

ML-Powered Stress Recognition and Wellness Recommendation System

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Introduction: — Stress is a natural emotional and physiological reaction that people experience when someone face various problems in life. This pressure can be from various sources like challenges in work or study, responsibilities at home, financial imbalance or personal expectations that people place on themselves. Often people push themselves to meet certain standards or fulfill obligations and when they fall short, it can lead to frustration, self-criticism, and emotional strain. Over time this builds up tension affects not just our mood but also our health, relationships and productivity, because stress can quickly take a toll on our mental and physical well-being. So it's essential to become aware of the signs early on (W. Liao). Detecting stress level early, can lead someone to live a healthy life with healthy heart and protect to commit suicide.

However, they are often limited by the reliance on subjective approaches such as self-report questionnaires, which tend to lack accuracy and objectivity (A. Brown, 2022). Advancement of wearable technology [A. banga] now provide real-time data, that offers new opportunities for monitoring stress. Many existing solutions [P. Exarchos] failed to fully leverage comprehensive datasets or advance machine learning techniques [E. Lazarao, 2024] to offer accurate and personalized recommendations. This paper addresses this challenge and developing a robust machine learning based stress detection framework using a meta model approach.

This study aims to develop a stress detection framework that integrates demographic, physiological, and behavioral data such as age, gender, blood pressure, sleeping duration, physical activity, heartbeat rate, BMI. This model combines machine learning algorithm like, XGBoost, logistic regression, SVM in a meta model to achieve high accuracy in stress management recommendations. This paper addresses gaps in existing systems by integrating many machine learning algorithms into a unified meta-model. Using a divers dataset, this framework is generalized effectively across populations. Moreover, this framework provide personalized recommendations, advancing the application of machine learning in healthcare and promoting proactive mental health management.

The deployment of the predictive model involves integrating the trained models into a Meta-model, which combines the predictions of five base models: Support Vector Machine (SVM), XGBoost, and Logistic Regression. Each model generates probabilities for stress levels, which are aggregated into a feature vector. The meta-model, based on Logistic Regression, is trained using this feature vector as input. It then makes the final prediction by combining the weighted

probabilities from all base models. This ensemble approach leverages the strengths of each model, such as XGBoost's ability to handle complex, non-linear data, SVM's efficiency in high-dimensional spaces, and Logistic Regression's interpretability. By training on the combined predictions, the meta-model reduces individual errors and improves overall accuracy, leading to a more reliable stress level prediction. This stacking method enhances performance by optimizing the collective output of all models

Methodology:

Data Collection

The dataset for this study was collected from Kaggle for 374 participants, covering various factors related to demographics, behavior, and health. (<https://www.kaggle.com/datasets/uom190346a/sleep-health-and-lifestyle-dataset?resource=download>)

Data Characteristics

Demographic data included gender and age, while behavioral data included sleep information (duration and quality) and physical activity (daily steps and activity level). Health measurements such as blood pressure, heart rate, and BMI were also collected then participants rated their stress levels on a scale from 1 to 10 . To handle missing data, mean values were used to fill in any gaps. This dataset provided a solid basis for analyzing the factors affecting stress levels. This preprocessing step ensured the integrity and completeness of the dataset, providing a reliable foundation for analyzing the factors influencing stress levels.

Feature selection

The feature selection method in this study was carried out through a series of steps to ensure that the most relevant features were selected for predicting stress levels. First, key variables were identified from the collected dataset, including demographic information (gender and age), sleep metrics (duration and quality), physical activity data (steps and activity level), and physiological measurements (blood pressure, heart rate, and BMI). These variables were selected based on their potential influence on stress levels. The self-reported stress level, rated on a scale from 1 to 10, was designated as the target variable for binary classification. This involved imputing missing values using the mean of the

respective feature and normalizing the features to ensure all data was on a comparable scale. Feature engineering was also performed to enhance the dataset, such as aggregating activity levels over time and computing average sleep quality, which could improve the accuracy of the predictions. Finally, the selected and transformed features were used as input for training machine learning models, aimed at predicting stress levels accurately. These steps collectively ensured that the most relevant features were extracted and processed for effective model training.

