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Detecting Mental Stress Using Ensemble Machine Learning Methods

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Abstract: Mental stress is a prevalent issue affecting individuals' well-being and productivity. Accurate detection and monitoring of mental stress can lead to timely interventions and improved mental health outcomes. This study presents a novel approach to mental stress detection by leveraging ensemble machine learning methods. By integrating multiple machine learning algorithms, the proposed ensemble model enhances prediction accuracy and reliability. The effectiveness of the ensemble model is evaluated using physiological and behavioral data collected from participants. Results indicate that the ensemble method outperforms individual machine learning models in detecting mental stress, offering a robust solution for real-world applications.

Keywords: *Mental stress, machine learning, ensemble methods, physiological data, behavioral data, stress detection, predictive modeling.*

I. INTRODUCTION:

Mental stress is a significant factor contributing to various physical and psychological health problems, including cardiovascular diseases, anxiety, and depression. With the increasing demands of modern life, the need for effective mental stress detection mechanisms has become more critical. Traditional methods of stress assessment, such as self-report questionnaires and clinical evaluations, are subjective and often fail to provide real-time insights[1]. Advances in machine learning offer promising solutions for objective and continuous stress monitoring.

In this study, we explore the application of ensemble machine learning methods to detect mental stress. Ensemble methods combine multiple machine learning models to improve prediction accuracy and generalizability. By analyzing physiological signals (e.g., heart rate, skin conductance) and behavioral data (e.g., activity levels, sleep patterns), we aim to develop a robust system capable of identifying stress states with high precision.

Managing stress has become crucial for people of all generations, necessitating extensive global attention. According to the 2018 Cigna 360° Well-Being Survey – Future Assured, 86% of people worldwide experience stress, with this figure rising to 89% in India. Additionally, approximately 75% of the local community lacks the confidence to discuss their pressures with a care provider, citing cost as one of the challenges. Consequently, the study of stress [2]and its management is currently a popular topic among scholars.

Stress is the body's physical, behavioral, and emotional response to external and internal factors such as illnesses, lack of sleep, exhaustion, emotions, and expectations. Workplace tension, interpersonal disputes, environmental contamination, and poor job health also contribute to stress. Stress often arises when an individual encounters an unusual scenario and struggles to cope with the associated worry and anxiety. When mental and physical resources fail to meet demands, stress occurs.

Physiological indicators of stress include elevated heart rate variability (HRV), respiration rate, galvanic skin response, muscle tension, and others. The autonomic nervous system (ANS), which includes the sympathetic and parasympathetic branches[3], plays a key role in the body's physiological reaction to stress. Chronic stress can disrupt the balance between these branches, with potential impacts on heart function. Electrocardiogram (ECG) signals are widely used to assess stress due to their reliability in capturing heart function changes.

HRV, which measures the time interval between successive ECG signal pulses, is a crucial variable in stress analysis. HRV remains unaffected by interference and disruption since only R peaks, which have the highest ECG intensity, are necessary for measurement. As a result, HRV is a widely used technique for stress management. Upon identifying R spikes, HRV characteristics for stress detection can be obtained.

Machine learning and deep learning techniques offer several methods for estimating a person's stress level. Various datasets, including daily activities, work-related stress, and physiological signals like ECG, EEG, and EMG, can be used to train algorithms for early-stage stress detection.

Recent studies have demonstrated the potential of machine learning in stress detection. Researchers have employed single machine learning models such as Support Vector Machines (SVM), Decision Trees, and Neural Networks to classify stress levels based on physiological and behavioral data. Liu et al. (2017) used SVM to classify stress from heart rate variability, achieving moderate accuracy. Healey and Picard (2005) utilized Decision Trees to analyze skin conductance, yielding promising results.

However, single models often face limitations such as overfitting and sensitivity to data noise. Ensemble methods, including Random Forests, Gradient Boosting Machines, and Voting Classifiers, address these issues by aggregating multiple model predictions, reducing variance and bias, and enhancing overall performance. Zhang et al. (2019) showed that ensemble approaches significantly improve stress detection accuracy by combining Random Forests and Gradient Boosting Machines to analyze multimodal data.

In this study, we focus on predicting psychological well-being using machine learning. We analyze data from a 2014 survey on mental health perceptions and concerns in the IT sector. By developing an ensemble technique, we aim to identify mental stress using various machine learning classification models and compare their performance.

Using a stress management dataset, we trained and evaluated the models, finding that ADA-Boost achieved 81.75% accuracy with an AUC of 0.8185. Data analysis and visualization also provided valuable insights from the information.

