Low-cost Multi-Modal Stress Detection: Integrating ECG and Facial Expression Analysis Using SVM, KNN and XGBoost Models

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***Abstract*—In today's fast-paced world, stress has become a major health concern, emphasizing the importance of good stress detection systems. This research describes a novel approach to stress detection that combines electrocardiogram (ECG) signals, heart rate measures, and facial expression analysis. We use the Support Vector Machine (SVM), K-Nearest Neighbors (KNN) and Extreme Gradient Boosting (XGBoost) models to categorize stress levels from various multi-modal data sources. Our effort includes data gathering, preprocessing to extract key features, and model training. We assess the performance of the SVM, KNN and XGBoost models in identifying stress levels, revealing the value of combining physiological and behavioral data for improved stress detection. This research helps to design more comprehensive and effective stress monitoring systems.**

***Index Terms*—stress detection, SVM, KNN, ECG, heart rate, facial expression**

I. Introduction

Stress has arisen as a serious health issue in today's fast-paced life, affecting the mental and physical well-being across diverse variety of groups. According to research, persistent stress can cause serious health consequences such as cardiovascular disease and mental disorders, making early detection critical for successful treatment and intervention. [1]

RRecent improvements in stress detection systems have focused on developing non-invasive ways for diagnosing stress by combining physiological signals such as heart rate and electrocardiogram (ECG) data with behavioral markers such as facial expressions. HRV and ECG signals are frequently investigated for their use in detecting stress, as they are powerful indicatiors of autonomic nervous system activity that responds to emotional and mental stressors [2]. Similarly, facial microexpressions, which are controlled by the sympathetic nervous system, convey information about emotional states and are hence an important component in stress detection.

Machine learning models, particularly K-Nearest Neighbors (KNN) and Support Vector Machines (SVM), have been widely used in stress detection systems due to their capacity to handle complicated, multidimensional data. KNN is well-known for its ability to classify physiological and behavioral data because to its simplicity and minimal data distribution assumptions. SVM is a common choice for stress classification problems due to its ability to determine optimal decision boundaries [3]. Both models are effective at detecting stress, according to research, particularly when applied to datasets including a combination of ECG signals andHRV features. [4]

This research investigates the improvement of stress detection systems, with a focus on incorporating heart rate, ECG signals, and facial expressions into machine learning frameworks, namely KNN and SVM models. It seeks to provide a detailed analysis of recent studies at a minimal cost.

II. Literature Review

There are several experiments have been undertaken on the topic of stress sensing, each distinct unique insights. In [5], a neural network model was successfully created to detect stress using heart rate data, attaining an accuracy of 93.33%. Despite the capacity to detect heart rate with low-cost sensors, its application in research has decreased in favor of electroencephalography (EEG). Thoriq, on the other hand, reintroduced heart rate as a stress detection method, examining seven datasets and showing promising results ranging from 93.33% to 85.40%. According to the study, heart rate is still an effective stress indicator. However, heart rate might reflect not only stress but also other medical disease, which may restrict its usefulness as a stand-alone stress indicator. To models more robust, extra biomedical features must be included.

In [6], the author successfully created an emotion detection system using the mini_XCEPTION(CNN) and eye drowsiness detection system and heart rate monitoring, to detect stress and assess lifestyle health. The drowsiness detection component uses eye area coordinates to calculate the eye-brow aspect ratio, which determines drowsiness and identifies unhealthy lifestyle behaviors that contribute to stress detection. The study examined emotion recognition across seven different emotion classes. Heart just for the aim of monitoring, each thresholds reflect a specific level of stress. However, because each system operates on distinct thresholds and is trained separately, the model lacks robustness and relies heavily on emotion detection, limiting its overall effectiveness.

In [7], the authors developed a stress detection model using Support Vector Machine (SVM) trained on Electroencephalogram (EEG) signals from the SAM40 dataset. EEG signals, which capture brain activity, were used to classify stress levels across 40 instances and 12 attributes. The study introduced an SVM-based classification model that categorized stress into four distinct levels: low, medium, high, and very high. By selecting appropriate features from the high-dimensional EEG data, the SVM method effectively distinguished between different stress levels. The model's performance was evaluated using a confusion matrix, achieving an accuracy of 93%. However, the combination of EEG signals and SVM models is widely utilized in stress detection research. Compared to other modalities, EEG is both resource-intensive and time-consuming, which poses limitations to its practicality and accessibility in broader applications.