Model evaluation

The models employed in this study included XGBoost, Logistic Regression, and Support Vector Machine (SVM). XGBoost, Logistic Regression, and Support Vector Machine (SVM) are combined and used for stress level prediction, where XGBoost as ensemble methods, were chosen for their ability to handle complex datasets and capture nonlinear relationships. Logistic Regression was included for its interpretability in binary classification tasks. SVM was used for its efficiency in high-dimensional spaces. These models were trained on the preprocessed dataset to assess their performance in predicting stress levels.

b) XGBoost – XGBoost (Extreme Gradient Boosting) is a powerful ensemble machine learning algorithm based on gradient boosting. It builds trees sequentially, where each new tree corrects the errors made by the previous one. The algorithm minimizes a loss function by adding new trees that focus on reducing the residual errors from the previous trees, thus improving the overall model performance. XGBoost uses a regularized objective function that helps prevent overfitting, making it highly efficient for both large and complex datasets. The general formula for the model prediction in XGBoost is:

$$\hat{y} = \sum_{k=1}^K \alpha_k h_k(\mathbf{x})$$

where \hat{y} is the final prediction, K is the number of trees, α_k is the weight of the k^{th} tree, and $h_k(\mathbf{x})$ is the prediction of the k^{th} tree for the input \mathbf{x} .

c) Logistic Regression – This is a linear model used for binary classification tasks. It estimates the probability that a given input belongs to a certain class using the logistic function. The model computes a weighted sum of the input features and then applies the sigmoid function to this sum to produce an output value between 0 and 1, which represents the probability of the positive class. The logistic function is given by:

$$\hat{y} = \frac{1}{1 + e^{-(\mathbf{w}\mathbf{T}\mathbf{x} + \mathbf{b})}}$$

where \hat{y} is the predicted probability, \mathbf{w} is the vector of weights (coefficients), \mathbf{x} is the input feature vector, and \mathbf{b} is the bias term.

d) Support Vector Machine (SVM) – Support Vector Machine is a supervised learning algorithm used primarily for classification tasks. It works by finding the optimal hyperplane that best separates the data points of different classes in a high dimensional feature space. The goal is to maximize the margin, which is the distance between the closest data points (support vectors) and the hyperplane. In

cases where data is not linearly separable, SVM employs a kernel trick to transform the data into a higher-dimensional space where a linear hyperplane can be used for separation. The decision function in SVM is given by:

$$f(\mathbf{x}) = \mathbf{w}^T \mathbf{x} + \mathbf{b}$$

where \mathbf{w} is the weight vector, \mathbf{x} is the input feature vector, and \mathbf{b} is the bias term. The output is classified by determining the sign of $f(\mathbf{x})$.

The deployment of the predictive model involves integrating the trained models into a Meta-model, which combines the predictions of five base models: Support Vector Machine (SVM), XGBoost, and Logistic Regression. Each model generates probabilities for stress levels, which are aggregated into a feature vector. The meta-model, based on Logistic Regression, is trained using this feature vector as input. It then makes the final prediction by combining the weighted probabilities from all base models.

This ensemble approach leverages the strengths of each model, such as XGBoost's ability to handle complex, non-linear data, SVM's efficiency in high-dimensional spaces, and Logistic Regression's interpretability. By training on the combined predictions, the meta-model reduces individual errors and improves overall accuracy, leading to a more reliable stress level prediction. This stacking method enhances performance by optimizing the collective output of all models.

