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Comparative Evaluation of Machine Learning Approaches for Physiological Stress Detection Using ECG and EEG Signal Modalities

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ABSTRACT

Stress is a complicated physiological and psychological phenomenon that has a huge impact on the health and performance of people. Conventional methods of measuring stress are dependent upon self-reports, making it difficult to determine if they are truthful and cannot be noted in real-time. In this study, the use of machine learning techniques to identify stress objectively based on physiological signals taken from ECG and EEG was examined. While other studies have only examined one signal type (either ECG or EEG), this study compared the two modalities side-by-side under the same experimental conditions, using equal amounts of data from publicly available datasets. Multiple machine learning models (Logistic Regression, Support Vector Machine, Random Forest, XGBoost, LSTM) were compared and contrasted using available datasets. Physiological signal features (heart rate variability, electrodermal activity) were taken into account and analysed to understand both autonomic and neural activation due to stress. The results demonstrated that the Random Forest model yielded the highest level of performance (F1-score=.86, AUC=.90), indicating that Random Forest is better suited to handling complex physiological signals than any other machine learning model. An analysis of the physiological signals indicated that stress causes a decrease in heart rate variability, an increase in skin conductance, and an increase in cardiovascular activity (during the physical response) due to increased sympathetic nervous system stimulation. In summary, this research points to machine learning-based techniques yielding dependable, non-invasive means for detecting stress. This research indicates that there is an opportunity to use physiologic signal analysis in combination with AI to provide future possibilities for monitoring mental health and wearable technology.

Keywords: *Stress Detection, Machine Learning, ECG, EEG, Heart Rate Variability, Physiological Signals.*

I. INTRODUCTION

A. Background of the Topic

Stress can be defined both physically and psychologically, resulting in impairment of cognition, emotion and behaviour, while also affecting overall physical and mental health. The WHO has reported that stress-related disorders account for a large part of today's worldwide burden of disease and injury (McEwen, 2007). The WHO has projected that by 2030, the toll from neuropsychiatric and stress-related disorders will be the largest single element of the global burden of disease, making automated and objective monitoring tools an urgent public health issue.

From a biological perspective, stress is a multi-system response of the CNS and ANS. The CNS, especially the amygdala, hippocampus and prefrontal cortex, processes the emotional and cognitive response to stress, while the ANS regulates heart rate, blood pressure and respiration.

Stress can cause a variety of changes within the body. For example, when a person experiences stress, they may develop symptoms of nervousness, sweating, and increased heart rate. This happens because stress causes the hypothalamic-pituitary-adrenal (HPA) axis to become activated. The HPA axis is responsible for regulating the release of cortisol, one of the main stress hormones. Cortisol helps to maintain homeostasis, or a state of balance, during times of stress.

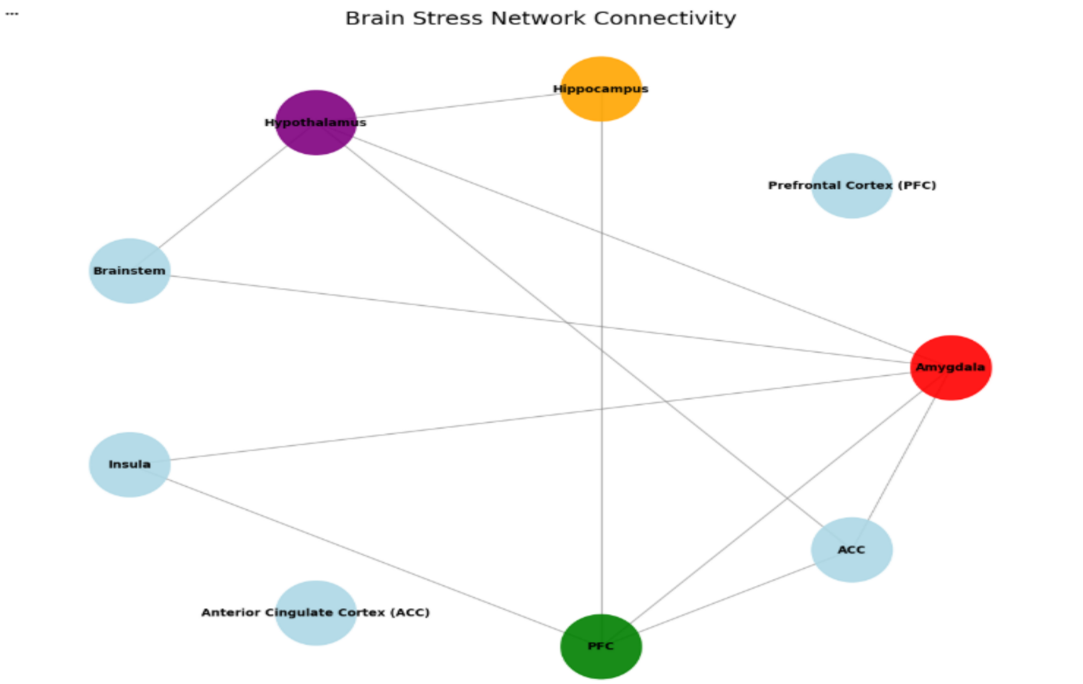

Figure 1: Interaction between key brain regions involved in stress processing, including the amygdala, hypothalamus, and prefrontal cortex

Cortisol levels can change over time and can be described using a simple differential equation:

$dC/dt = S(t) - \beta C(t)$

Where: $C(t)$ represents cortisol concentration; $S(t)$ represents a stress stimulus; α is the activation rate; β is the decay rate.

