Project Phase 2 Report On

Stress Detection from EEG Signal

Submitted in partial fulfillment of the requirements for the award of the degree of

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in

Computer Science and Engineering

By

Anantha Krishnan G (U2003035)

Anjoe S Nambadan (U2003036)

Ashwin Saji (U2003047)

Chackochan Sanjai (U2003059)

Under the guidance of

Dr. Sminu Izudheen

Department of Computer Science and Engineering
Rajagiri School of Engineering & Technology (Autonomous)
(Parent University: APJ Abdul Kalam Technological University)
Rajagiri Valley, Kakkanad, Kochi, 682039
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CERTIFICATE

This is to certify that the project report entitled ***Stress detection from EEG signal*** *is a bonafide record of the work done by* ***Anantha Krishnan G (U2003035), Anjoe S Nambadan (U2003036), Ashwin Saji (U2003047), Chackochan Sanjai (U2003059)****, submitted to the Rajagiri School of Engineering & Technology (RSET) (Autonomous) in partial fulfillment of the requirements for the award of the degree of Bachelor of Technology (B. Tech.) in Computer Science and Engineering during the academic year 2023-2024.*

Dr. Sminu Izudheen
Project Guide
Professor
Dept. of CSE
RSET

Dr. Sminu Izudheen
Project Coordinator
Professor
Dept. of CSE
RSET

Dr. Preetha K.G
Head of the Department
Professor
Dept. of CSE
RSET

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Anantha Krishnan G
Anjoe S Nambadan
Ashwin Saji
Chackochan Sanjai

Abstract

Our study introduces a novel framework that merges machine learning techniques with electroencephalography (EEG) data analysis to effectively classify mental states of stress and relaxation. We meticulously preprocess EEG signals to eliminate artifacts and noise, followed by window segmentation. To achieve robust classification performance, we devise a Convolutional Neural Network (CNN) architecture tailored specifically for learning discriminative features from EEG data, which is then rigorously trained and evaluated. Additionally, we employ Gradient-weighted Class Activation Mapping (Grad-CAM) to interpret the decisions made by the CNN model, offering valuable insights into the neural mechanisms underlying stress and relaxation responses. By integrating machine learning with EEG data, our approach significantly enhances the understanding of psychological states and their neural correlates. This contributes to the burgeoning field of neuroinformatics by providing a reliable method for categorizing EEG data into stressed and relaxed states. The interpretability offered by Grad-CAM advances our comprehension of brain processes related to stress and relaxation, thereby offering fresh perspectives on stress management strategies and mental health interventions. Overall, our study presents a robust methodology for EEG-based psychological state evaluation with potential applications in clinical settings and beyond.

Contents

List of Abbreviations

EEG - Electroencephalogram

CNN - Convolutional Neural Network

LSTM - Long Short-Term Memory

ERP - Event-Related Potential

Grad-CAM - Gradient-weighted Class Activation Mapping

GPU - Graphics Processing Unit

ICA - Independent Component Analysis

EDF - European Data Format

GUI - Graphical user interface

HFD - Higuchi Fractal Dimension

ROC - Receiver Operating Characteristic

PSD - Power Spectral Density MSC- Magnitude Square Coherence

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Chapter 1

Introduction

1.1 Background

Stress-related disorders are on the rise in today's world; though seemingly a worldwide issue, they cut across demographics and affect everyone who is navigating modern life. Recognizing the importance of timely intervention, this project tackles the urgent necessity for correct detection of stress especially with regard to signal analysis derived from EEG.

Current situations underline the diversity of challenges of identifying and addressing stress appropriately. World Health Organisation warned that stress-related mental health disorders will be the main cause of disability-adjusted life years by 2030, hence there is urgent demand for better tools.

Understanding human behavior and mental health is significantly impacted by the categorization of stress and relaxation states from EEG data. This research uses interpretable artificial intelligence approaches and state-of-the-art deep learning technique to build a strong framework that tackles this difficulty. To precisely categorize people's stress patterns, we use a Convolutional Neural Network model that has been tuned for EEG signal processing. Transparency and interpretability are further improved by the use of Grad-CAM, which makes it possible to visualize prominent areas within the EEG signals that influence the categorization choice.

Moreover, we investigate the calculation of EEG characteristics, such as relative theta power and relative alpha power, after Grad-CAM analysis, going beyond conventional feature extraction techniques. The interpretative capacity of the categorization framework is enhanced by these traits, which offer more profound insights into the underlying brain correlates linked to stress and relaxation responses. Our project aims to advance the field of EEG-based stress pattern identification and contribute to the development of personalized interventions for stress management and mental well-being by combining cutting-edge machine learning algorithms with sophisticated feature extraction methodologies customized to EEG data.

This project has the potential to influence not only personal mental health, but public health strategies as well workplace interventions and educational programs. This effort aims to trigger a paradigm shift in stress detection processes by uncovering complex patterns of physiological strain recorded as EEG signals, converting them towards more resilient and healthy society.

1.2 Problem Definition

An important method for tracking brain activity and analyzing cognitive processes is electroencephalography. However, because brain responses are complex and dynamic, classifying stress and relaxation states from EEG data is a substantial difficulty. Current approaches frequently depend on arbitrary self-reporting or oversimplified categorization algorithms, which may be imprecise and miss subtle patterns that indicate tension and relaxation. Furthermore, the interpretability of classification models is still restricted, which makes it more difficult to comprehend the brain correlates of stress reactions.

This project aims to address these challenges by developing a comprehensive framework for EEG-based classification of stress and relaxation states. Our goal is to improve the interpretability, speed, and accuracy of stress pattern recognition from EEG data by utilizing cutting-edge deep learning techniques and interpretable artificial intelligence paradigms. Our research intends to offer objective insights into people's stress patterns, opening the door for individualized therapies and enhanced mental health by fusing cutting-edge machine learning algorithms with cutting-edge feature extraction techniques made specifically for EEG data.

1.3 Scope

The scope of this study revolves around addressing the growing issue of stress in today's fast-paced lifestyle. Stress detection is crucial, and this research focuses on utilizing electroencephalography techniques to identify brain activities through electrical bio-signals. The complexity of EEG signals requires a specialized approach, and to overcome this challenge, we suggest a specific deep learning model that uses Grad-CAM for interpretability and Convolutional Neural Networks to tackle this complexity.. The model aims to detect stress levels in humans, providing valuable support to neurologists, mental health counselors, and physicians in making informed decisions. The study employs the Physionet EEG dataset, applies preprocessing, and utilizes advanced techniques for feature selection and stress classification.