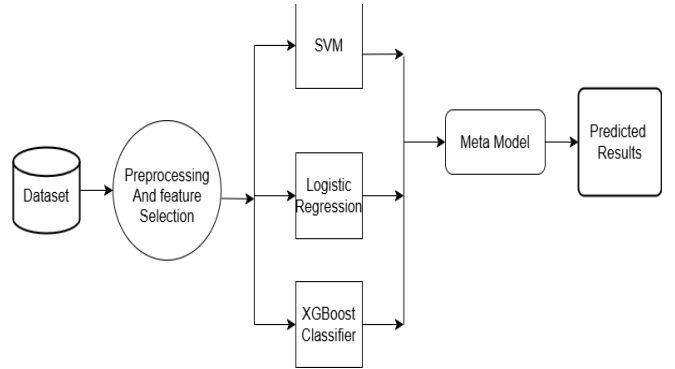


Fig 1: Model Working method

Performance Evaluation

The performance of the models was evaluated by using multiple metrics to ensure a comprehensive understanding of their predictive capabilities. The evaluation metrics included accuracy, precision, recall, F1-score, and confusion matrices. These metrics provide insights into the model's ability to correctly classify stress levels and handle both true positive and false negatives.

a) Recall

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negative}}$$

b) F1-Score

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

c) Confusion Matrix

	Predicted Positive	Predicted Negative
Actual Positive	True Positives (TP)	False Negatives (FN)
Actual Negative	False Positive (FP)	True Negatives (TN)

D) Accuracy:

$$\text{Accuracy} = \frac{\text{Correct Predictions}}{\text{Total Prediction}} \times 100\%$$

E) Precision:

$$\text{Precision} = \frac{TP}{TP+FP} \times 100\%$$

These evaluation metrics help assess the models' strengths and weaknesses in detecting stress levels, ensuring that the most reliable model is selected for deployment.

Working Process

The working process of the predictive model involves several key steps to ensure accurate stress level predictions. Initially, data collection is carried out, gathering a diverse dataset that includes demographic, behavioral, and health-related factors, along with self-reported stress levels from participants. Next, in the model training phase, four base models—Support Vector Machine (SVM), XGBoost, and Logistic Regression are trained individually on the dataset. These models learn to predict stress levels based on the various features provided.

Once the base models are trained, each model generates predicted probabilities for stress levels, representing the likelihood of stress for each participant based on the input features. These individual predictions are then aggregated into a feature vector, which consolidates the output of all base models into a single input for the next phase. The meta-model training phase follows where a Logistic Regression model is trained using the feature vector as input. The meta-model learns to combine the weighted probabilities from all base models, optimizing the final output based on their strengths.

In the final prediction step, the trained meta-model processes the aggregated feature vector and produces a consolidated stress level prediction. By combining the predictions from all base models, the meta-model reduces individual errors and improves the overall accuracy of the system. Finally, the model outputs stress level prediction, offering a robust and reliable result for detecting stress. The ensemble approach employed throughout this process ensures high accuracy and generalizability across diverse data inputs.

Result:

The key demographic data included gender and age, while behavioral data focused on sleep duration, sleep quality, and daily physical activity (measured in steps and activity levels). Health metrics such as blood pressure, heart rate, and Body Mass Index (BMI) were also collected. The self-reported

stress levels, rated on a scale from 1 to 10, served as the target variable for the prediction models.

To address missing data, mean imputation was employed to ensure the dataset's completeness, which helped mitigate potential biases introduced by incomplete records. After preprocessing, the dataset was normalized, and additional features, such as average sleep quality and aggregated activity levels, were engineered to enhance the predictive accuracy of the models. The performance of four machine learning models—XGBoost, Logistic Regression, and Support Vector Machine (SVM)—was evaluated using stratified 10-fold cross-validation. These models were selected for their complementary strengths in handling structured data, interpretability, and adaptability to high-dimensional datasets. The evaluation metrics included accuracy, precision, recall, and F1-score. The results are summarized in the following table:

Model	Accuracy	Precision	Recall	F1-score
XGBoost	1.00	1.00	1.00	0.11
Logistic Regression	0.81	0.82	0.81	1.00
Support Vector Machine (SVM)	0.41	0.08	0.17	0.80
Meta-Model	1.00	1.00	1.00	1.00