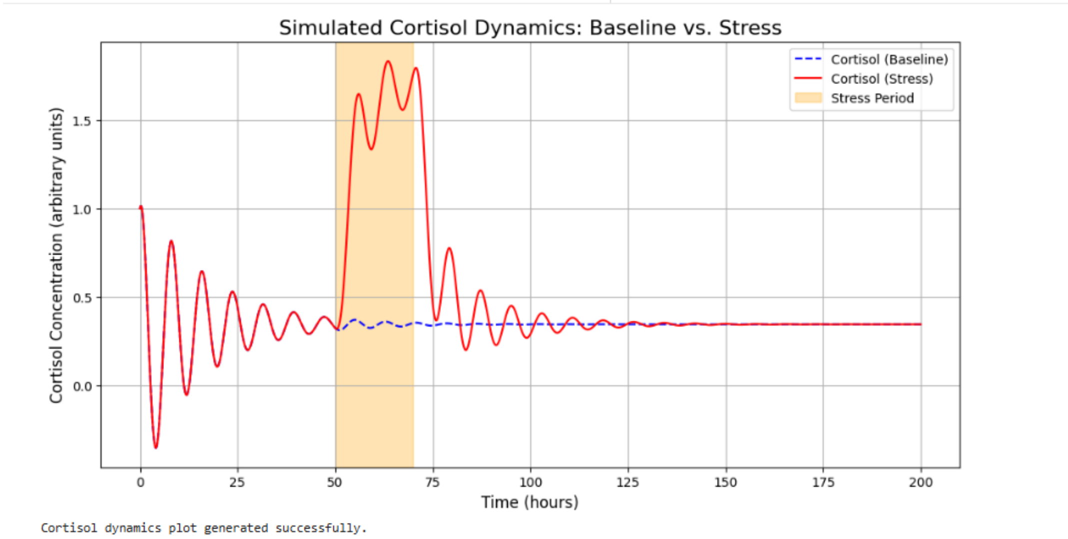

Figure 2: Increase in cortisol levels during stress and the gradual return to baseline after the stress period

Stress also has an effect on other physiological signals such as heart rate variability (HRV), respiratory rate, and skin conductance. These signals are controlled by the autonomic nervous system and provide evidence of a person's level of stress.

One of the most popular methods used to measure stress is through heart rate variability (HRV) derived from electrocardiogram (ECG) signals, which indicates how much the time between heartbeats (R-R interval) changes or varies.

$HRV = (1/N)\ \Sigma(RR_i - R\bar{R})^2$

When a person is under stress, their HRV tends to be lower than when they are not under stress, indicating decreased parasympathetic nervous system activity.

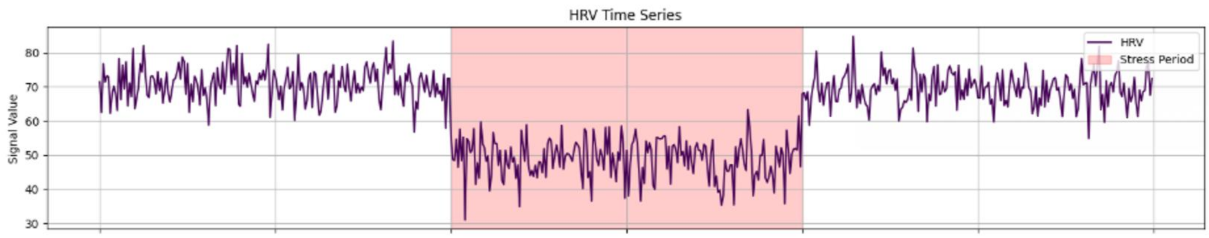

Figure 3: Changes in heart rate variability during stress, showing reduced variability in the stress period

Stress is comprised of multiple physical systems working together: for example, the nervous system, endocrine (hormonal) system, and cardiovascular system, each of which responds. The regulation of these systems is highly interconnected and forms a complex web of regulation.