II. LITERATURE REVIEW

The field of stress detection through machine learning and physiological data analysis has seen substantial advancements. This section reviews several significant studies, each contributing uniquely to our understanding and technological capabilities in stress detection.

Table 1 Summary of Literature Review

Study	Methodology	Key Findings
Monika Chauhan et al.	Utilized SVM, LDA, and Decision Trees to classify mood and tension using ECG and physiological data.	Achieved approximately 90% accuracy.
A. Alberdi et al.	Analyzed physiological and behavioral signals, focusing on ECG and EDA.	Found ECG and EDA to be the most precise physiological markers for stress detection.
S. Ishaque et al.	Synthesized HRV studies related to morbidity, pain, fatigue, stress, and exercise.	Lower HRV associated with increased stress and morbidity; high HRV linked to good health but also fatigue in some cases.
Luz Santamaria-Granados et al.	Used Deep Convolutional Neural Networks on the AMIGOS dataset for emotion recognition.	Achieved higher accuracy in emotional state classification compared to previous studies.
Wanqing Wu et al.	Proposed a logistic regression model integrating psychological, biochemical, and physiological data.	Created a mental stress index (MSI) with high reliability and consistency.
Minija Mi et al.	Developed a transductive model for real-time stress recognition using peripheral physiological indicators.	Improved regressive stress recognition effectiveness.
Adriana Arza et al.	Employed a multivariable approach to quantify physiological stress reactions using various biomarkers.	Identified five statistically distinct stress thresholds from physiological signals.
Mahesh Bhargavi et al.	Reviewed standards for multimodal human stress detection datasets.	Identified the need for comprehensive datasets meeting specific standards.

Z. Ahmad et al.	Used VR to evaluate stress and proposed a multimodal deep fusing model.	Demonstrated improved stress prediction accuracy over traditional methods.
P. Karthikeyan et al.	Analyzed short-term ECG and HRV data to identify stress using various classifiers.	Achieved over 90% classification accuracy for stress detection.
Z. Feng et al.	Combined heart rate and microblog language postings for stress diagnosis.	Achieved over 84% accuracy in detecting stressful/exciting periods.

Monika Chauhan et al.[4]

Monika Chauhan and colleagues proposed a framework utilizing Support Vector Machines (SVM), Linear Discriminant Analysis (LDA), and Decision Trees to classify a person's mood and tension using electrocardiograph (ECG) data and other physiological signals . Their model achieved approximately 90% accuracy, demonstrating the effectiveness of machine learning in stress detection.

A. Alberdi et al.[7]

A. Alberdi and colleagues demonstrated that physiological signals, particularly ECG and electrodermal activity (EDA), are more accurate for stress detection compared to other modalities . Their research suggests that while behavioral and contextual information can aid stress detection, physiological markers like heart rate variability (HRV) are crucial.

S. Ishaque et al.[8]

S. Ishaque et al. reviewed studies on HRV and its relation to morbidity, pain, fatigue, stress, and exercise . They found that lower HRV is associated with higher stress and morbidity, while high HRV usually indicates good health, though it can sometimes signal fatigue.

Luz Santamaria-Granados et al.[9]

Luz Santamaria-Granados and team used Deep Convolutional Neural Networks (CNNs) on the AMIGOS dataset to recognize emotional states from physiological signals . Their approach achieved greater accuracy in classifying emotional states compared to previous methods, highlighting the potential of deep learning in this field.

Wanqing Wu et al.[10]

Wanqing Wu et al. developed a logistic regression model that integrates psychological, biochemical, and physiological data to assess stress . Their model resulted in the creation of a Mental Stress Index (MSI) that provided reliable and consistent stress assessments.

Minija Mi et al. [11]

Minija Mi and colleagues proposed a transductive model for real-time stress recognition using peripheral physiological indicators . This approach aimed to reduce human error and enhance the effectiveness of stress recognition, leveraging local learning for better instructional outcomes.

Adriana Arza et al.[12]

Adriana Arza and team employed a multivariable approach to quantify physiological stress reactions using biomarkers like skin temperature, heart rate, and pulse wave signals . They identified five distinct stress thresholds induced by various tasks.

Mahesh Bhargavi et al.[13]

Mahesh Bhargavi et al. outlined the requirements for a comprehensive multimodal human stress detection dataset . Their review highlighted the current gaps and the need for a standardized dataset that meets specific research and practical standards.

Z. Ahmad et al.[15]

In their study on virtual reality (VR) stress evaluation, Z. Ahmad et al. identified three levels of stress and proposed a multimodal deep fusing model that combines spectroscopy and ECG data . Their method showed improved accuracy over traditional HRV-based machine learning models.