In [8], the authors developed a stress detection model based on a Tree-Optimized Support Vector Machine (SVM) using Electrocardiogram (ECG) signals, achieving a high accuracy of 96.3%. The study utilized ECG signals to extract QT, RR, and EDR intervals, which served as input features for the SVM model. The primary objective of using ECG signals was to measure heart rate variability (HRV) as an indicator of stress. The model was trained using Linear, Quadratic, and Cubic optimized SVMs, with the lowest accuracy recorded at 88.9%.

In [9], the authors developed a machine learning model using K-Nearest Neighbors (KNN) and Support Vector Machine (SVM) to analyze heart rate variability (HRV) based on 120 segments of ECG signal data, focusing on the collection of R-peak and RR intervals. Both models were fine-tuned with optimized hyperparameters, including distance metrics and kernels, to classify subjects into "relaxed" and "stressed" states. The KNN model achieved the highest accuracy of 80.56%. The authors emphasize the potential of machine learning for stress detection using ECG signals and HRV analysis. However, the study notes that the model's performance on unseen data remains limited, highlighting the need for further improvement to enhance robustness.

In [10], the authors developed machine learning and deep learning models using handcrafted ECG features and Heart Rate Variability (HRV) data extracted from two well-known stress datasets, WESAD and SWELL-KW. The study explored various models, including Random Forest Classifier (RFC), Support Vector Machine (SVM), Multilayer Perceptron (MLP), an ECG Emotion model, and Deep ECGNet, for stress detection. The highest accuracy was achieved by the deep learning model, MLP, demonstrating the effectiveness of HRV in stress detection compared to other modalities. The authors further highlighted the importance of large datasets and emphasized the necessity of cross-dataset evaluations to improve model robustness and generalization.

III. Approach

We will following these step to acheive the stress detection model:

The data collection process will incorporate the AD8232 heart rate sensor in conjunction with the Arduino Nano IoT 33 to gather electrocardiogram (ECG) signals effectively. This setup allows for the accurate monitoring of heart rate data. In parallel, we will capture video footage of the test subjects to analyze their facial expressions. The recorded videos will be processed using OpenCV, a powerful computer vision library, to identify and classify the emotions displayed by the participants. By synchronizing these two methods, we aim to gain deeper insights into the relationship between heart activity and emotional states, paving the way for further research and potential applications in fields such as healthcare, psychology, and human-computer interaction.

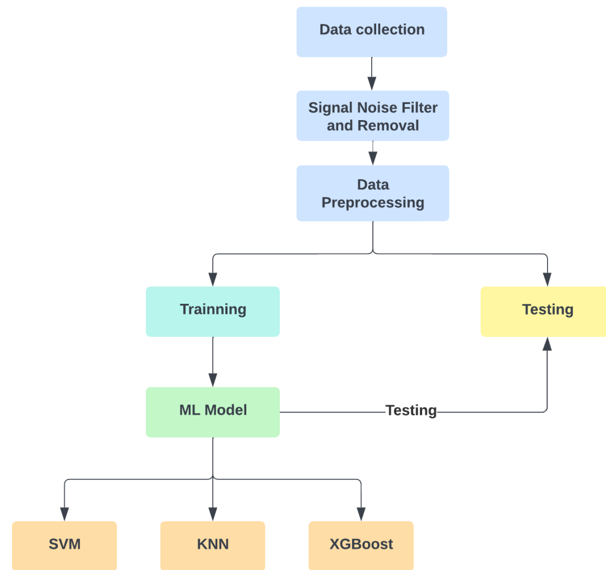

Fig. 1. Process Work Flow

A. *Facial Expression Recognition (FER) models*

Facial Expression Recognition (FER) models are AI systems designed to identify and classify human emotions based on facial expressions, often achieving accuracy rates exceeding 70% in controlled environments [16]. These models can recognize seven stages of expression, including happiness, sadness, surprise, disgust, fear, and more. In this project, the FER model was applied to detect facial expressions in each frame of a video while simultaneously collecting ECG data. By integrating the emotional insights from facial expressions with the physiological data from the ECG, we aim to gain a comprehensive understanding of the relationship between emotional states and heart activity, enhancing our ability to analyze human responses in various contexts.