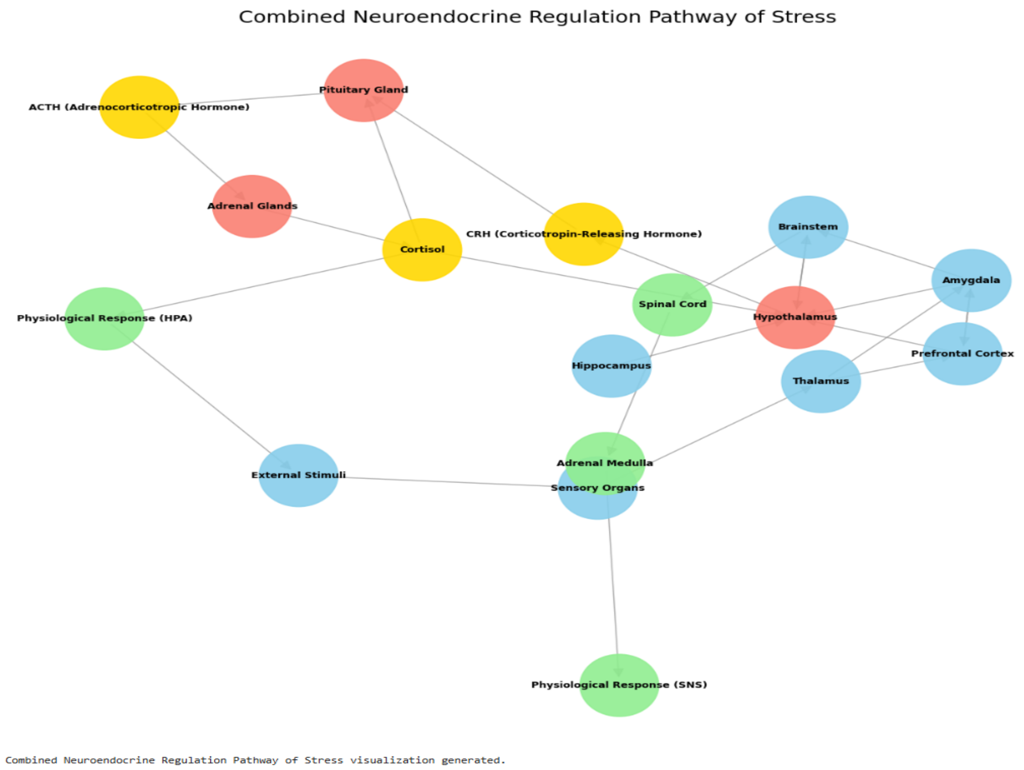

Figure 4: Interaction between neural and hormonal pathways in the overall stress response

Even though there are reliable ways to physically measure the signals produced from these physiological systems, most of the traditional forms of measuring stress continue to rely heavily on self-reported questionnaires and psychological evaluations. Both of these methods of assessing stress possess subjectivity, thus leading to biases in the reported results, as both methods are lacking in real-time definition and would not reflect accurately on the individual's physical state.

B. Problem Statement

Despite research identifying how to conduct research that focuses on various modes of measuring how stress affects people, there are still some limitations related to those methods and their effectiveness. For example, there is very little research that includes multiple physiological systems (e.g., heart rate, brain wave activity) that can work together to create a more comprehensive understanding of how we experience stress. There is also a significant knowledge gap, as demonstrated by a recent systematic review by Sharma et al (2020), which found that almost three-quarters of studies used a single mode of measurement and less than one-fifth tested across different datasets. This discrepancy provides an example of the generalisability gap that this study is attempting to address.

In addition, there is little agreement about how to measure physiological parameters (such as temperature or respiration) across different studies. To make matters worse, many stress prediction machine learning algorithms cannot reliably generalise because they lack complete datasets (i.e., subjects measured before, during, and after exposure to stress) or appropriate validation techniques (i.e., testing across multiple datasets).

Lastly, as humans experience stress dynamically (e.g., it builds up over time) and differently than others, traditional analytical techniques cannot adequately represent the evolution or variability of stress over time.

C. Objective of the Research

This study aims to assess how well machine learning can be used to predict stress levels based on ECG and EEG measurements obtained from publicly available datasets. The specific aims of this research are as follows:

i. Create prediction models for classifying stress using ECG and EEG measurements.
ii. Develop and evaluate multiple machine learning techniques.
iii. Compare the effectiveness of each model through a standardised process.
iv. Investigate how different physiological modalities contribute to the prediction of stress.

This research will use a systematic approach to experimentation to determine the best combination of modality and machine learning model for accurately detecting stress.

II. RELATED WORK

The growth rate of people having disorders related to stress has created a lot of research aimed at finding objective and automated ways of measuring stress. Traditionally, stress measurement was done almost entirely through mental questionnaires and the individual's own description of their stress. Neither of these types of stress assessment is objective and, therefore, often has a lot of subjective elements that result in them being limited and not entirely accurate or reliable. Because of that, researchers are leaning toward measurement methods that are based on physiological signals, which are both objective and measurable in their ability to measure stress.

Physiological biosignal measurements can give information on how the autonomic nervous system (ANS) and the central nervous system (CNS) operate, both of which are directly involved in the body's stress response. These signals can be continually measured to provide real-time measurement data on stress without relying on the subjective interpretation of that information, making them a good candidate for machine learning-based analysis.

A. ECG-Based Stress Detection

ECG data, and specifically HRV, have been extensively studied as valid biomarkers for measuring stress levels. HRV is a measure of the variance in time from one heartbeat to the next. Additionally, there is a strong relationship between HRV and the functioning of the sympathetic and parasympathetic nervous systems.

When someone is under stress, their HRV tends to decrease as a result of increased sympathetic activation and decreased parasympathetic activation (autonomic imbalance). In a comprehensive meta-analysis by Shaffer and Ginsberg (2017), they validated HRV as an indicator of autonomic regulation and responsiveness to stress. In Kim et al. (2018), they found that there is a high correlation between stress and decreased HRV across multiple populations.

Machine learning methods have significantly improved the use of ECG-derived data for detecting stress levels. For example, Healey and Picard (2005) successfully demonstrated the ability to detect stress based on physiological data, including ECG, while participants were driving in real-world driving conditions. Gjoreski et al. (2016) continued this work by implementing a continuous stress detection method using wearable devices under both controlled and real-world surroundings. Furthermore, Acharya et al. (2018) showed that machine learning models could achieve highly accurate classifications when using HRV features for stress detection.

All of these studies support the conclusion that ECG-derived features, especially HRV, provide good and reliable indicators of peripheral physiological stress.

