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Stress Net: Multimodal Stress Detection using ECG and EEG Signals

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Abstract

This research work introduces Integrity of Time Domain Features & Machine Learning for Stress Classification using ECG & EEG Signals. Stress is a prevalent mental health issue in our daily lives, affecting many individuals. The impact of stress can lead to various problems, including heart attacks and depression. This research work aims to identify anxiety through a physical examination using both EEG and ECG signals. By analyzing and monitoring these signals, we can improve stress detection exactness, ultimately identifying and addressing mental health problems. This research work is used to prevent early detection of diseases such as depression and suicidal attempts. This task can benefit society as a whole. Moreover, using ECG signals to assess cardiovascular and related risk factors in the early stages has been explored through machine learning techniques.

Keywords

EEG, ECG, Stress Net, Multimodal, AUC, Kappa

Introduction

Stress is the body's physiological and psychological response to external or internal pressures or demands. It is natural when individuals face challenging, overwhelming, or threatening situations. Stress can arise from various sources, including work-related pressures, personal relationships, financial difficulties, or life changes. Stress can have various sources that differ from one person to another. Here are some causes of stress, like heavy workloads and long working hours: Students also face a lot of stress, such as exams, assignments, financial problems, etc.

Other people also face financial problems. Stress can lead to depression, heart attacks, anemia, suicide, etc. The symptoms of stress can vary from person to person, but some common signs and symptoms are headaches, Muscle tension, sleep disturbance, fatigue, sweating, increased heart rate, Irritability, mood swings, anger, etc. It divides into two parts, such as physical stress and mental stress. It is an electrophysiological, non-invasive approach to recording the human brain's electrical activity. This device has electrodes usually inserted into the human scalp, giving results like stress, no stress, Interruption, etc.

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Electrocardiography (ECG) This device processes the electrical signal from the heart. This shows the status of the heart when the person is stressed or not. Nowadays, more people are prone to various diseases due to stress. Early detection of stress may help individuals manage and control their stress levels. This has motivated me to take up this challenging work and contribute in this direction. This project aims to provide accurate and faster detection of stress from the given Data. To contribute to the well-being of humans by improving mental health through the detection of stress. To detect Stress from electroencephalograph (EEG) signals with improved accuracy by testing various classifiers.

Methodology

Technology can be used to monitor changes in a person's physiological signals, which can help detect stress. Artificial intelligence can be used to analyze a person's behavior to identify signs of stress. Through early detection of stress, individuals can take measures to manage it.