B. *Classification model*

There are 3 main machine learning that works effectively on detecting stress including Support vector machine, K-Nearest Neighbors and Extreme Gradient Boosting: a)

1) Support Vector Machine (SVM): is a powerful supervised learning algorithm in handling high-dimensional data. SVM operates by finding the optimal hyperplane that separates data points of different classes, maximizing the margin between them. In the context of stress detection, features extracted from physiological signals, such as heart rate variability or skin conductance, serve as input data for the SVM model. The algorithm constructs a decision boundary that distinguishes between stress and non-stress states, leveraging kernel functions to manage non-linear relationships in the data. The robustness and ability to generalize well to unseen data make SVM a suitable choice for accurately identifying stress levels in individuals.

2) K-Nearest Neighbors (KNN): is a widely used non-parametric algorithm for classification tasks, including stress detection. In stress detection, KNN classifies an individual's stress level based on physiological features like heart rate or skin conductance. When a new data point is introduced, the algorithm identifies the k closest training samples using distance metrics. The class of the new data point is determined by a majority vote among its k nearest neighbors. The choice of k is crucial; a small k may make the model sensitive to noise, while a larger k can smooth out important distinctions.

3) Extreme Gradient Boosting (XGBoost): is a highly efficient machine learning algorithm known for its performance in classification tasks, making it an excellent choice for stress detection applications. Its ability to handle large datasets and model complex interactions between features allows it to effectively identify patterns indicative of stress. With built-in regularization techniques, XGBoost reduces the risk of overfitting, ensuring robust predictions. Additionally, its interpretability features enable researchers to gain insights into the key predictors of stress, facilitating a deeper understanding of the underlying factors contributing to stress responses. Overall, XGBoost's efficiency and effectiveness make it a valuable tool for stress detection mod

C. Data Collection

The data after capture will be stored as a CSV file, in order to process the machine learning model.

- ECG and heart beat data: will capture data using the Arduino Nano 33 IoT and send to the backend via WiFi.
- Facial Expression Data: capture image every interval and process in real-time using OpenCV on the laptop.

D. Dataset

The data will be collected from more than 2 students who currently faces with stress. It will consists of 4 different features including the HRV, heart rate, emotion and label of stress and not stress. We will mainly focus on predict whether stress or not. This dataset was made through 30 hours continuous measuring, where:

- ECG Data: Continuous time-series data representing heart's electrical signals.
- Facial Expression Data: image data from the laptop camera, labelled for emotional states.

During the data collection process, the Plotly library can be used to provide a dynamic data dashboard for real-time monitoring. Plotly supports interactive visualizations and includes a robust toolkit for showing ECG signals, heart rate readings, and facial expression analysis. By connecting Plotly with the data gathering system, users may examine patterns, track variations, and receive immediate insights into the data. This real-time dashboard not only allows for effective data analysis, but it also helps to recognize any noteworthy changes or stress signs throughout the data collection period.

E. Data Preprocessing

1) ECG signals: The ECG after collecting require to filter and remove noise of low-pass and high-pass frequency, including the noise from baseline wander, powerline interference and EMG. Reducing these noise will return a higher accruracy for the trainning model. [10]

Baseline wander is a low-frequency noise typically ranging from 0.5 to 0.6 Hz, which causes the ECG signal to drift up and down. This fluctuation can obscure the critical features of the ECG waveform, making it difficult to accurately interpret the cardiac activity. To mitigate this issue, a high-pass filter is often employed. This type of filter effectively removes low-frequency components, thereby stabilizing the baseline of the ECG signal and enhancing the visibility of the essential waveform features.

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Lastly, EMG noise refers to high-frequency noise produced by muscle contractions and movements of the subject during the ECG recording. This type of noise can significantly interfere with the accuracy of the ECG signal. To reduce EMG noise, techniques such as applying a moving average filter can be effective. This approach smooths out the high-frequency fluctuations in the signal, allowing for clearer identification of the underlying cardiac activity

There are three main components in ECG that should be considered that is P-wave, QRS complex and T-wave:

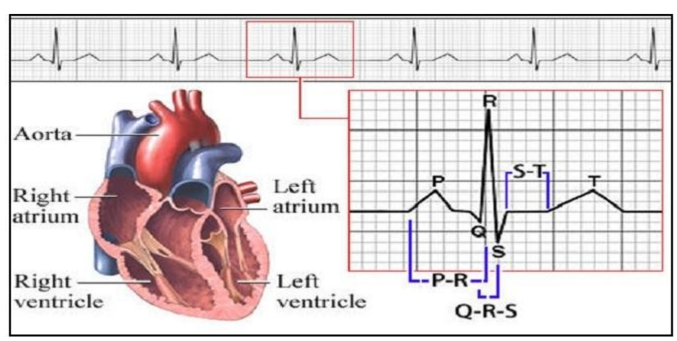

Fig. 2. ECG Components and Intervals [11]

The QRS complex of the ECG signal will be examined closely during the development of a stress detection model. The QRS complex is important because it represents the fast depolarization of the ventricles, which is required for heart rate measurement and stress analysis.

In this study, we will utilize one-minute segments of ECG signal data, with each segment containing 31,980 samples sampled at 533 Hz. Given that we are conducting an ultra-short-term analysis, we will implement a sliding window approach to enhance the number of training samples available for model training. Specifically, each one-minute segment will be analyzed with a 50-second overlap, [10] allowing us to extract more representative features from the data while maintaining temporal continuity. This method not only increases the volume of training samples but also helps capture the dynamic changes in the ECG signal that may be indicative of varying emotional states or stress levels. By leveraging this approach, we aim to improve the model's accuracy and robustness in predicting emotional responses based on the ECG data.

2) Heart Rate Variability: To extract Heart Rate Variability (HRV), we will focus on recognizing R-peaks within the QRS complex and calculating RR intervals.

The HRV is primarily derived from the RR intervals, which represent the period between successive R waves in the ECG signal. These intervals provide information about the difference in time between heartbeats, which is an essential indicator of autonomic nervous system function and stress levels. By studying the RR intervals, we can calculate the HRV, which is a measure of heart rate variation across time.

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3) Heart Rate: An electrocardiogram (ECG) may be used to precisely determine heart rate by measuring the time intervals between successive R-waves, which show the ventricles' depolarization. The significant peaks on the ECG signal are these R-waves. The heart rate is determined by taking the inverse of the RR interval, which is the time gap between two consecutive R-waves.

F. Dataset features

1) HRV features: We will utilize the Neurokit2 Python library to extract heart rate variability (HRV) features from ECG data. HRV is fundamentally derived from the R peaks and the subsequent RR intervals, which represent the time between successive heartbeats. The first step in the analysis involves extracting the R peaks from the ECG signal, followed by the calculation of essential HRV features.

The following table summarizes the key HRV features we will extract:

TABLE I
HRV FEATURES SUMMARY

Feature	Description
HR	Number of R peaks detected within one minute.
MeanNN	The mean of the RR intervals.
MedianNN	The median value of the RR intervals.
MadNN	The median absolute deviation of the RR intervals.
StdNN	The standard deviation of the RR intervals.
CVNN	Coefficient of variation, calculated as the ratio of StdNN to MeanNN.
IQRNN	Inter-Quartile Range of the RR intervals between the 25th and 75th percentiles.
RMSSD	Root Mean Square of successive differences of RR intervals
StdSD	Standard deviation of successive differences of RR intervals.
pNN50	The percentage of successive differences of RR intervals that exceed 50 ms.
pNN20	The percentage of successive differences of RR intervals that exceed 20 ms.
TINN	Triangular interpolation of the histogram of the RR intervals.
HTI	Heart Rate Variability Triangular Index.
LF	Power of the low-frequency band (0.04 Hz – 0.15 Hz) in the HRV spectrum, associated with sympathetic activity.
HF	Power of the high-frequency band (0.15 Hz – 0.4 Hz) in the HRV spectrum
LF/HF	Ratio of LF to HF power.
LFn	Normalized low-frequency power.
HFn	Normalized high-frequency power.
SD1	Spread of HRV on the Poincaré plot perpendicular to the identity line.
SD2	Spread of HRV on the Poincaré plot along the identity line.
SD1/SD2	Ratio of SD1 to SD2.
S	Area of the ellipse formed in the HRV Poincaré plot.