1.4 Motivation

The motivation behind this research stems from the imperative need to address stress in contemporary society. Stress has become a significant health concern, impacting both physical and mental well-being. The detrimental effects of stress on various physiological systems necessitate effective detection methods. Traditional EEG analysis requires expertise, and the proposed model seeks to automate and enhance this process. By employing a CNN-based deep learning approach, the study aims to contribute to the field by achieving higher accuracy in stress level classification compared to existing methods. The motivation is to empower healthcare professionals with a reliable tool for stress detection, ultimately improving the overall well-being of individuals in the face of the challenges posed by stress in today's society. The research evaluates the proposed model against established benchmarks, providing cutting-edge findings in stress detection from EEG signals.

1.5 Objectives

1. **Develop Specialized Deep Learning Model:** Design and implement a Convolutional Neural Network model tailored for accurately classifying EEG signals into stress and relaxation states.

2. **Implement Feature Extraction Techniques:** Implement feature extraction techniques to compute additional EEG features such as relative theta power and relative alpha power post Grad-CAM analysis.

3. **Transparency through XAI Methods:** Ensure the model is interpretable and transparent by incorporating eXplainable Artificial Intelligence XAI methods like GRAD-CAM, which reveal insights into how stress was detected leading to greater awareness of these mechanisms.

4. **Advancement in Stress Detection:** Present an all-encompassing framework to drive stress detection research in order not only to enhance accuracy but also improve the classification of patterns related to stress.

1.6 Challenges

The reliability of stress predictions depends on data quality management. Results may be compromised by poor or non-consistent EEG data, highlighting the need for thorough preprocessing of all types of input data when using electrode wise CSV files and frame extraction.

In addition, generalizability of the findings beyond specific conditions studied in this research is an issue. Caution is noted when extrapolating results into broader scenarios as it might be full of potential pitfalls in applicability. Moreover, the ethical concerns involve putting participants under stress by making them perform mental arithmetic tasks which may lead to health problems. It is crucial to balance technical intricacies with ethical considerations for the success of the project.

1.7 Assumptions

1. **Homogeneous Stress Response:** The project assumes a relatively consistent physiological and neurological response to stress across the selected participant group. It presupposes that the identified stress-related features, extracted through techniques like Magnitude Square Coherence and Mutual Inference, exhibit general

patterns applicable to diverse individuals within the study cohort.

2. **Reproducibility of Stress Induction Tasks:** It is assumed that the stress-inducing mental arithmetic tasks reliably evoke consistent stress responses in participants. The project relies on the assumption that the chosen stressors effectively simulate real-world stress conditions, facilitating the extraction of meaningful features for stress detection.

3. **Standardized EEG Data Acquisition:** The project assumes a standardized and uniform EEG data acquisition process, ensuring that electrode-wise CSV files consistently capture relevant neural activity. This assumption underlines the necessity for a well-controlled experimental setup to minimize variability in data acquisition and enhance the reliability of stress-related feature extraction.

1.8 Societal / Industrial Relevance

The proposed deep learning model for stress detection from EEG signals holds significant relevance for both societal and industrial applications. In the societal context, the increasing prevalence of stress in today's fast-paced lifestyle necessitates effective tools for early detection and intervention. This model can be applied in healthcare settings, benefiting individuals by providing timely insights into their stress levels. Health professionals, including neurologists, mental health counselors, and physicians, can utilize the automated stress detection system to make informed decisions regarding patient care and treatment plans.

In an industrial context, the relevance of this work is evident in the potential impact on workforce productivity and well-being. Chronic stress among employees is a pervasive issue that can lead to decreased productivity, increased absenteeism, and higher healthcare costs for companies. The proposed model offers a practical solution for industries to monitor and address stress levels among their workforce efficiently. By implementing such a system, companies can proactively identify and mitigate stress-related issues, thereby improving overall employee health and contributing to a more productive and resilient workforce.

Moreover, the financial implications of stress-related productivity losses make this research particularly relevant for industries. The model's ability to detect stress accurately can potentially lead to substantial cost savings for companies by preventing long-term health issues, reducing employee turnover, and enhancing overall organizational performance.

1.9 Organization of the Report

This report is organized to provide a coherent presentation of the research work. The introductory chapter (Chapter 1) establishes the background, defines the problem, outlines the scope, discusses motivation and objectives, identifies challenges, makes assumptions, and highlights the societal/industrial relevance. Additionally, it offers a brief overview of how the report is structured.

Following the introduction, Chapter 2 conducts a literature survey, summarizing key findings from relevant papers. This chapter aims to provide context and identify existing gaps in the research landscape.

Chapter 3 delves into the requirements for the proposed system, covering both hardware and software aspects. Functional requirements are enumerated, either in a numbered list or described within a use case model.

Moving on, Chapter 4 focuses on the system design. It includes an architectural diagram of the system, a division of modules, and a Gantt chart illustrating the work schedule for different project activities.

Chapter 5 focuses on the system implementation, which includes the algorithm and wire-frames of the GUI.

Chapter 6 focuses on the results and discussions. It includes the various model evaluation parameters and the final GUI screenshots.

The concluding chapter, Chapter 7, summarizes the report, presents conclusions drawn from the research, and outlines potential areas for future work and improvement.

Finally, the report includes a references section listing all the sources cited throughout, and a list of publications section, if applicable, highlighting any publications resulting from the research. This organizational structure is designed to present a logical and comprehensive overview of the research undertaken.

1.10 Conclusion

In conclusion, this chapter establishes the groundwork for the research, providing an overview of the project's background, problem definition, scope, and motivation. It outlines the objectives, challenges, and assumptions, emphasizing the societal and industrial relevance of the proposed CNN-based deep learning model for stress detection from EEG signals [1]. The chapter concludes with a brief overview of the report's organizational structure, setting the stage for the subsequent chapters that delve into the literature survey, requirements, system design, and overall findings of the research.

Chapter 2

Literature Review

This section provides a comprehensive overview of existing methodologies for stress diagnosis. The papers found in the domain primarily focused on the analysis of physiological data, utilization of electroencephalography signals, and the application of machine learning algorithms. Physiological data analysis involves measuring responses such as heart rate, blood pressure, and cortisol levels, offering insights into the body's reaction to stress-related disorders. The exploration of machine learning techniques, notably Support Vector Machine , showcases the diverse computational approaches employed for stress detection from EEG signals. Additionally, advanced algorithms such as Long Short-Term Memory for emotion recognition and hybrid models like Bidirectional LSTM combined with LSTM for mental workload classification have played pivotal roles in advancing stress detection methodologies utilizing EEG signals.

2.1 Hybrid LSTM and CNN model for stress detection from EEG

2.1.1 Introduction

In the fast-paced and demanding landscape of contemporary life, stress has become an increasingly prevalent concern with significant implications for mental health. The intricate interplay between stress and physiological responses, particularly those manifested in brain activity, has prompted the exploration of innovative methodologies for stress detection. This paper addresses the imperative need for effective stress detection through the lens of Electroencephalography signal processing, proposing a novel approach that harnesses the power of deep learning.