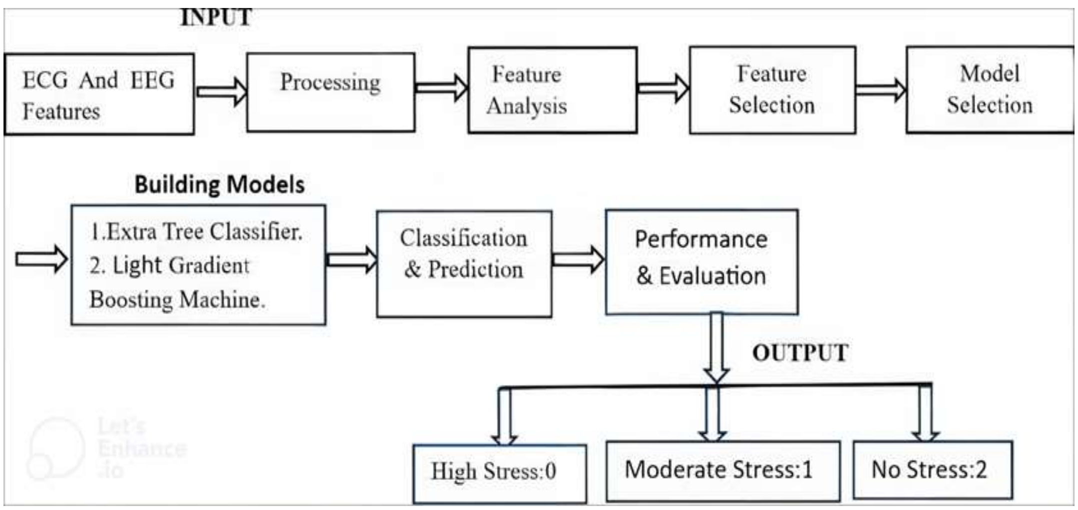

Figure 1. Architectural Design

In the methodology proposed, input is defined as ECG and EEG features, pre-processing, feature analysis, feature selection, and Model selection were included. It can potentially classify stress into different levels. The proposed system includes a comparison of various feature analysis methods. Univariate Analysis, Bivariate Analysis, Multivariate analysis, and classification algorithms (Extra Tree Classifier, Light Gradient Boosting Machine, Random Forest Classifier (RF), Gradient Boosting Classifier, Decision Tree Classifier, K Neighbors Classifier (KNN)).

1. Design And Data Collection

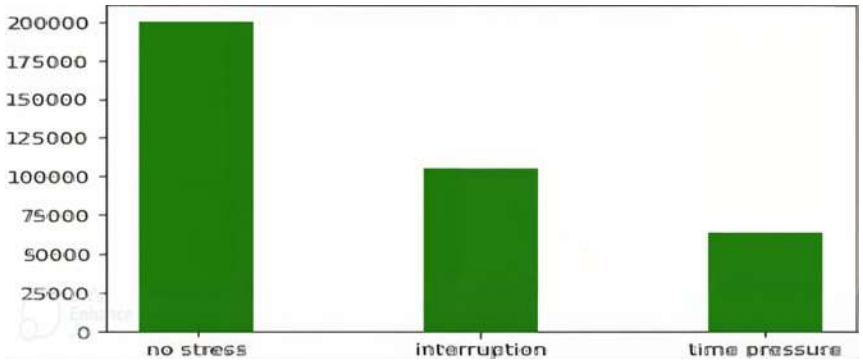

Figure 2. Distribution of data in the Stress dataset

Researchers at Radboud University collected ECG and EEG data as the initial step. To conduct our research, we utilized a benchmark dataset consisting of 369,290 rows and 37 columns. We employed 13 different machine learning algorithms, including Extra Tree classifiers, light gradient boosting machines, random forest classifiers, etc.

- No Stress: Participants work for 45 minutes without stress, Maximum unaware of task duration.
- Time pressure: Time pressure reduces job completion time to 2/3 of normal.
- Interruption: Participants experienced interruption from 8 emails during an activity, with some pertinent and others irrelevant

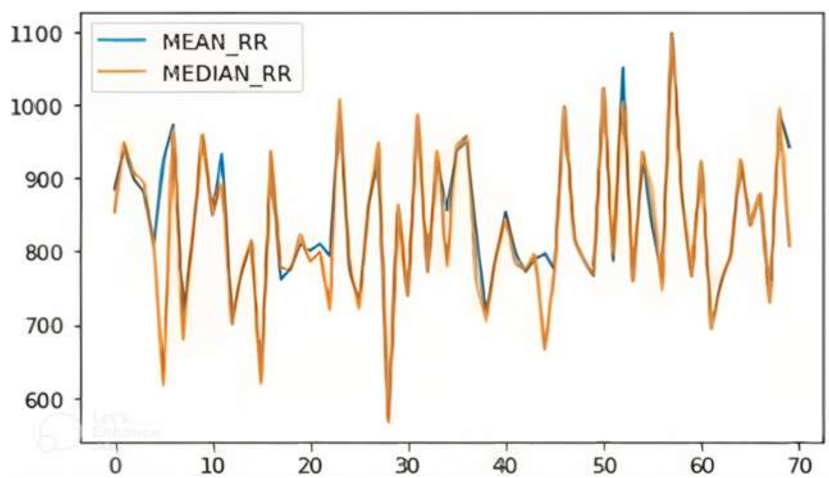

Figure 3. Reduced Train of Mean_RR and Median_RR

Fig 2. displays data distribution for three stress classes, HRV indices computed using IBI signal. We train both the modules of Mean_RR and Median_RR modules and we get results like the above Fig 4.