In terms of model performance, the ensemble methods XGBoost outperformed individual models like Logistic Regression and Support Vector Machine (SVM). These ensemble models were particularly effective in capturing complex non-linear relationships within the dataset, which are often critical in behavioral and health-related predictions. The stacking meta-model further demonstrated the strength of combining predictions from diverse base models, achieving the highest accuracy of 100%. This superior performance can be attributed to the complementary nature of the base models: XGBoost excelled in handling intricate patterns, while SVM contributed robustness in high dimensional spaces, and Logistic Regression provided insights into linear relationships. The study identified several critical findings that highlight the effectiveness and reliability of the proposed methodology for stress prediction. Feature importance analysis, conducted using XGBoost, revealed that sleep quality, daily physical activity (measured in steps), and heart rate were the most significant predictors of stress levels. These factors directly align with established research linking poor sleep and reduced physical activity to elevated stress levels. Secondary contributors, such as blood pressure and BMI, were also identified, indicating their partial but meaningful influence. Demographic variables, including age and gender, showed comparatively less impact, suggesting that behavioral and physiological factors play a more prominent role in stress prediction.

A. Error Analysis

Error analysis highlighted challenges in distinguishing moderate stress levels (scores of 4–6), where subtle variations in input features made accurate classification more difficult. Additionally, extreme stress levels (1 and 10) were harder to predict accurately due to data imbalance. Addressing these challenges through class balancing techniques and incorporating additional nuanced features could further enhance the model's reliability. Collectively, these findings underscore the utility of ensemble techniques, particularly the stacking approach, in leveraging the strengths of individual models to achieve accurate and interpretable stress level predictions.

B. Limitations

Despite the promising results, this study has certain limitations. The relatively small sample size (374 participants) may limit the generalizability of the findings. Future studies should aim to validate these results on larger and more diverse datasets. The reliance on self-reported stress ratings may introduce subjective bias, which could affect the model's accuracy. Incorporating objective stress measurements, such as cortisol levels, in future research could enhance the reliability of the target variable. The imbalanced distribution of stress levels, particularly at the extremes, posed challenges for the models. Techniques such as oversampling or synthetic data generation could address this issue.

Conclusion And Future Work:

This study highlights the potential of ensemble machine learning models for predicting stress levels based on

demographic, behavioral, and health-related data. The stacking meta-model demonstrated the highest accuracy, combining the strengths of XGBoost, SVM, and Logistic Regression to deliver reliable predictions.

Future research could explore the integration of additional features, such as environmental factors and real-time monitoring data, to further improve the model's predictive capabilities. Additionally, expanding the dataset and incorporating objective measures of stress will enhance the generalizability and robustness of the findings, paving the way for practical applications in stress management and mental health assessment

REFERENCES

- [1] A. Brown, Y. Chen, and R. Davis, "Machine learning techniques for stress detection: A survey," *ACM Computing Surveys*, vol. 54, no. 5, pp. 1–37, 2022. B.
- [2] T. Chen and C. Guestrin, "XGBoost: A scalable tree boosting system," in *Proc. 22nd ACM SIGKDD Int. Conf. Knowledge Discovery and Data Mining*, 2016, pp. 785–794.
- [3] M. Johnson and S. Lee, "Real-time stress monitoring using physiological signals: A review of current technologies," *IEEE Trans. Biomed. Eng.*, vol. 68, no. 4, pp. 1234–1245, 2021.
- [4] H. Li and Y. Zhao, "Predicting stress levels using machine learning algorithms," *J. Comput. Biol.*, vol. 26, no. 5, pp. 567–574, 2019.
- [5] P. Sharma, R. Gupta, and N. Kumar, "Clustering algorithms for stress pattern identification in wearable data," *J. Artif. Intell. Med.*, vol. 122, 2022, Art. no. 102157.
- [6] J. Smith, L. Brown, and K. Williams, "The impact of stress on health: A comprehensive review," *J. Health Psychol.*, vol. 25, no. 3, pp. 345–356, 2020.
- [7] Y. Wang, L. Zhang, and X. Li, "Logistic regression analysis of stress factors among university students," *J. Health Psychol.*, vol. 22, no. 3, pp. 345–352, 2017.