The recognition and management of stress-related disorders have spurred the evolution of medical assistive technologies, with EEG signal-based analysis emerging as a promising frontier. Leveraging neural network platforms, particularly Long Short-Term Memory networks and Convolutional Neural Networks , this research seeks to refine stress detection accuracy through advanced signal processing techniques.It introduces a revolutionary architecture StressNet amalgamates strengths of 2D CNN and LSTM network for finding stress states in EEG signals[2].

The methodological itinerary shall begin from the dissection of EEG signals into alpha, beta and theta components after which it will be transformed in to the azimuthal projection based images. Since feature extraction by 2D CNN has been applied to the images, they become the basis of StressNet and are further processed by LSTM for fine temporal processing. This makes the LSTM very appropriate in modeling the dynamic temporal behaviors of the EEG signals that require retention of memory of past states. Finally, the features that are extracted from the model undergo a classification process using fully connected layers to classify them into stress or normal classes as indicated in the model called StressNet.

The research included extensive experiments on the DEEP and SEED datasets to prove the efficiency of the proposed StressNet model compared to other similar approaches. Particularly, a series of the results showed a high accuracy of stress detection amounting to 97.8%, which is superior even to human abilities. Moreover, this study proposes the use of a new preprocessing technique and hybrid LSTM-CNN model, hence not only causing a boost in papers published along this line but a corresponding expansion in dataset size to ameliorate stress detection accuracy.

This paper transcends the conventional boundaries of EEG-based stress detection, addressing pivotal questions surrounding the interpretability, performance evaluation, and potential applications of machine learning models in this domain. The ensuing sections delve into a comprehensive literature review, the proposed methodology, dataset specifics, and a meticulous presentation of experimental results. Through its innovations and promising outcomes, this research heralds a significant stride in the realm of stress detection, with broader implications for mental health monitoring and real-time applications.

2.1.2 Methodology

Dataset Acquisition

- The study utilized EEG recordings from two distinct datasets, namely the SEED and DEAP datasets. These datasets featured EEG recordings from 44 and 32 patients, respectively.

Preprocessing

- Prior to model training, EEG data underwent preprocessing to eliminate noise and artifacts, ensuring the accuracy of subsequent analyses. This critical step involved the use of the SciPy library in Python to read 'mat' files containing the EEG data.

Feature Extraction

- EEG signals were disassembled into three frequency components: alpha (8–12 Hz), theta (4–7 Hz) and beta (13–30 Hz). These frequency components were pivotal in understanding the cognitive states of individuals, as their amplitudes and frequencies fluctuate with varying mental states.

Azimuthal Projection

- Azimuthal projection was employed as an effective technique to analyze changes in RGB color patterns corresponding to stress changes. This projection method facilitated the transformation of EEG data into 2D projections, forming the basis for subsequent pattern analysis.

Image Augmentation

- To enhance the dataset's variability and improve model generalizability, image augmentation techniques were applied. These included horizontal and vertical flips, shifting, and zooming operations. Signal augmentation involved the introduction of random noise equivalent to 20

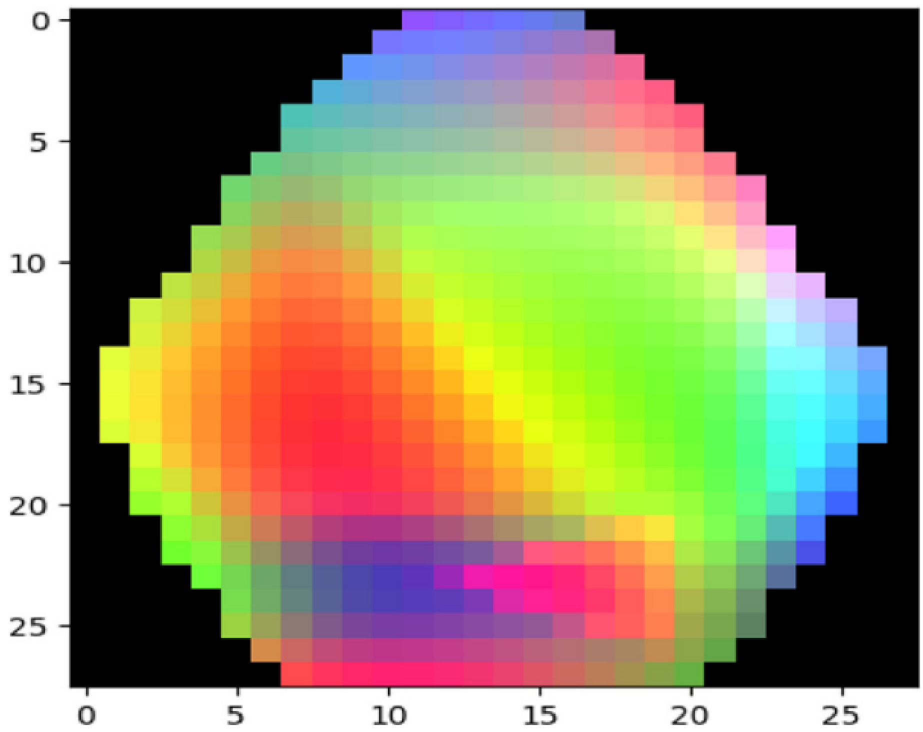


Figure 2.1: Azimuthal projection of input EEG signal by projecting mixed Alpha, Beta and Theta signals.

Model Architecture

- The proposed StressNet model is a hybrid architecture comprising a multi-channel LSTM and a 2D CNN. The LSTM network, consisting of three layers, processed EEG signals, capturing temporal dynamics effectively. Simultaneously, azimuthal projection-based images underwent feature extraction through a 2D CNN inspired by the VGG16 model.