1.1. Pre-processing

In this module, the machine will be processing

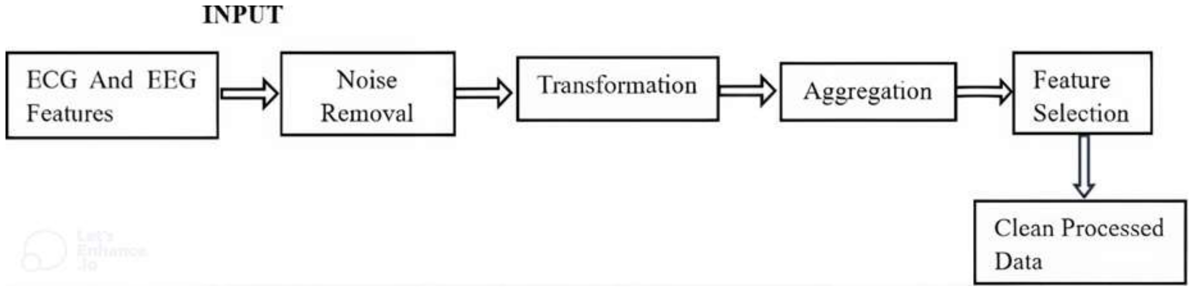

Figure 4. Pre-processing

To analyze ECG or EEG data, start with raw data, including electrical signals from the heart or brain. Remove noise using techniques like baseline wander removal, powerline interference removal, and filtering out high-frequency noise. Perform signal transformations to enhance specific features or make the data more amenable for further analysis.

1.2.Feature Analysis

Feature analysis is a crucial step in data analysis and machine learning, identifying relevant and informative features to improve model performance, interpretability, and efficiency, reducing dimensionality, and focusing on significant predictors

1.2.1. Univariate Analysis

Univariate analysis of stress effect detection examines individual variables, stress levels, summary statistics, and outliers. It helps understand stress patterns and characteristics in isolation, such as self-reported stress levels and demographic differences

1.2.2. Bivariate Analysis

Bivariate analysis detects stress effects by studying the relationship between stress and other variables and identifying potential factors associated with stress levels. Techniques like correlation and regression analysis measure the strength and direction of the relationship.

1.2.3. Multivariate Analysis

The multivariate analysis focuses on detecting stress effects by examining complex relationships among multiple variables. Techniques like multiple regression analysis, structural equation modeling, and factor analysis help determine the relative importance of different variables and their interactions.

1.3. Building Models

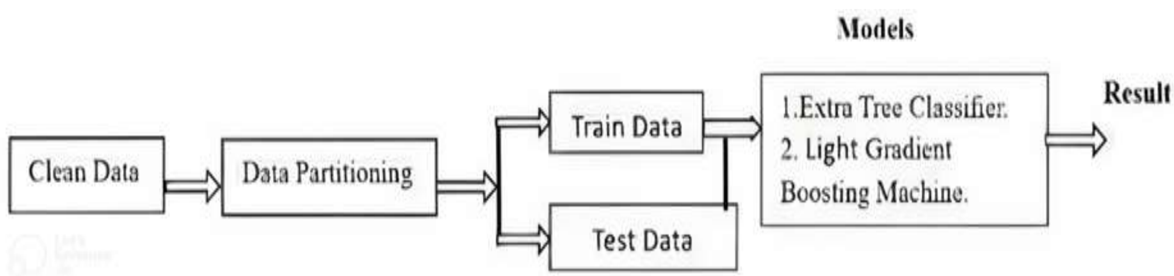

Figure 5. Building Models

To detect stress effects using models like Extra Tree Classifier, Light GBM, Random Forest, and K-Nearest Neighbors (KNN), follow steps such as data cleaning, partitioning, feature selection/extraction, model selection, training, evaluation, comparison, and deployment. Among these algorithms, the Extra Tree classifier yielded the highest accuracy of 0.8843. We obtained three types of results, represented as [0, 1, 2], along with other performance metrics such as AUC (0.742), recall (0.8843), precision (0.8894), F1 score (0.8839), kappa (0.8098), and MCC (0.8130).