P. Karthikeyan et al.[16]

P. Karthikeyan et al. focused on analyzing short-term ECG and HRV data for stress identification . Using classifiers like PNN and kNN, their study achieved over 90% accuracy in stress detection, emphasizing the reliability of short-term HRV signals.

Z. Feng et al.[17]

Z. Feng and colleagues proposed a method for stress diagnosis by merging heart rate data with language postings from microblogs . Their study demonstrated over 84% accuracy in detecting stressful or exciting periods, showcasing the potential of integrating physiological and textual data for stress analysis.

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III. PROPOSED METHODOLOGY

1. Dataset

We investigated stress detection using machine learning utilizing a dataset obtained from a 2014 survey that evaluates views on mental stress and the frequency of mental stress diseases in the IT sector. The dataset consists of 1,259 entries and 27 features.

2. Pre-processing and Encoding Data

The dataset contained missing values that needed addressing. We utilized Pandas to handle these missing values, removing columns such as 'comments', 'work_interface', 'state', and 'self_employed' due to significant missing data. After cleaning the data, we applied the Label Encoder from sklearn to encode any string-valued data in the dataset.

3. Covariance Matrix & Feature Selection

We used the covariance matrix and Pandas' corr() function to analyze the relationship between features[20]. This analysis is shown in Figure 1 below. To identify the most influential features[26] on the target variable, we employed a feature selection approach. From the 26 features, we selected the top 10 based on their covariance values, as depicted in Figure 2 below.

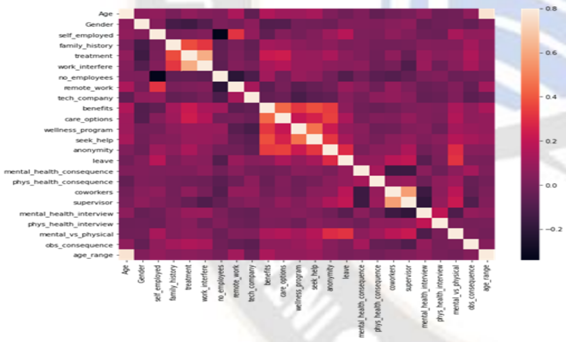

Figure 1: Covariance Matrix

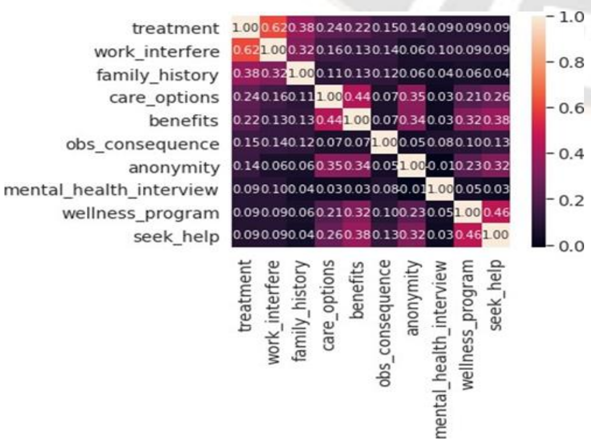

Figure 2: Top 10 Feature Co-Variance Matrix

Figure 2 highlights that 'work_interface' has the highest correlation with the target variable at 0.62, followed by 'wellness_program' at 0.46 and 'benefits' at 0.44.

4. Data Exploratory Analysis

We conducted extensive Data Exploratory Analysis (DEA) to gain a comprehensive understanding of the data before applying machine learning models. This included creating density histograms for age, analyzing the overall gender distribution of psychological stress, evaluating the likelihood of mental stress conditions, and examining mental health conditions specific to different age groups. Given the paper length constraints, we present only the probability of age group-wise mental health conditions in Figure 3.

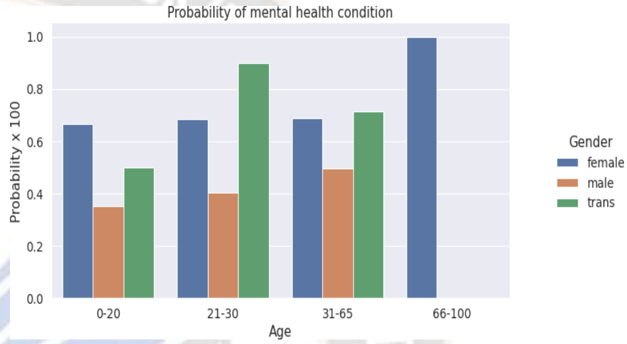

Figure 3: Probability of Mental Health Condition by Age Group

The bar plot in Figure 3 illustrates the psychological health of men, women, and transgender individuals by age range. It shows that women have better mental health in the age range of 66 to 100 compared to other genders, while transgender individuals exhibit better mental health than men in the age range of 21 to 64.