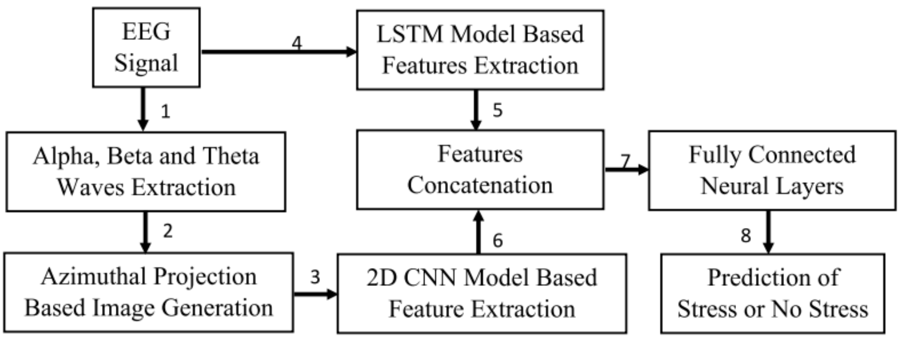


Figure 2.2: Block diagram of for stress detection using EEG signals

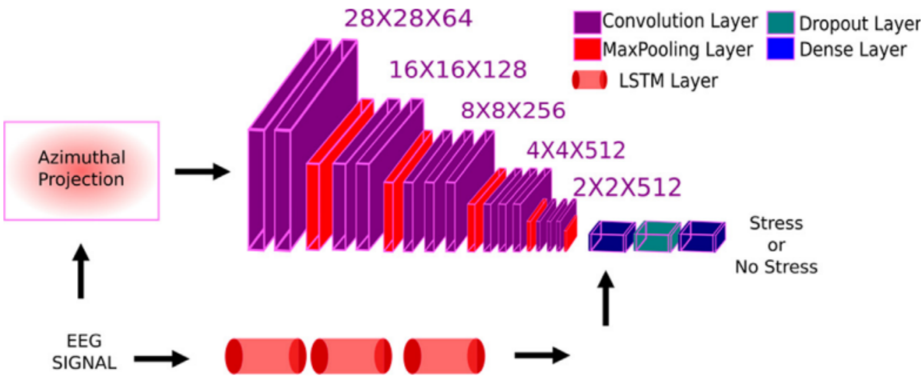


Figure 2.3: Hybrid LSTM and 2D CNN model

Concatenation and Classification

- The features extracted from both the LSTM and CNN pathways were concatenated and fed into fully connected layers for final stress classification. The last dense layer employed the Softmax activation function to classify features into stress or normal classes.

Training and Evaluation

- The dataset got divided into the two sets with an 80:20 ratio for train and test sets, respectively. In training, the model is optimized using epochs through which it is possible to evaluate several parameters representing performance like loss rates, accuracy, among others. As training progressed, there were created plots showing the progression of how good the model performed.

2.1.3 Conclusion

Emerging techniques as well as advance in methods of stress detection have thus taken the leading step to advance the practice of mental health research. This key contribution to this ongoing debate was made in this paper through the presentation of an innovative method in detecting stress through the framework of EEG signal processing that ultimately broadcast the groundwork for developing the ground-breaking StressNet model.

The modern context of the critically important aspect of stress has occasioned countless studies about the effectiveness and accuracy of methods to detect and interpret stress.

For instance, most traditional methods miss out capturing complex dynamics with relation to physiological manifestations related to stress. This contributed to filling this gap by proposing a novel architecture, StressNet, which leverages the complementary strengths of a two-dimensional Convolutional Neural Network and a Long-Short-Term Memory network. This fusion between those networks enables extraction of subtleties from EEG signals which provide a strong basis to classify stress. The entire process involved the dissection of EEG signals into alpha, beta and theta components following by conversion of these components into azimuth projection based images. The most important method that will assist in the effective representation of changes in RGB color patterns corresponding to voltage fluctuations is the azimuth projection.

Afterward, an integrated novel multi-channel LSTM for temporal dynamics and 2D CNN for image-based feature extraction cleared the way of the hybrid model of both data and images processing techniques to raise the accuracy level over 97.8 percent in deformation detection on DEEP and SEED datasets.

The comprehensive methodology included careful preprocessing, sophisticated feature extraction, innovative image enhancement, and the development of a model architecture optimized for stress classification. In particular, the paper went beyond stress detection by considering real-time applications and extending the model to detect different emotional states, showing its adaptability and potential for wider use in mental health monitoring. A comparative analysis showed the superiority of the proposed StressNet model compared to existing methods, highlighting its effectiveness in stress detection.

In conclusion therefore, the use of the StressNet model brings a great milestone in stress detection area using the proposed method. Beyond the limited possibilities of traditional approaches giving reliance to EEG, this research opened it for real-world application ushering a new era in mental health monitoring and paved way to more adaptive and effective interventions of stress-related disorders. The current framework realized in this study thus provides a success that paves way for future studies and applications that give more positive environments to enhance diagnosis and interventional strategies regarding the mental health.

2.2 Interpretable ML Approach to Multimodal Stress Detection

The methodology presented in the research article "An interpretable machine learning approach to multimodal stress detection in a simulated office environment" offers a thorough and intricate approach to the automated detection of stress levels utilizing machine learning models. This study not only addresses the challenges inherent in detecting stress levels within a controlled laboratory environment but also provides valuable insights and practical implications for the application of automated stress detection in real office settings. The methodology comprises several crucial steps, each of which is detailed below, contributing to a comprehensive understanding of the research framework.

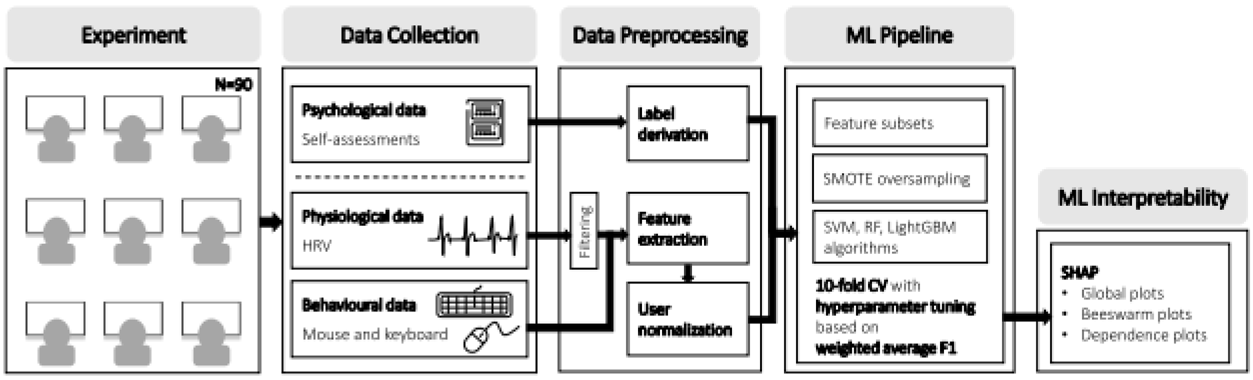


Figure 2.4: Methodology for Stress Detection using Keystrokes, Mouse Data & HRV

2.2.1 Laboratory Experiment

The foundational phase of the research involved the creation and implementation of a simulated office environment at the Decision Science Laboratory, ETH Zurich. A cohort of ninety participants was strategically assigned to different stress conditions and a control condition, forming the basis for robust experimentation. The induction of stress was meticulously carried out using a modified Trier Social Stress Test for Groups , a widely recognized and validated stress-elicitation methodology. The data collection process incorporated a multifaceted approach, encompassing behavioral mouse and keyboard data, physiological heart rate variability data, and the collection of psychological self-reported stress levels. This nuanced experimental design aimed to capture a holistic view of stress responses in a controlled yet dynamic setting.