Results and Discussion

Heart problems and related diseases are often predicted based on abnormalities in the electrocardiogram (ECG), with the corrected QT interval (QTc) being the most important pathological finding. QTc prolongation is associated with cardiovascular mortality due to fatal ventricular arrhythmias caused by QTc prolongation. Mitochondrial dysfunction leads to oxidative stress,.Mental stress also affects the physiological functions of the endocrine, nervous, and immune systems, leading to various health problems. Psychosocial stress influences cardiovascular diseases, with negative emotions and work- related stress being key triggers.

Male workers suffering from fatigue and psychological stress have shortened sympathetic activity, increased sympathetic activity, and decreased Hypothalamic Pituitary Adrenal axis response, leading to dysregulation of mitochondria and sympathetic-vagal balance. This type of mental stress stimulates the sympathetic nervous system and changes cardiac arrhythmias, leading to changes in ECG signals. To identify and treat cardiovascular problems and metabolic disorders, it is recommended to examine heart functions using ECG and echocardiography.

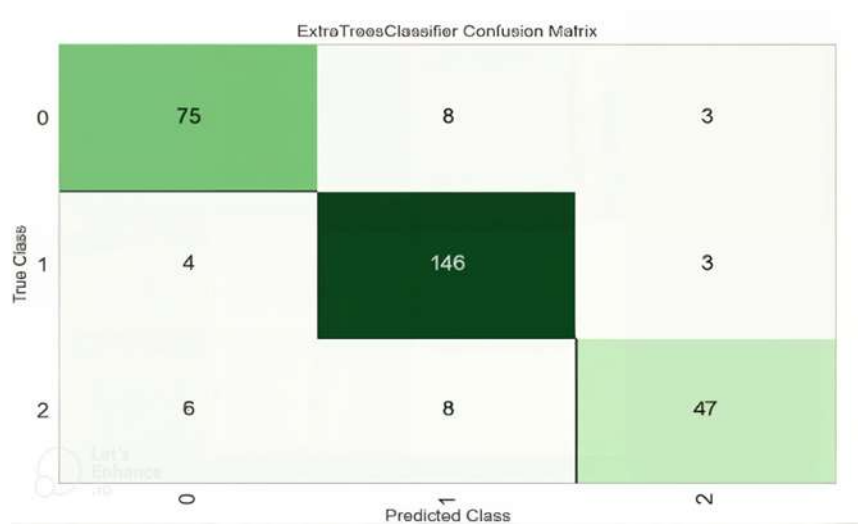

Figure 6. Extra Trees Classifier

Confusion matrix obtained based on stress class classification The matrix shows correctly predicted classes with diagonal elements, while off-diagonal elements represent misclassified classes. For example, 146 samples with true class 0 were correctly predicted as class 0, while 47 samples with true class 0 were misclassified as class 3. We obtained three Results like [0,1,2] and each indicates High Stress:0, Moderate Stress:1, and No Stress:2

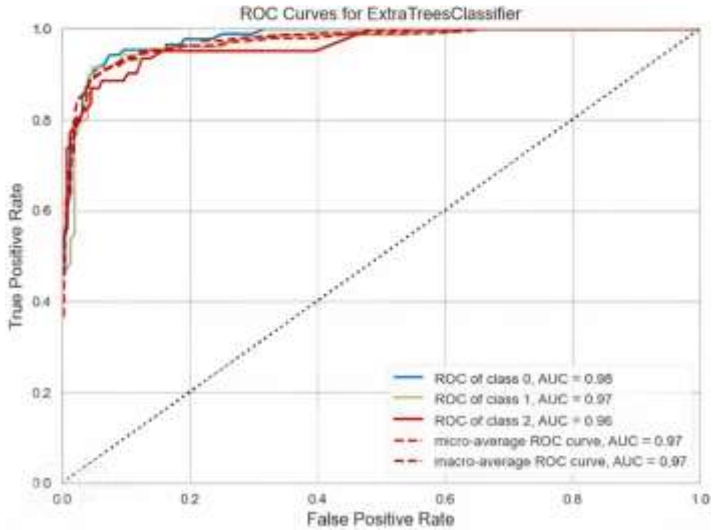

Figure 7. ROC Cures for Extra Trees Classifier

In the context of evaluating classification models, ROC (Receiver Operating Characteristic) curves and AUC (Area Under the Curve) are commonly used performance metrics. ROC curves and AUC have commonly used performance metrics in evaluating classification models. ROC Class of 0 (AUC = 0.98) indicates a specific ROC curve and corresponding AUC for predicting class 0 (negative class), indicating strong performance in classifying negative samples.