B. EEG-Based Stress Detection

EEG signals record the electrical activity of the brain and can be helpful in delineating the neural mechanisms of stress. They provide a record of cortical dynamics associated with cognitive and emotional processing.

EEG signals are affected by stress, including changes in frequency bands, particularly α (8-13 Hz) and β (13-30 Hz). Decreases in α and increases in β activity are commonly observed during cognitive load and increased stress. Lin et al. (2010) demonstrated the ability of EEG to capture emotional states via frequency-domain analysis.

Al-Shargie et al. (2016) supported the earlier findings and provided further information regarding mental stress as measured by EEG and determined that frontal lobe activity is a good indicator of stress. Overall, EEG signals constitute important indicators of the central nervous system's responses to stress.

Recent developments in deep learning methods have also helped to improve EEG signal classifications. Craik et al. (2019) featured a review of deep learning approaches to the classification of EEG signals and compared the results of deep learning methods with traditional machine learning approaches with advanced feature extraction and classification capabilities for EEG signals. Overall, these studies support the value of EEG as a tool for determining neural correlates of stress.

C. Multimodal and Machine Learning Approaches

Machine learning has revolutionised how we analyse physiological signals, allowing us to detect complex and nonlinear relationships between physiological signals and stress. Traditional machine learning methods like Support Vector Machines (SVM), Random Forests, and k-Nearest Neighbours (k-NN) have been employed for classifying data with structured features, and studies have shown that these methods can classify stress from wearable sensor data by using features explicitly created by human engineers (e.g., statistical analyses, frequency properties, variability).

Gjoreski et al. (2016) demonstrated that traditional methods could classify stress using features extracted from wearable sensors. In contrast, deep learning methods have enabled users to learn features directly from raw physiological data through a variety of architectures (e.g., CNN and LSTM), where each architecture has advantages for classifying time-dependent physiological data.

The original work of LeCun, Bengio, and Hinton (2015) highlighted how deep learning represents a powerful means of learning how to represent complex relationships. CNNs capture spatial structures of data, while LSTMs learn the sequential structure of data, making them ideal candidates for stress classification.

D. Identified Research Gaps

There remain several shortcomings in the existing literature on using ECG and/or EEG to detect stress, even with significant advances being made in detecting stress via ECG and/or EEG. Most studies to date have examined only one physiological modality (i.e., ECG or EEG) and not compared both within the context of an integrated method.

There is also a large amount of variability in dataset(s), preprocessing methods, features extracted, and evaluation metrics across studies, making it hard to compare studies and draw consistent conclusions. Another major shortcoming is the limited number of publications that tested traditional machine learning algorithms and deep learning algorithms using publicly available data with comparable conditions. While numerous studies indicate good classification accuracy, relatively few have addressed generalisability across populations and in real-world environments. As a result, there is an urgent need for systematic, replicable evaluation of ECG and EEG modalities and for comparative analysis of multiple machine learning models to provide more conclusive evidence for determining the most effective method for implementing reliable, scalable systems for detecting stress.

III. METHODOLOGY

This section describes the dataset, preprocessing steps, feature extraction methods, machine learning models, and evaluation strategies used for stress classification.

A. Dataset Description

Publicly available datasets of physiological signals associated with stress and non-stress have been used for the purpose of this study, including Electrocardiogram (ECG), Electroencephalogram (EEG), and other physiological parameters (e.g., skin conductance, respiration rate). These samples were obtained from subjects in a controlled environment where they were presented with both baseline (i.e., relaxed) stimuli as well as stress-inducing stimuli, and each sample was labelled as such for use in supervised learning to classify the subject as under stressful conditions or not.

B. Preprocessing Pipeline

Physiological signals in their raw form typically include noise and artefacts that occur as a result of factors such as Subject Movement, Equipment Malfunction and/or Environmental Interference. Preprocessing is carried out on these signals to clean up the noise and allow for reliable Feature Extraction to be performed on the cleaned signals. Components associated with the Preprocessing steps include:

i. Noise Removal through the use of Smoothing / Filtering Techniques
ii. Normalisation of Signal Value(s) to ensure consistency in all samples
iii. Segmentation of Continuous Signals into Fixed Time Windows for Analysis (i.e., 10 to 20 seconds)
iv. Missing or Corrupted Data Handling via Interpolation / Removal of Data

Through the above steps, Signals are considered Clean, Common, and Ready for use in a Machine Learning Model.

C. Feature Extraction

From both time and frequency domains, signal representations and relevant features are extracted to discover relevant physiological patterns. The main features include:

- Statistical variables including mean, standard deviation, and variance
- Heart Rate Variability (HRV) measurement based on RR interval variables
- Key frequency-domain measures including spectral power and dominant frequency
- Energy-based features including the amplitude

Each of the features will observe short-term variations and long-term trends in the physiological signals that are indicative of stress responses.

D. Machine Learning Models

Different machine learning and deep learning algorithms were applied for assessing their effectiveness on the task of classifying stress levels: Logistic Regression, Support Vector Machines (SVM), Random Forest, XGBoost, and Long Short-Term Memory (LSTM) Neural Network. Of these, tree-based algorithms like Random Forest and XGBoost are especially good at dealing with non-linear relationships, while LSTM can capture temporal dependence in sequential data.