2.2.2 Data Collection

The environment for data collection was meticulously set up, with participants' desks equipped with essential components such as computers, mice, and keyboards. A bespoke software application was crafted to guide participants seamlessly through the experiment, displaying instructions, questionnaires, and experimental tasks. The data collection spanned three sessions, each involving 30 participants, and the software was adeptly synchronized across all participants. The customization of the software for each experimental condition ensured precision and relevance in data collection.

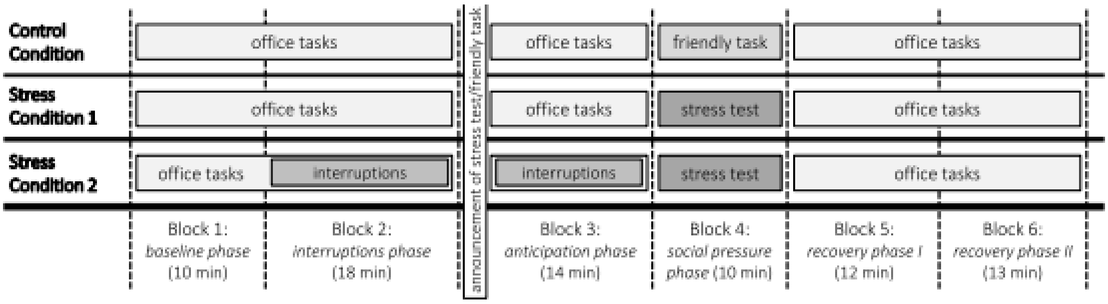


Figure 2.5: Data Collection Cycle

2.2.3 Data Preprocessing

Ensuring the quality and reliability of collected data is imperative for the success of any machine learning model. The collected data underwent a comprehensive preprocessing phase, which likely included tasks such as data cleaning, feature extraction, and normalization. The specifics of these preprocessing steps, although not explicitly outlined in the provided text, play a pivotal role in shaping the integrity of the data for subsequent stages in the methodology.

2.2.4 ML Pipeline

The core of the methodology lies in the development and evaluation of ML models for stress detection. This involved the strategic use of support vector machines , random forests , and light gradient boosting machines for creating multiclass stress detection models. The pipeline also incorporated extensive hyperparameter tuning, a crucial aspect in fine-tuning the models for optimal performance. Addressing the challenge of multiclass imbalance, the researchers applied the Synthetic Minority Oversampling Technique to enhance the robustness of the models. Evaluation metrics for the ML models were derived from the results of the modeling procedures and the SHAP value analysis of the best-performing models, providing a holistic understanding of model performance.

2.2.5 ML Interpretability

The significance of interpretability in understanding machine learning model results cannot be overstated. It plays a pivotal role in transforming complex predictions into actionable insights and instilling trust in the models. In the presented methodology, the researchers prioritized interpretability by employing SHapley Additive exPlanations value plots. This advanced technique stands out, surpassing traditional off-the-shelf tree-based feature importance methods.

The utilization of SHAP value plots allowed the researchers to delve into the intricate web of explanations for features and their interactions. This depth of analysis provided a nuanced understanding of the various dimensions of perceived stress, valence, and arousal within the context of the stress detection models. By unraveling the complexity of these interactions, the interpretability approach adopted in this methodology goes beyond merely identifying influential features. It extends to elucidating how these features interplay and contribute to the model's decisions.

This sophisticated interpretability approach significantly enhances the transparency of the stress detection models. Transparency, in this context, refers to the clarity with which the model's decision-making process can be understood and scrutinized. The SHAP value plots contribute to this transparency by offering detailed insights into the relative importance of different features and their effects on the predicted outcomes.

2.2.6 Conclusion

The presented methodology exemplifies a systematic and rigorous approach to automated stress detection. By integrating behavioral, physiological, and psychological data and leveraging advanced ML techniques, this research significantly advances the field of stress detection. Furthermore, the method's adaptability and potential real-world applications, particularly in office environments, underscore its relevance and contribution to both academia and industry.

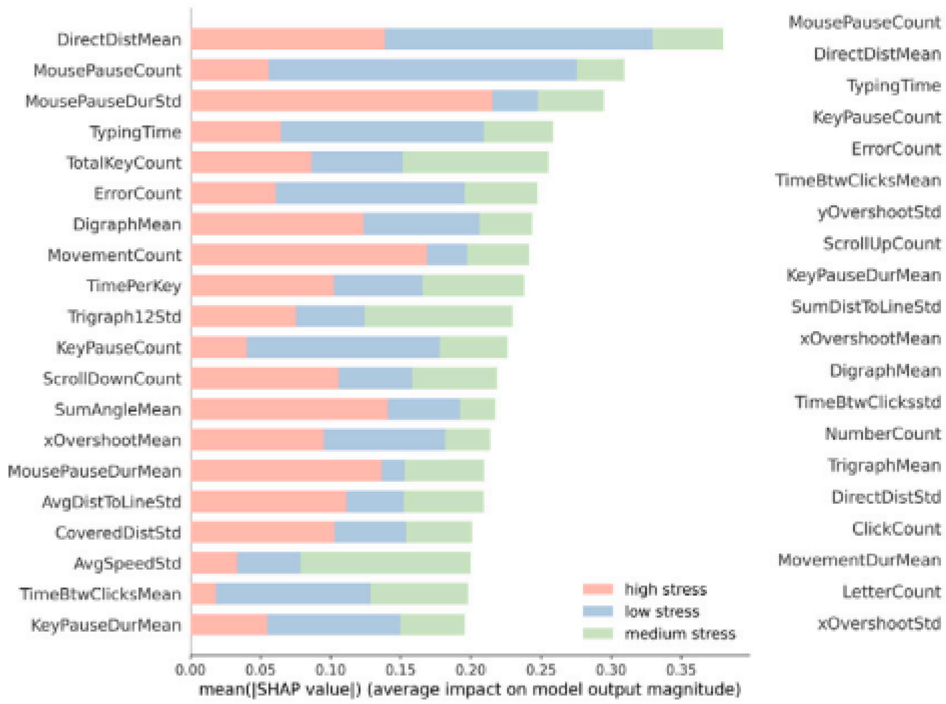


Figure 2.6: Global SHAP Plot for Perceived Stress

2.3 Explainable Deep-Learning model to stage sleep states

2.3.1 Overview

This study developed a deep learning model employing a CNN architecture for accurate and interpretable sleep stage classification in children using single-channel EEG recordings. The model was trained on two datasets and evaluated across three different architectures, with the standard CNN demonstrating remarkable performance in sleep stage classification and total sleep time estimation tasks. To enhance interpretability and understand the model's decision-making process, the Grad-CAM technique was integrated, enabling explanations for the model's predictions, including cases of misclassified sleep stages. By visualizing the important regions of the EEG signal contributing to the model's output, the study aimed to gain insights into the reasoning behind the predictions, particularly for epochs featuring non-obvious sleep stages based on the EEG features, thereby enhancing the transparency and interpretability of the deep learning model's decision-making process.