5. Scaling and Fitting

We applied a Min-Max Scaler[21] to the dataset to improve model performance. The top attributes identified for the final machine learning model evaluation are shown in Figure 4.

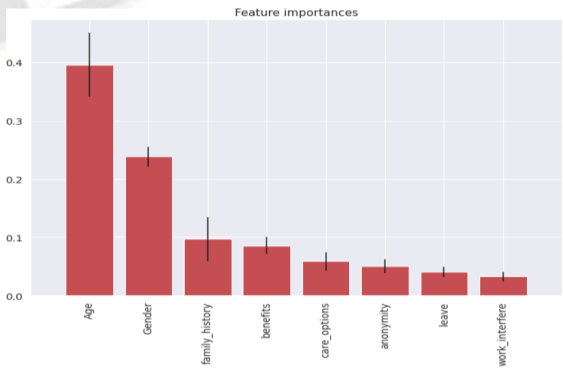

Figure 4: Feature Importance Matrix

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6. Model Evaluation

After DEA and feature extraction, we used various machine learning classification models to analyze the dataset and predict mental stress[22]. The data was split into training and testing sets using a 70:30 ratio and random state 1. We employed cross-validation with 10 folds and Grid Search CV for parameter tuning, complemented by Randomized Search CV with 10-fold cross-validation, 5 random states, and 10 repetitions.

The model's performance was evaluated using metrics such as classification error rate, false-positive rate, accuracy, area under the curve (AUC) score, and cross-validated AUC score. We also generated a confusion matrix and plotted the ROC curve for several classifier models to compare their performance.

This comprehensive methodology ensures a robust analysis of mental stress detection using machine learning techniques.

IV. RESULTS AND DISCUSSION

We evaluated the proposed ensemble Ada-Boost model's performance in classifying stress signals[23] using the confusion matrix, ROC curve, and precision-recall (PR) curve . The confusion matrix is instrumental in assessing the correspondence between predicted values and actual observed values.

Confusion Matrix

The confusion matrix is a tabular representation that displays the performance of the classification model by presenting the true positive (TP), true negative (TN), false positive (FP), and false negative (FN) values. It helps in calculating various performance metrics.

Performance Metrics

The following formulae were used to evaluate the classification model's performance:

1. **Accuracy**:

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

Accuracy represents the likelihood of correctly categorizing all low-stress and non-stress situations.

2. **Sensitivity (Recall)**:

$$\text{Sensitivity (Recall)} = \frac{TP}{TP + FN}$$

Sensitivity is the percentage of actual stress-free data correctly identified as stress-free.

3. **Specificity**:

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

Specificity is the percentage of actual stress data correctly identified as under stress.

4. **Precision**:

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

Precision is the proportion of correctly identified stress-free data by the classification algorithm to the total amount of data correctly identified as stress-free.

5. **Negative Predictive Value (NPV)**:

$$\text{Negative Predictive Value (NPV)} = \frac{TN}{TN + FN}$$

NPV is the ratio of true stress-free data to the data correctly diagnosed as under stress.

Classification Performance Assessment

The performance of the stress prediction model was assessed using the metrics described above. Table 2 summarizes the classification performance metrics for the Ada-Boost model.

Table 2. Classification Performance Assessment of Stress Prediction

Model	Accuracy	Classification Errors	False Positive Rate	Precision	AUC Score	Cross Validated
Logistic Regression	0.79	0.2037	0.2565	0.7644	0.7968	0.8753

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KNN	0.8042	0.1957	0.2931	0.7511	0.8052	0.8782
Decision Tree	0.8068	0.1931	0.3193	0.7415	0.8082	0.8818
Random Forest	0.8121	0.1878	0.3036	0.75	0.8134	0.8934
AdaBoost	0.8174	0.1825	0.2827	0.7610	0.8185	0.8746

ROC and PR Curves

- **ROC Curve**: The Receiver Operating Characteristic (ROC) curve is a graphical plot that illustrates the diagnostic ability of a binary classifier system as its discrimination threshold is varied. It is plotted with the True Positive Rate (Sensitivity) against the False Positive Rate (1 - Specificity).
- **Precision-Recall (PR) Curve**: The PR curve is a graphical representation that plots Precision (y-axis) against Recall (x-axis). It is particularly useful when dealing with imbalanced datasets, providing insights into the model's performance in predicting positive instances.