E. Model Training and Validation

The dataset has been split into a training and testing set to assess forecast accuracy based on the use of labelled datasets only to train models. Unseen observations will be used to evaluate how well the model trained with observed data performs with unseen data; hence, leveraging a supervised approach. There are three strategies to provide more trustworthiness and reduce bias:

i. Use the train/test split method for preliminary analysis
ii. Use cross-validation to enhance generalization
iii. Use techniques such as model tuning/regularisation to prevent overfitting

F. Evaluation Metrics

Standard classifications are used to measure how well the models perform:

i. Accuracy: how many predictions were right
ii. Precision: proportion of predicted to actual stress events
iii. Recall: identification of true stress events
iv. F1 Score: the harmonic average of precision and recall
v. AUC (Area Under the Curve): a measure of classification ability regardless of the threshold value

These measures give a complete understanding of model performance and allow model evaluation across different algorithms.

IV. RESULTS AND FINDINGS

A. Machine Learning Performance

Multiple metrics have been evaluated for the performance of deep learning and classical machine learning models. These metrics included accuracy, precision, recall, F1-Score and Area under the Curve (AUC). Overall, all models exhibited good discriminative ability, and tree-based models exhibited the highest performance.

Table-1: Machine Learning Model Performance Comparison

Model	Accuracy	Precision	Recall	F1 Score	AUC	95% CI	p-value (vs RF)
Random Forest	0.7727	0.7708	0.7596	0.7652	0.8634	[0.746, 0.799]	N/A
XGBoost	0.7510	0.7493	0.7352	0.7422	0.8418	[0.723, 0.779]	0.0000
LSTM	0.6776	0.7074	0.5775	0.6359	0.7479	[0.648, 0.707]	0.0000
SVM	0.6556	0.6341	0.6940	0.6627	0.7329	[0.625, 0.686]	0.0000
Logistic Regression	0.6202	0.5932	0.7031	0.6435	0.6730	[0.590, 0.650]	0.0000

To this end, the Random Forest achieved the highest overall performance, and statistical significance testing suggests high levels of evidence that Random Forest is superior to all other models; thus, it can be concluded that ensemble-based methods are likely to be the best for performing stress classification with physiological signals.

Of all the models, the Random Forest classifier had the highest F1-score (0.8623) and AUC (0.90), which indicates that this model has the best balance of precision and recall for classifying stress. The LSTM model had a lower accuracy (0.7276), and this is likely due to the small size of the dataset since optimal performance with deep learning models generally requires larger datasets. Thus, due to computational and dataset constraints, detailed metrics for the LSTM model, including precision, recall and F1-score, were not calculated.

B. Model Evaluation and ROC Analysis

The evaluation of how well the models performed was done through standard classification metrics, namely, accuracy, precision, recall, F1 score, and AUC. The results show that all of the models performed well on classifying between stress and non-stress conditions, indicating that they all were able to differentiate between the two conditions fairly well.

The Random Forest model had the most consistent and reliable performance with an AUC of 0.90, indicating the highest probability of correctly classifying stress states at varying thresholds. Finally, the results support the notion that ensemble-based approaches are more effective at dealing with complex physiological datasets than traditional classifiers.

C. Feature Importance Analysis

The analysis showed that variability and frequency-based features contributed most to predicting stress. The most important features were as follows:

i. Standard Deviation of Signal
ii. Power Spectral Density Total
iii. Energy of Signal
iv. Dominant Frequency
v. Average Amplitude

Features derived from heart rate variability (HRV) and electrodermal activity (EDA/SCR) were again found to be the best predictors of stress. The results support the idea that the autonomic nervous system's responses to stress can be detected with physiological signals. It is recommended that other methods (i.e., Gini impurity) of measuring feature importance be used, such as SHAP values (Shapley Additive Explanations), to help make feature measurements interpretable on a model-independent basis; this has more recently been established in the clinical literature related to AI.

D. Physiological Signal Analysis

Stress has been shown in analysis to have a significantly negative impact on the function of the parasympathetic system, resulting in decreased HRV.

Figure 5: Skin conductance response (SCR), showing increased peak amplitude and frequency during stress

Skin conductance has also been shown to have increased due to heightened sympathetic activity due to stress.