2.3.2 Dataset

This study employed two datasets of pediatric EEG recordings: CHAT (1639 trials) and UofC (980 studies) [3]. Participants who were suspected of having OSA were included in both datasets, which were used to train and evaluate CNN models for total sleep time estimation and sleep staging. While the CHAT data were organized into training, validation, and test sets, the UofC data served as an external validation source and were used to compare Grad-CAM explanations. Both datasets were resampled to a constant frequency of 125 Hz using the C4-M1 EEG channel. [3].

2.3.3 Deep-learning architectures

The purpose of this work was to evaluate how well three deep learning architectures performed in identifying different phases of sleep using 30-second EEG epochs. The phases of sleep that were taken into account were:

- Wake (W)
- NREM Stage 1 (N1)
- NREM Stage 2 (N2)
- NREM Stage 3 (N3)
- REM

1. **Standard CNN**

   A Standard Convolutional Neural Network , acknowledged as a popular technique for time series processing, is the first design examined [4]. This CNN processes EEG epochs in 30-second chunks, using a design suggested by Sors et al [5] for identifying sleep phases in adult OSA patients. A 120-second input segment is formed by concatenating the target epoch with two previous and one posterior epochs [3]. The architecture encompasses 12 convolutional blocks, each incorporating 1-D convolution, batch normalization , activation, and dropout [5]. To enhance the model's performance and generalization capabilities, several improvements were made by incorporating batch normalization and dropout layers, which helped to mitigate the issue of overfitting. Specifically, the dropout layers within each block were employed with a probability of 0.1, a value that was empirically determined to be optimal for maximizing the accuracy on the validation set. The inclusion of these techniques allowed the model to learn more robust and generalizable features from the EEG ıg the

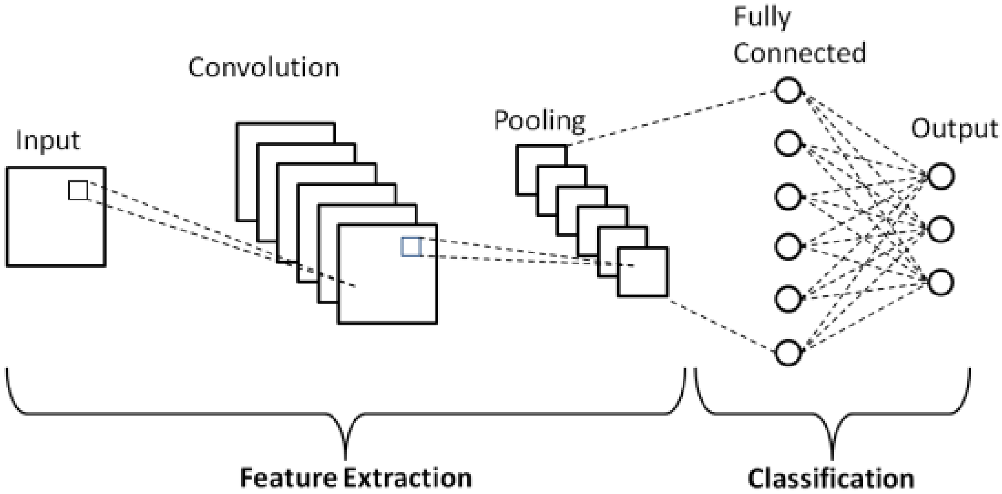


Figure 2.7: CNN architecture.

2. **CNN-Inception**

The second architecture explored is the CNN-Inception, adapted from the EEG-Inception network developed by Santamaría-Vazquez et al. [6] for detecting event-related potentials. The proposed CNN architecture incorporates inception modules, enabling parallel processing of the 120-second input EEG segment, similar to the standard CNN approach. Two inception modules are employed, each consisting of three branches with a convolutional block designed to learn features at distinct temporal scales (500 milliseconds, 250 milliseconds, and 125 milliseconds). The outputs from these branches are concatenated, followed by an average-pooling operation, and further processed through two additional convolutional blocks with average-pooling layers.

Certain modifications were introduced to the architecture, including the removal of depth-wise 2D convolutions, adjustments to the number of convolutional filters and the average-pooling factor, and the elimination of the dropout layer. These alterations were made to tailor the architecture to the specific requirements of the

EEG data and the sleep stage classification task, potentially improving the model's performance and efficiency.

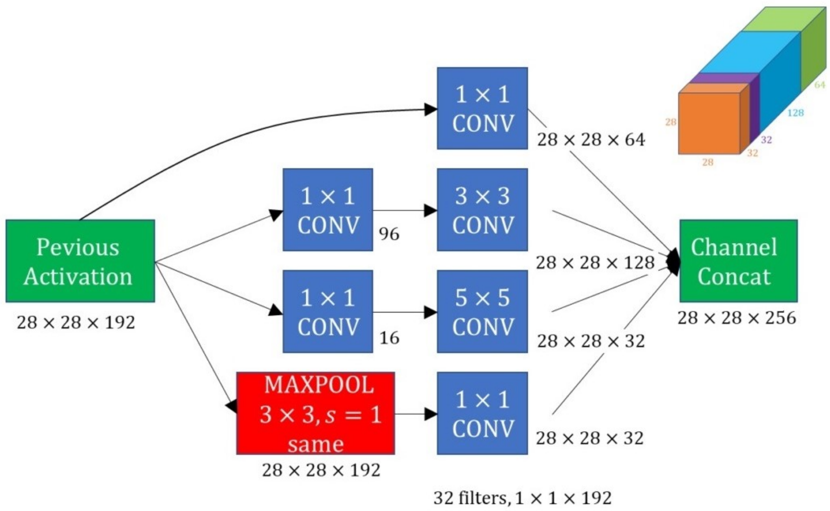
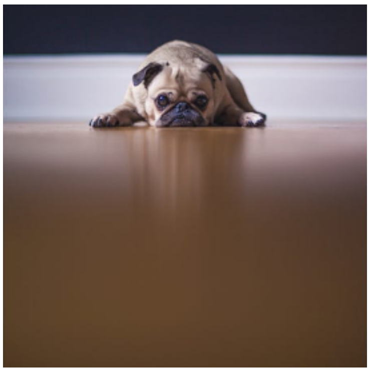


Figure 2.8: CNN-Inception architecture.

The Inception network marks a pivotal advancement in the evolution of Convolutional Neural Network classifiers, introducing a complex and heavily engineered architecture to enhance both speed and accuracy. Unlike its predecessors that simply deepened the stack of convolution layers, the Inception network employed a range of strategies to address issues of performance, particularly in handling variations in salient object sizes within images.

