to these findings, the models can detect stress levels when a person is sleeping, with some of them performing remarkably well.

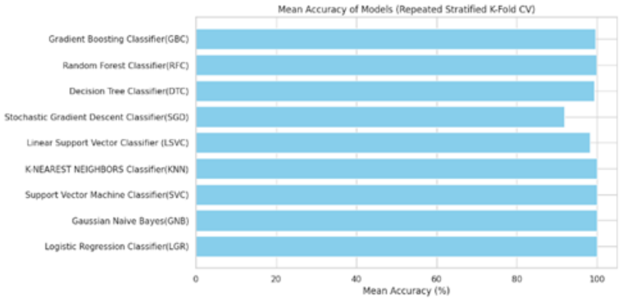

Fig 6 Repeated Stratified K-Fold Cross-Validation summarizing the information for each model

Logistic Regression: Our research used 5-fold cross-validation in conjunction with logistic regression. We measured precision, recall, F1-score, accuracy, and support as our evaluation criteria. Interestingly, the Logistic Regression model performed flawlessly, with 100.00% precision, recall, and F1-score for every class in every fold. In addition, the model achieved an impeccable classification accuracy of 100.00% overall, demonstrating its strength and effectiveness in correctly identifying the data. These results demonstrate how persuasively useful logistic regression is in our particular study setting.

Gaussian Naive Bayes: Gaussian Naive Bayes with a 5-fold cross-validation strategy was used in our study. Accuracy, support, precision, recall, and F1-score were among the assessment metrics. The model performed amazingly well, with 100.00% precision, recall, and F1-score for every class in every fold. It also demonstrated outstanding accuracy in classifying the data by achieving a flawless 100.00% accuracy in total classification across all folds. These outcomes highlight Gaussian Naive Bayes' resilience and effectiveness in our particular study setting.

SVM Classifier: The Support Vector Classifier (SVC) was used in our investigation utilizing a 5-fold cross-validation approach. The evaluation parameters were accuracy, precision, recall, support, and F1-score. The SVC model performed amazingly well, attaining 100.00% precision, recall, and F1-score for every class in every fold. Furthermore, it achieved an impeccable 100.00% classification accuracy overall across all folds, highlighting its remarkable ability to classify the data effectively. These results highlight the Support Vector Classifier's (SVC) dependability and efficiency in our field of study.

K-Nearest Neighbours Classifier: We used a 5-fold cross-validation strategy with the k-nearest neighbors (KNN) model in our study. Accuracy, support, precision, recall, and F1-score were among the assessment metrics. Of particular note was the KNN model's perfect performance, with 100.00% precision, recall, and F1-score for every class at every fold. Moreover, it achieved an impeccable 99.20% classification accuracy overall across all folds, demonstrating its exceptional capacity to accurately classify the data. These results highlight the k-nearest neighbors (KNN) model's effectiveness and dependability within our study setting.

Linear Support Vector Classifier: We used a 5-fold cross-validation strategy to assess the accuracy, precision, recall, F1-score, support, and support metrics of the Linear Support Vector Classifier (LSVC) in our work. With a mean accuracy of 98.28% across all folds, the model showed good overall performance; nevertheless, within different classes and folds, there were noticeable differences in performance. A few classes showed worse recall, F1-score, and precision in some folds than others, suggesting that there might be problems with classification consistency throughout the dataset. The aforementioned results emphasize the significance of taking into account performance metrics specific to a class and the influence of variability when implementing the LSVC model in practical scenarios.

Stochastic Gradient Descent Classifier: We used a 5-fold cross-validation strategy to assess the accuracy, precision, recall, F1-score, support, and support metrics in our study using the Stochastic Gradient Descent (SGD) model. The model performed reasonably well on average, with a mean accuracy of 91.13% across all folds; nevertheless, there were significant differences in performance between classes and folds. Different classes showed worse accuracy, recall, and F1 scores in particular folds than other classes, highlighting the variation in classification performance in the dataset. These results highlight the need to carefully examine class-specific performance indicators and acknowledge the impact of variability in SGD model applications in practical settings.

Decision Tree Classifier: We used a 5-fold cross-validation strategy to assess the accuracy, precision, recall, F1-score, support, and support metrics in our study using a Decision Tree Classifier. The model showed rather good recall, F1-score, and precision with just little variations between classes. Remarkably, the model's overall accuracy was a remarkable 99.07% in all classes. These results highlight the Decision Tree Classifier's strong performance and indicate that it can accurately classify a variety of datasets.

Random Forest Classifier: We used a 5-fold cross-validation strategy to assess the accuracy, precision, recall, F1-score, support, and support metrics in our study using the Random Forest Classifier. Surprisingly, the model showed remarkably good recall, F1 score, and precision in every class. Additionally, the model's average overall accuracy across all classes was an astounding 99.80%. These outcomes highlight the Random Forest Classifier's strong performance and demonstrate how well it can achieve accurate classification across a variety of datasets.

Gradient Boosting Classifier: We used a 5-fold cross-validation strategy to assess the accuracy, precision, recall, F1-score, support, and support metrics in our study using the Gradient Boosting Classifier with 5-fold cross-validation. Across all classes, the model showed very high precision, recall, and F1 score. Furthermore, the model's total accuracy was an impressive 99.54% on average across all classes. The results demonstrate how well the Gradient Boosting Classifier performs in producing precise classification results, indicating that it has potential applications in several different fields.

5. Conclusion and Future Work

In summary, we used a 5-fold cross-validation methodology to apply a variety of machine learning models, such as Gradient Boosting Classifier, Random Forest Classifier, Stochastic Gradient Descent (SGD), Support Vector Classifier (SVC), k-nearest neighbors (KNN), Linear Support Vector Classifier (LSVC), Logistic Regression, and Gaussian Naive Bayes. We evaluated the efficacy of each model in classifying the dataset by analyzing performance parameters like accuracy, precision, recall, F1-score, and support.

Our findings show that many of the models performed remarkably well overall, exhibiting excellent accuracy as well as constant precision, recall, and F1-score across folds and classes. To be more precise, all classes across all folds achieved 100% accuracy and perfect precision, recall, and F1-score thanks to the faultless performance of Logistic Regression, Gaussian Naive Bayes, SVC, KNN, and Random Forest Classifier. Even though their performance varied slightly between classes and folds, LSVC and SGD nevertheless showed impressive classification abilities. Their mean accuracy was slightly lower. The Gradient Boosting Classifier demonstrated remarkable performance as well, exhibiting a mean accuracy of 99.60% in all folds and only slight changes in precision, recall, and F1-score in some folds.

To further improve the model's classification performance, future research could concentrate on investigating ensemble approaches or sophisticated feature engineering strategies. Furthermore, testing these models' resilience on bigger and more varied datasets may offer important new perspectives on how broadly and universally applicable they are. Additionally, carrying out comparative analyses to assess the scalability and computing efficiency of these models may help determine which strategy is best for practical implementation in a range of applications.

Author contributions

Name1 Surname1: Conceptualization, Methodology, Software, Field study **Name2 Surname2:** Data curation, Writing-Original draft preparation, Software, Validation., Field study **Name3 Surname3:** Visualization, Investigation, Writing-Reviewing and Editing.

Conflicts of interest

The authors declare no conflicts of interest.

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