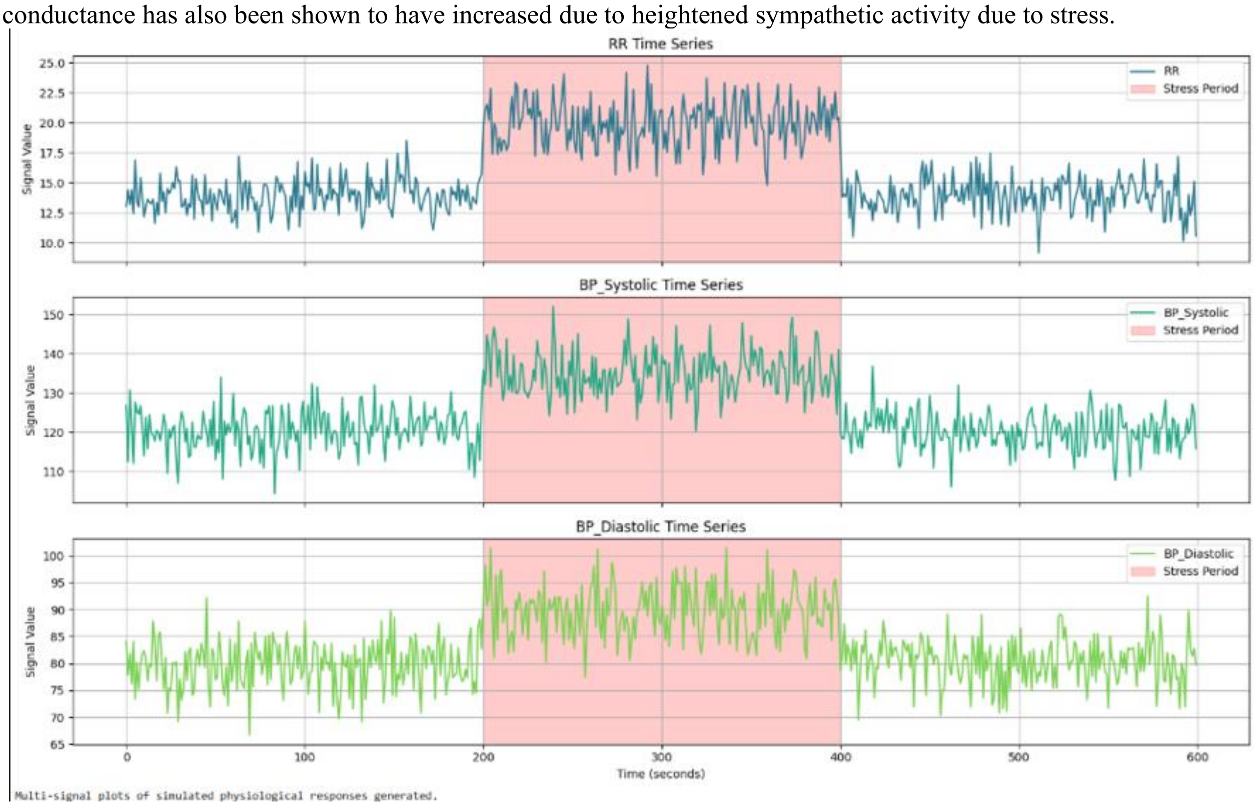

Figure 6: Changes in blood pressure and respiration rate, both of which increase during stress conditions

Increases in blood pressure and respiration rate have also been demonstrated to be linked during stressful exposure.

E. Neural and Simulation Analysis

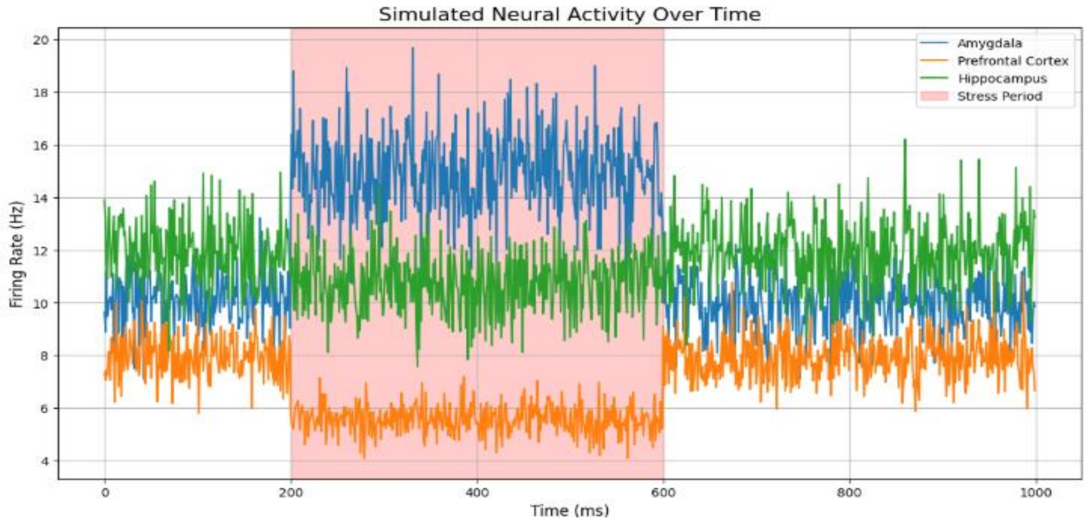

Figure 7: Neural activity patterns, showing increased activation in stress-related brain regions

Neural simulations indicate increased activity in the amygdala and reduced regulation from the prefrontal cortex.