(a) Dog occupying most of the image

(b) Dog occupying a part of it



(c) Dog occupying very little space

Figure 2.9: Three Dogs

One key challenge in image processing arises from the substantial variation in the size and location of important features. For instance, Figure 2.9 containing three different dogs can exhibit diverse sizes and positions of the dog within the frame. Determining the optimal kernel size for convolution becomes intricate in such scenarios. The Inception network tackled this challenge by incorporating filters of multiple sizes within the same level, opting to broaden the network's width rather than deepening it.

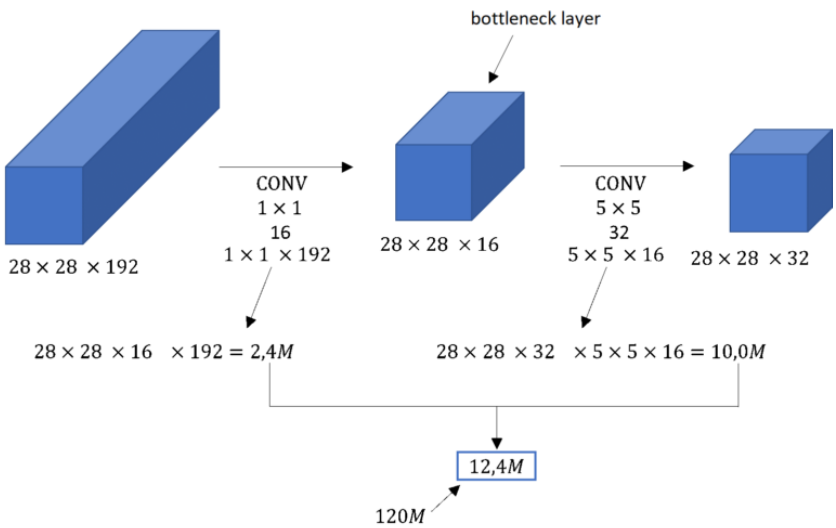


Figure 2.10: CNN-Inception architecture with 1x1 filters.

The core idea behind the Inception module, illustrated below, involves performing convolutions with filters of different sizes (1x1, 3x3, 5x5) and applying max pooling. The resulting outputs are concatenated and fed into the subsequent inception module. To manage computational costs, especially in very deep networks prone to overfitting, the authors introduced an additional 1x1 convolution before the 3x3 and 5x5 convolutions. While seemingly counterintuitive, this approach proves more cost-effective, considering that 1x1 convolutions are computationally cheaper than their larger counterparts. Importantly, the reduction in the number of input channels further contributes to computational efficiency. Notably, the 1x1 convolution is strategically placed after the max pooling layer, optimizing its impact within the overall architecture.

3. **CNN-RNN**

The third architecture, CNN-RNN, draws inspiration from the neural network developed by Korkalainen et al. for sleep stage detection using EEG signals. This architecture processes a sequence of 100 EEG epochs of 30 seconds, combining a CNN with a bidirectional Gate Recurrent Unit RNN. Each 30-second epoch undergoes individual processing through a time-distributed layer containing a CNN with six convolutional blocks, two max-pooling layers, and a global average layer. This extracts EEG features associated with sleep stages. The time-distributed CNN output feeds into a bidirectional GRU RNN, chosen over LSTM for similar performance with lower computational load. Specific adjustments include removing the gaussian dropout layer and dropout at the input of the GRU layer (probabilities set as 0.0), while setting recurrent dropout in the GRU layer at 0.75 for optimal performance on the validation set.

2.3.4 Explainable artificial intelligence: Grad-CAM

1. **Class Activation Mapping:CAM**

Originally proposed by Zhou et al, Class Activation Mapping is an eXplainable Artificial Intelligence technique specifically designed for identifying discriminative regions that significantly impact CNN predictions in image classification. However, CAM is constrained to the last convolutional layer of CNNs, utilizing Global Average Pooling feature maps followed by a softmax layer.

2. **Grad-CAM: Advancing Interpretability**

Grad-CAM, an evolved iteration of CAM, overcomes these limitations by leveraging gradient information from a specified convolutional layer. This enhancement makes Grad-CAM applicable to various CNN-based architectures. To craft a class-discriminative localization map or heatmap, Grad-CAM computes gradients ($\frac{\partial y_c}{\partial A_k}$) of the target class output (y_c) concerning the 2-D feature maps (A_k) of the chosen convolutional layer. These gradients are then averaged to obtain weights α_c^k signifying the importance of each feature map k for the target class c.

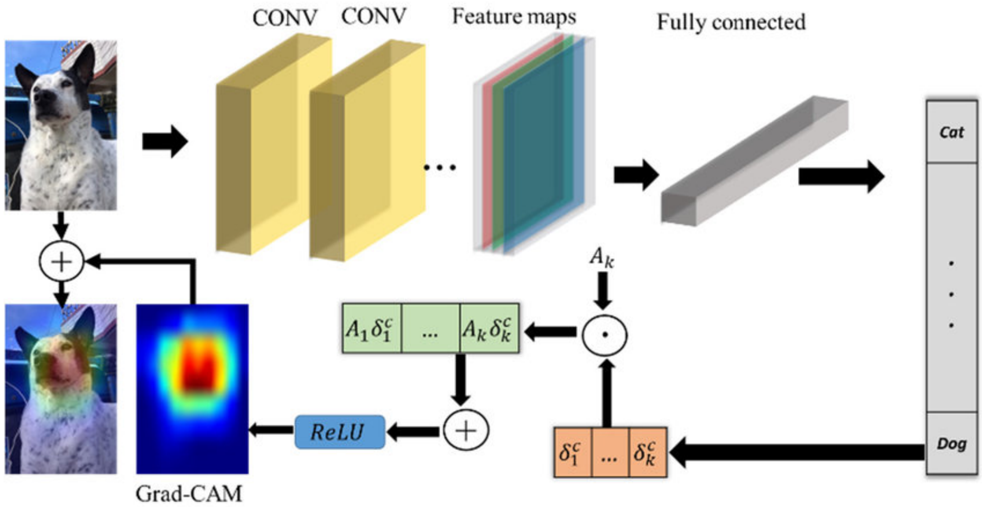


Figure 2.11: Grad-CAM architecture.

Step 1: Compute the gradient Compute the gradient of y_c with respect to the feature map activations A_k of a convolutional layer. $\frac{\partial y_c}{\partial A_k}$.

Step 2: Calculate Alphas by Averaging Gradients Global average pool the gradients over the width dimension (i) and the height dimension (j) to obtain neuron importance weights α_c^k.

$$\alpha_c^k = \frac{1}{Z}\sum_i \sum_j \frac{\partial y_c}{\partial A_k}$$

Step 3: Calculate Final Grad-CAM Heatmap

$$L_c^{\text{Grad-CAM}} = \mathrm{ReLU}\left(\sum_k \alpha_c^k A^k\right)$$

We use each alpha value as the weight of the corresponding feature map and calculate a weighted sum of feature maps as the final Grad-CAM heatmap.