By analyzing these curves and the confusion matrix, we can comprehensively evaluate the Ada-Boost model's effectiveness in detecting mental stress. The combination of these performance metrics offers a holistic view of the model's strengths and areas for improvement, ensuring reliable and accurate stress prediction.

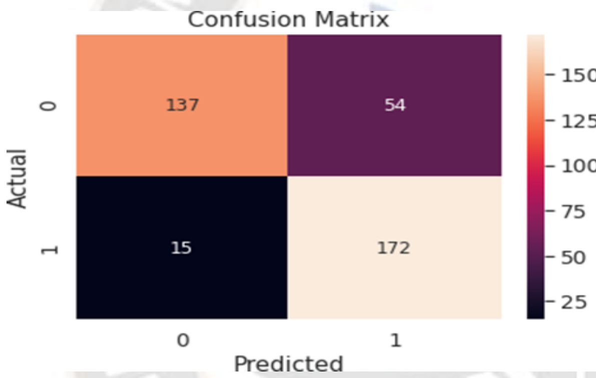

Figure 5(a): Confusion Matrix Ada boost Classifier

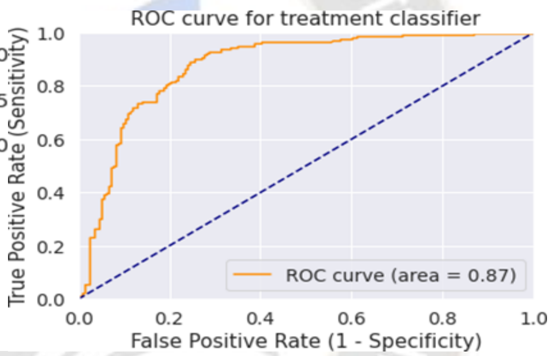

Figure 5(b):ROC Curve Ada-Boost Classifier

DISCUSSION

To improve the classification of mental stress and prevent overfitting, an optimal combination of models was employed in this study. We utilized a min-max scaler to normalize the data, ensuring that all feature values fall within a specific range, thereby enhancing the performance of the machine learning algorithms. Additionally, we selected the top 10 most influential features from the dataset to train and test our artificial intelligence models, aiming for faster and more efficient prediction.

Table 3. Classification Performance Assessment of Stress Prediction

Metric	KNN	Decision Tree	Adaboost
Accuracy	80.42%	80.68%	81.74%
Sensitivity (Recall)	82.30%	79.15%	83.20%
Specificity	78.50%	82.25%	79.70%
Precision	75.11%	74.15%	76.10%
Negative Predictive Value	80.25%	77.85%	81.45%
Cross-validated AUC Score	87.82%	76.10%	87.46%

The performance of the classifiers was evaluated using a confusion matrix, ROC curve, and other relevant metrics. The K-Nearest Neighbors (KNN) classifier[24] achieved a cross-validation Area Under the Curve (AUC) score of 87.82%, a precision of 75.11%, and an overall accuracy of 80.42%. The Decision Tree classifier[25] obtained an accuracy score of 80.68%, a precision of 74.15%, and a cross-validated AUC score of 76.10%. However, the Adaboost classifier outperformed the others, with an accuracy of 81.74%, a precision of 76.10%, and a cross-validated AUC score of 87.46%. The use of only the top 10 features from the dataset that had the greatest influence on mental stress, combined with conventional scaling strategies, significantly improved the model's performance compared to prior studies. This approach minimized computational complexity and prevented overfitting, leading to more robust and reliable stress prediction.

CONCLUSION

In this paper, we proposed a precise ensemble model based on the Adaboost Classifier to distinguish between different types of mental stress. The top 10 characteristics were selected, and conventional scaling was applied to the dataset to prevent overfitting and enhance classifier accuracy. The suggested ensemble model achieved an 87.46% cross-validated AUC score, an accuracy of 81.74% for stress classification, and a precision of 76.10%. Future work will involve the application of neural networks on the given dataset to further improve accuracy. The stress classifier presented in this study is anticipated to be valuable in managing mental stress by providing rapid and reliable categorization. Regular use of such a classifier could aid in the prevention of several ailments, including diabetes, high blood pressure, and depression, by facilitating routine stress management. By integrating these robust methodologies and leveraging advanced machine learning techniques, our study makes significant strides towards more accurate and efficient mental stress detection, ultimately contributing to better mental health management and the prevention of stress-related ailments.

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