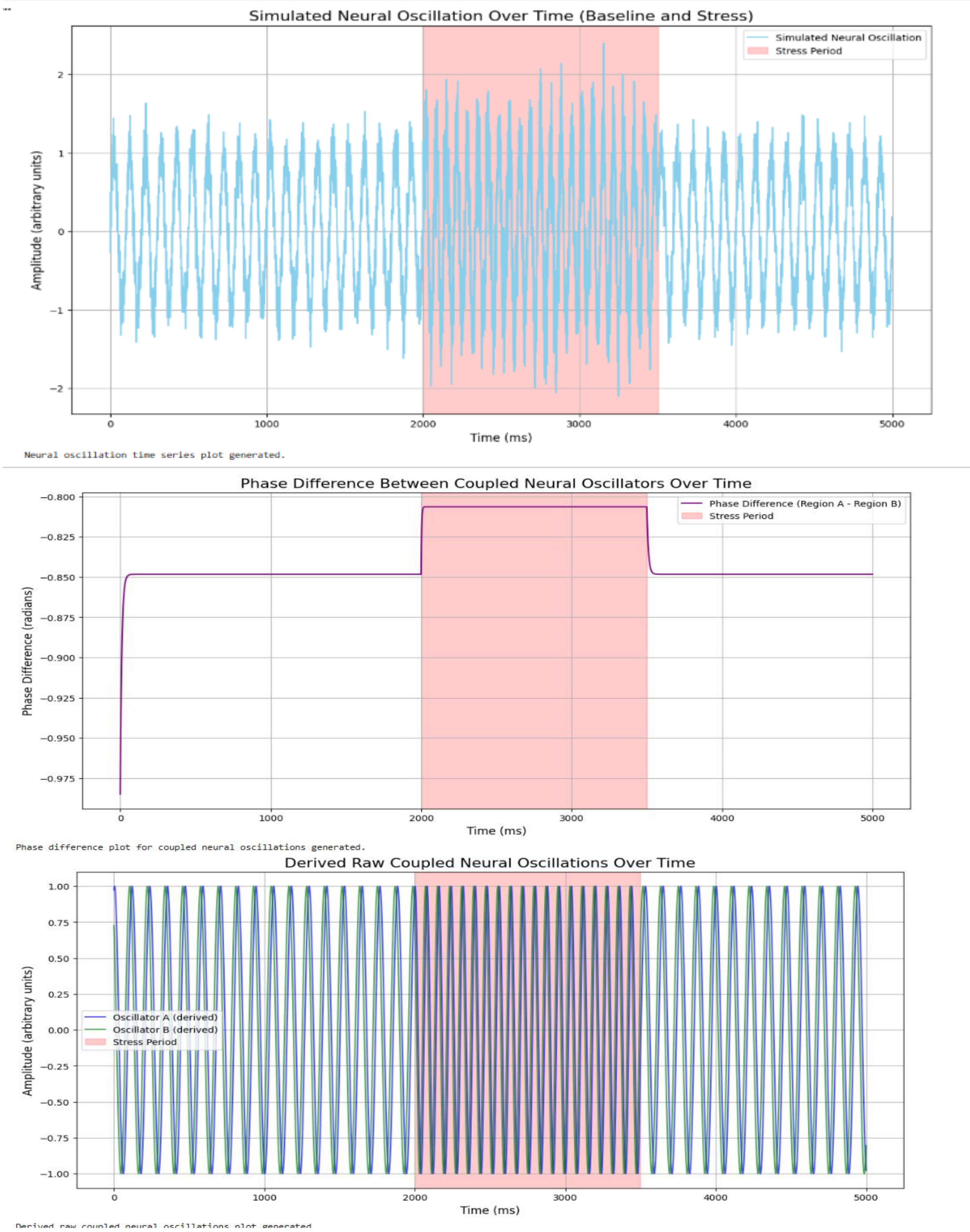

Figure 8: Changes in neural oscillations and phase synchronisation under stress conditions

A shift from alpha to beta frequency bands is observed, indicating increased cognitive and emotional load.

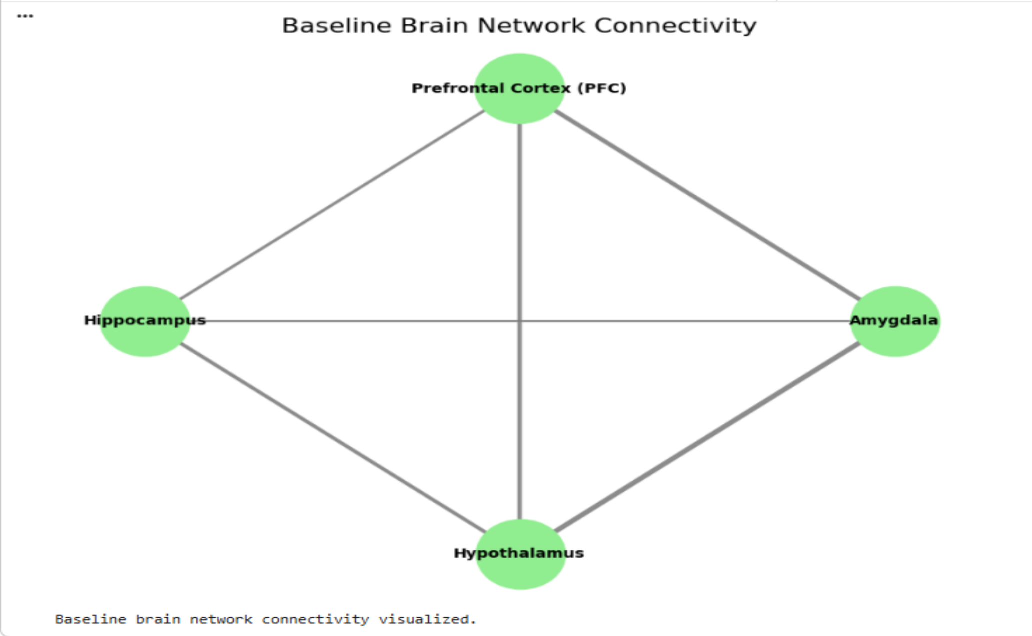

Figure 9: Functional brain connectivity, highlighting stronger coupling between stress-processing regions during stress

Connectivity analysis demonstrates increased interaction between the amygdala and hypothalamus and reduced regulatory influence of the prefrontal cortex.