ROC Class of 1 (AUC = 0.97) indicates a high discriminatory power of the model in differentiating class 1 instances from other classes, demonstrating good performance in classifying positive samples. ROC Class of 2 (AUC = 0.96) corresponds to the ROC curve and AUC for predicting class 2 (another class potentially different from classes 0 and 1). Micro-average ROC curve (AUC = 0.97) calculates the aggregate performance of the model across all classes, while the Macroaverage ROC curve calculates the average performance metrics separately for each class.

True positive rate (TPR) measures the proportion of actual positive instances correctly classified as positive by the model, while false positive rate (FPR) measures the proportion of actual negative instances incorrectly classified as positive by the model. Both TPR and FPR are important indicators of a classifier's performance and are often plotted on the xaxis and y-axis in a ROC curve.

	Model	Accuracy	AUC	Recall	Prec.	F1	Kappa	MCC	TT (Sec)
et	Extra Trees Classifier	0.8843	0.9742	0.8843	0.8894	0.8839	0.8098	0.8130	1.6580
lightgbm	Light Gradient Boosting Machine	0.8671	0.9601	0.8671	0.8698	0.8664	0.7816	0.7839	0.2950
rf	Random Forest Classifier	0.8657	0.9608	0.8657	0.8694	0.8641	0.7781	0.7818	0.9550
gbc	Gradient Boosting Classifier	0.8029	0.9321	0.8029	0.8086	0.7999	0.6727	0.6789	0.8840
dt	Decision Tree Classifier	0.7729	0.8160	0.7729	0.7798	0.7709	0.6295	0.6339	0.3010
knn	K Neighbors Classifier	0.6714	0.7981	0.6714	0.6759	0.6670	0.4556	0.4600	0.3200
ridge	Ridge Classifier	0.6029	0.0000	0.6029	0.6068	0.5793	0.2958	0.3138	0.4090
lda	Linear Discriminant Analysis	0.6000	0.7440	0.6000	0.5940	0.5865	0.3151	0.3228	0.3030
ada	Ada Boost Classifier	0.5929	0.7302	0.5929	0.5896	0.5777	0.3126	0.3229	0.6160
lr	Logistic Regression	0.5657	0.7131	0.5657	0.5574	0.5476	0.2453	0.2538	0.1620
nb	Naive Bayes	0.5171	0.7107	0.5171	0.5462	0.5185	0.2570	0.2635	0.2900
dummy	Dummy Classifier	0.5129	0.5000	0.5129	0.2630	0.3477	0.0000	0.0000	0.1010
svm	SVM - Linear Kernel	0.4714	0.0000	0.4714	0.4880	0.3834	0.0817	0.1261	0.2810
qda	Quadratic Discriminant Analysis	0.3000	0.5064	0.3000	0.3787	0.2653	0.0138	0.0168	0.3400

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Figure 8. py caret Classification Experiment

The list of machine learning models and their corresponding evaluation metrics is unclear, but they are applied to various tasks and datasets. The models include Extra Trees Classifier, Random Forest Classifier, Gradient Boosting Classifier, Decision Tree Classifier, K Neighbors Classifier, Ridge Classifier, Linear Discriminant Analysis, Ada Boost Classifier, Logistic Regression, Naive Bayes, Dummy Classifier, SVM, and Quadratic Discriminant Analysis. Performance metrics We get the first module as Extra Trees Classifier this classifier offers High Accuracy Results Such as AUC (0.742), Accuracy (0.8843), recall (0.8843), precision (0.8894), F1 score (0.8839), kappa (0.8098), and MCC (0.8130), etc.

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