2) Facial Expression features: The Facial Emotion Recognition (FER) model will be used to analyze testers' facial expressions and categorize them into seven emotional states: Happiness, Sadness, Anger, Surprise, Disgust, Fear, and Neutral. These features will be employed to predict stress levels among testers. Notably, during periods of stress, the values for Sadness, Fear, and Neutral tend to increase, while the other emotions—Happiness, Anger, Surprise, and Disgust—diminish. In contrast, when testers are in a relaxed state, Happiness and Neutral emotions show higher values. Each feature will represent the likelihood of the corresponding emotion being present. By integrating these emotion data points with Heart Rate Variability (HRV) metrics, we aim to build a predictive model that accurately assesses stress levels, offering a comprehensive analysis by combining emotional and physiological factors.

IV. RESULTS AND DISCUSSION

In this section, we will present a comprehensive discussion of the results obtained from the stress detection model. This analysis will cover several key aspects, including the systematic selection of hyperparameters for each machine learning model employed, which is crucial for optimizing their performance. Furthermore, we will evaluate the performance metrics of the various models, providing a comparative analysis of their effectiveness in stress detection. Additionally, we will address the limitations observed during the modeling process, discussing potential factors that may have influenced the outcomes. This thorough examination aims to provide insights into the overall efficacy and robustness of the stress detection model.

A. Hyper-parameter tunning

Each machine learning model possesses distinct hyperparameters, which can vary significantly depending on the characteristics of the dataset. Consequently, hyperparameter tuning is a crucial step in developing an optimal stress detection model. In this phase, we employed the GridSearch technique to identify the optimal hyperparameters for our machine learning models. Each GridSearch implementation utilized 5-fold cross-validation, with accuracy serving as the evaluation metric. The table below presents the hyperparameters selected for each machine learning model.

TABLE II
MACHINE LEARNING MODEL HYPERPARAMETERS

Model	Hyperparameters
SVM	'C': 10, 'gamma': 0.01, 'kernel': RBF
KNN	'metric': 'euclidean', 'n_neighbors': 10
XGBoost	'colsample_bytree': 1.0, 'learning_rate': 0.1, 'max_depth': 7, 'min_child_weight': 2, 'n_estimators': 200, 'subsample': 1.0

B. Performance metrics

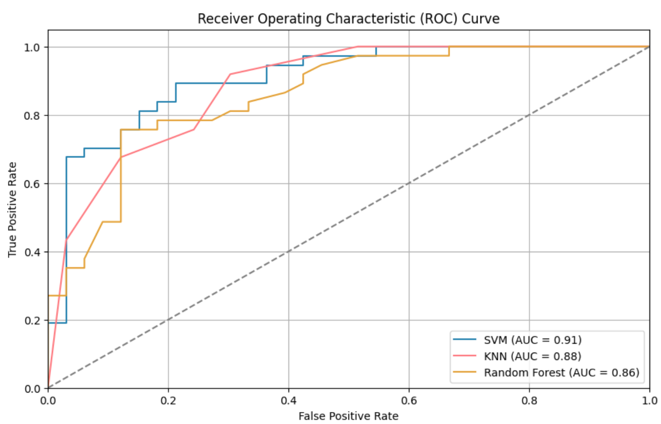

Fig. 3. ROC curve of three models

This ROC curve compares the performance of three models—SVM, KNN, and Random Forest—on the same classification problem. The curves represent the trade-off between true positive rates and false positive rates at various thresholds. The SVM model, with the highest AUC of 0.91, demonstrates the best performance in distinguishing between classes, indicating that it works well in detecting stress. The KNN model follows with an AUC of 0.88, and the Random Forest model, with an AUC of 0.86, also shows strong classification capability. Importantly, all stress detection models achieve an AUC of over 86%, verifying their strong overall performance. These high AUC values among the three classifiers collectively confirm the reliability of the models in stress detection.

The SVM model stands out with an accuracy of 88.6%, precision of 85.4%, and an impressive recall of 94.6%, resulting in an F-measure of 89.7%. This indicates SVM's strong ability to correctly identify stressed individuals while maintaining a high level of reliability in its predictions. KNN follows with an accuracy of 81.4%, a precision of 85.3%, but a lower recall of 78.4%, leading to an F-measure of 81.7%. This

TABLE III
PERFORMANCE METRICS FOR SVM, KNN, AND XGBOOST MODELS.