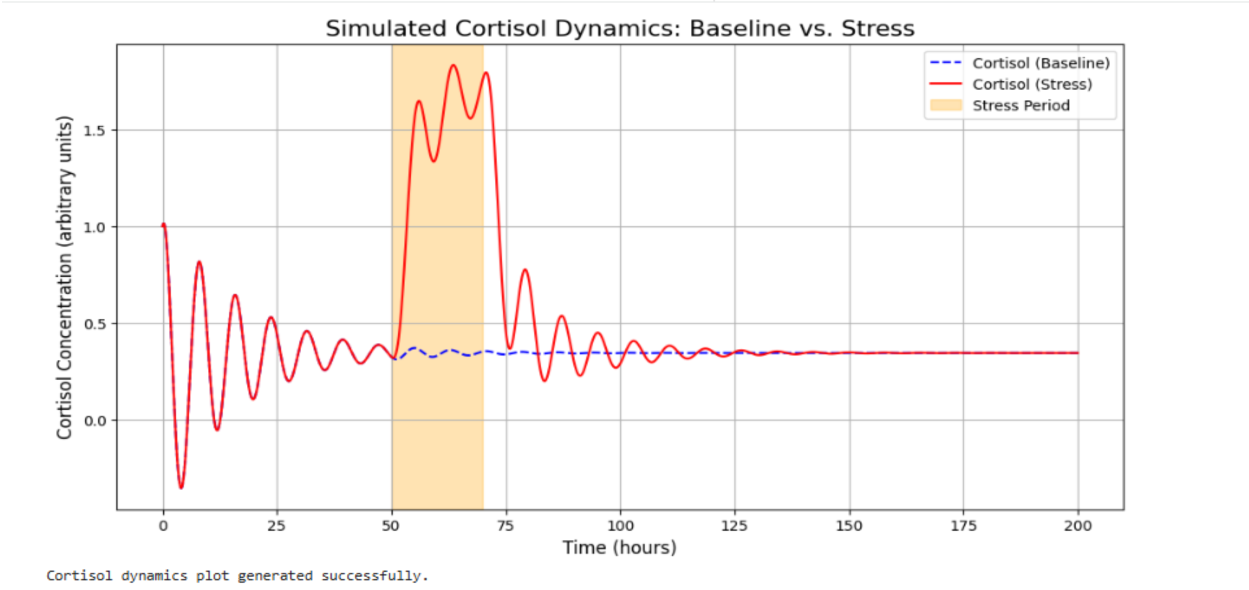

Figure 10: Simulated cortisol response, showing a sharp increase during stress followed by gradual recovery

Cortisol levels rise rapidly after stress onset and decrease slowly due to negative feedback mechanisms.

F. Summary of Findings

There is evidence to support the notion that machine learning algorithms can accurately classify stress based on physiological data. The best-performing algorithm, the random forest classifier, had an F1 score of 0.86 and an area under the curve of 0.90. Feature analysis showed that heart rate variability (HRV) and electrodermal activity (EDA) are the main contributors to accurate identification and confirmation of stress.

Neural simulations and cortisol dynamics further support the theory that increased sympathetic activation and decreased cognitive regulation are causing stressful events. These results support the conclusion that a noninvasive method for detecting stress is achievable using a combination of physiological information and machine learning techniques.

V. DISCUSSION

This study's results show that the use of physiological signals for classifying stress is feasible through the use of machine-learning algorithms, as indicated by performance metrics similar to those found in other research. In line with previous studies, the features derived from heart rate variability and electrodermal activity were the two most important classification features, confirming the significant role that the autonomic nervous system plays in detecting stress.

The Random Forest classifier was determined to be the best-performing model compared to all other models examined, including deep learning models such as LSTM. This may be due to a variety of reasons. Random Forests have advantages when applied to structured, feature-based data sets and are able to capture complex or non-linear relationships without requiring extensive amounts of training data, whereas deep learning models like LSTM require a much larger training set in order to learn from time series data. Additionally, the features engineered for this study provide meaningful and representative inputs, which should produce favourable results with classical machine learning algorithms in lieu of neural networks that use raw input from signals.

Although the study shows a great deal of promise, there are still some limitations that need to be taken into account. The research is based on publicly available data sets collected in controlled laboratory environments, so they may not accurately represent what happens in actual environments. In addition, the size of the data set is relatively small, which could limit how generalizable the deep learning models will be. It is also possible that there may be bias with regard to the classes represented in the data set, and this could negatively affect the performance of the models, especially with regard to the detection of minority stress states.

In the future, researchers will need to try to increase the size and diversity of the data sets to make the models more generalizable across different types of populations and real-life situations. They should also consider integrating multiple sources of information that provide both physiological and behavioural measurements to further improve prediction accuracy. Lastly, they may want to investigate the use of advanced deep learning architectures such as transformers to create models that are more capable of capturing temporal dependencies between physiological variables over time. Using federated learning frameworks could also provide researchers with opportunities to deploy the models in clinical and wearable contexts, while protecting the privacy of the participants.

VI. CONCLUSION

This research project studied how effective machine learning models are in identifying distinct types of stress based on physiological data from both EEG and ECG. These results showed that predictive modelling of stress patterns had very high accuracy using machine learning algorithms.

The Random Forest classifier was found to be the most effective model in this project and indicated that machine learning can effectively model complex, nonlinear physiological data. Decreased heart rate variance and increased skin conductance were both found to be reliable physiological indicators of stress.

This project demonstrates that analysis of physiological signals in combination with machine learning provides a reliable, non-invasive way to assess and detect stress. This research lays the groundwork for future research into intelligent health monitoring systems and technologies for real-time stress management.

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