Model	Accuracy	Precision	Recall	F-Measure
SVM	0.8857	0.854	0.946	0.897
KNN	0.8143	0.853	0.784	0.817
XGBoost	0.7857	0.806	0.784	0.795

suggests KNN is effective but may miss some cases of stress. XGBoost has the lowest performance, with an accuracy of 78.6%, precision of 80.6%, recall of 78.4%, and an F-measure of 79.5%, indicating less reliability in stress detection. Overall, SVM emerges as the most reliable model for identifying stress, while KNN and XGBoost show respectable performance but with notable limitations.

These performance metrics clearly demonstrate that the SVM model is the most prominent among the three models evaluated. Its superior accuracy, precision, and recall metrics indicate its effectiveness in accurately identifying stress cases. To gain a deeper understanding of SVM's performance, we can analyze its confusion matrix, which will provide valuable insights into the model's classification behavior. The confusion matrix will illustrate the distribution of true positives, true negatives, false positives, and false negatives, shedding light on how well the model distinguishes between stressed and non-stressed individuals: The confusion matrix indicates the

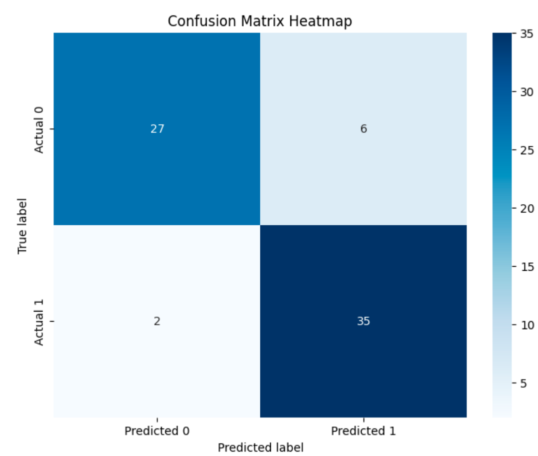

Fig. 4. Confusion matrix for SVM

performance of a binary classification model, showing that it correctly identified 35 true positives (TP) and 27 true negatives (TN). However, it misclassified 6 negative instances as positive (false positives, FP) and failed to recognize 2 positive instances (false negatives, FN). This results in an overall accuracy of approximately 88.6%, reflecting the model's ability to make correct predictions for the majority of cases.

C. Limitation

While FER models demonstrate high accuracy rates, they have significant limitations when used for ultra-short-term analysis. This approach may not effectively capture the emotional states of individuals experiencing prolonged stress, as fleeting facial expressions can miss underlying issues. Additionally, low-cost sensors, although affordable, may not provide the same level of accuracy as professional-grade equipment. They can introduce noise, leading to unreliable heart rate monitoring, especially in the presence of electromyography (EMG) signals from muscle activity. External factors like lighting conditions and individual variability in expressions can further complicate accurate emotion detection. These limitations highlight the need for caution in interpreting results and the importance of using additional data sources for a more comprehensive understanding of emotional states.

V. Conclusion

In conclusion, the stress detection model utilizing ECG and facial expression recognition demonstrated promising results across 232 segments, with the Support Vector Machine (SVM) achieving the highest performance at an accuracy of 88%. In comparison, the K-Nearest Neighbors (KNN) model recorded an accuracy of 81%, while XGBoost achieved 78%. These findings suggest that even low-cost sensors can effectively contribute to stress detection systems, making them accessible for widespread use. Such technology can help individuals recognize their stress levels, especially since many people may not be aware of their emotional states. This approach has the potential to enhance mental health monitoring and support, allowing for better awareness and management of stress in everyday life.

VI. Future works

In the future, we can enhance the accuracy of our stress detection model by collecting long-term data from patients with mental health records, which would provide a more comprehensive real-world approach. This long-term data capture of stress responses over time, allowing for a deeper understanding of the emotional states of individuals. Additionally, developing an application based on this model could enable users to monitor their stress levels actively and receive tailored support.

Another improvement is the integration of electroencephalogram (EEG) signals into the model. EEG data can provide insights into brain activity associated with stress, potentially offering a more holistic view of emotional states. Combining ECG, facial expressions, and EEG could significantly enhance the model's performance and reliability, leading to better stress detection and management solutions for a wider audience. By pursuing these strategies, we can create more effective tools to help individuals recognize and manage their stress, ultimately contributing to improved mental health outcomes.

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