2.4 Hybrid Deep Learning for EEG-based Stress Detection

Introduction

The study utilizes an electroencephalography technique to capture and analyze the brain's electrical bio-signals, which are indicative of the individual's stress levels. The complexity of EEG signals necessitates the use of sophisticated methods for accurate interpretation.

In this context, the paper introduces a DWT-based hybrid deep learning model, combining the power of Discrete Wavelet Transform , Convolutional Neural Network , and Bidirectional Long Short-Term Memory to detect stress levels in humans[?].

2.4.1 Data Acquisition

The initial part of the methodology centers on data acquisition, outlining the EEG dataset utilized in the research. This includes recordings following the international 10/20 system from 36 subjects. The subjects are categorized according to their performance in subtraction tasks, and additional demographic details like age and gender are supplied. The dataset encompasses a total of 19 channels, with each channel having 1116000 data points (31000x36). In this context, 70% of the data is allocated for training, and the remaining 30% is earmarked for testing[?].

2.4.2 EEG Feature Extraction

EEG feature extraction is a critical component of the proposed model and here the Discrete Wavelet Transform is used for denoising and decomposition.

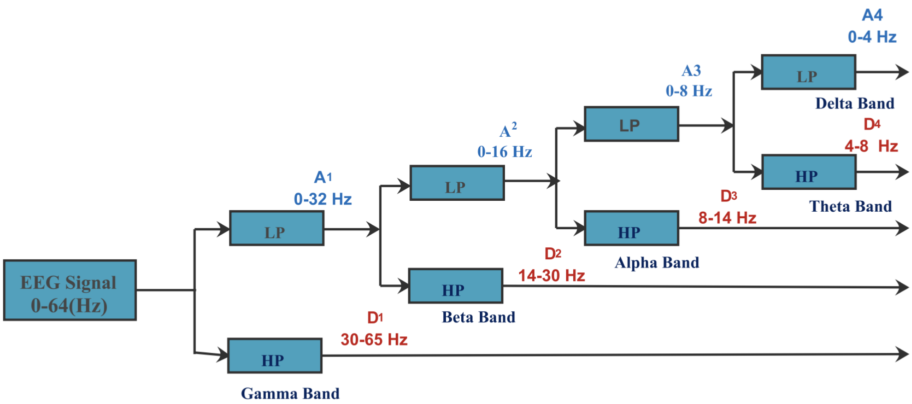


Figure 2.12: Wavelet coefficients sequence through EEG range filters

DWT is used for the extraction of five frequency bands from each EEG channel and the utilization of mean and median filters for denoising the signals. The multi-resolution analysis for extracting data on the signal across multiple frequency bands using Eight-order

Daubechies wavelet function is also described[**?**].

Frequency Range(Hz)	**Wavelet Sub-band**	**Decomposition Steps**	**Band Name**
30-65	D1	1	Gamma
14-30	D2	2	Beta
8-14	D3	3	Alpha
4-8	D4	4	Theta
0-4	A4	5	Delta

Table 2.1: Frequency band of the EEG signal using fourth level decomposition

2.4.3 Convolutional Neural Network

Convolutional Neural Network has its role in feature selection. CNN identifies and utilizes specific features from the model's layers to create a set of refined features for detecting stress. The integration of CNN into the proposed hybrid deep learning model is also discussed.

2.4.4 Bidirectional Long Short-Term Memory

BLSTM captures temporal dependencies within the input sequence by processing the data in both forward and backward directions. It describes how BLSTM complements the feature selection by CNN and its integration into the proposed hybrid deep learning model.

2.4.5 Model Architecture

Proposed algorithm of stress-detection is multi step that takes data from Physionet EEG dataset during mental arithmetic tasks. The main result of the experiment is the generation of stress labels for people indicating whether they are stressed or relaxed. The methodology is outlined as follows:

To begin with, in Step 1, DWT is employed to extract features of the EEG signal channel data. In this, the signal will be cleaned out, the eight-order Daubechies wavelet function will be used for the study and the signal will be split into four level each presenting a particular frequency band such as Alpha, beta, gamma, delta, theta. In Step 2, a CNN based automatic feature selection is applied to multi-channel EEG signals. This stage is important for discovering the necessary features that aid in stress recognition[?].

A BLSTM deep learning model is used in Step 3 for classification. This model is trained for 100 epochs to enhance its capacity to capture temporal dependencies of an input sequence. Step 4 generates and stores different metrics like precision, F1-score, sensitivity, specificity, accuracy, +LR, -LR, NPV These criteria act as measures of how good the algorithm is for stress detection.

Finally, Step 5 entails repeating the process and utilizing the same classification steps using the CNN-LSTM model. This enables the comparison of the performance measures between the proposed algorithm and the CNN-LSTM model.

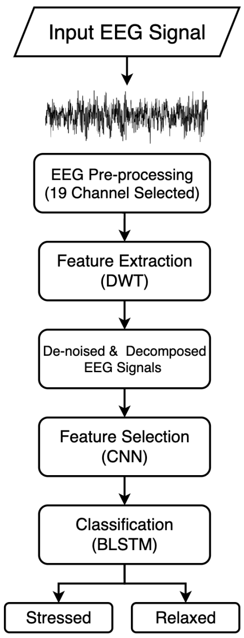


Figure 2.13: Model Architecture

2.4.6 Validation of the Model

It explains how the stratified tenfold cross-validation method is used to train and test, while quantitative statistical results are obtained by re-sampling procedures. The statistical analysis to pick the best model possible, including comparisons of average classification accuracy between existing models and that proposed here, in particular.

2.4.7 Conclusion

Finally, the methodology concludes by summarizing the detailed methodology for stress detection from EEG signals using the proposed DWT based hybrid deep learning model. This has been discussed in the context of its implications for health care and research, and future directions are outlined including potential applications of the methodology in other disease-related prediction tasks.

In a nutshell, the methodology to detect stress from EEG signals using a DWT-based hybrid deep learning model involves several important components such as data acquisition, EEG feature extraction, model architecture as well as its validation. This comprehensive methodology tries to provide a coherent framework for the researchers and practitioners who aspire to apply the deep learning techniques towards the purpose of detection of stress. The model proposed in this paper uses Discrete Wavelet Transform for denoising as well as the decomposition of EEG signals further applying CNN and BLSTM[**?**] for feature selections as well as classification. The methodology gets validated using a stratified tenfold cross-validation method and the resultant gets compared with previous state of the art models.

2.5 Multi-level stress identification using EEG signals and smoothing filters.

Introduction

The paper investigates the effect of smoothing filter window length on the multi-level stress classifier that operates on the basis of EEG recording during stress-provoking tasks and relaxation exercises is followed by pre-processing and feature extraction. Several stress classification models are critically reviewed in order to establish the impact of smoothing on classification[**?**]. Smoothed EEG signals appear to increase accuracy in stress classification. These findings inform the improvement of more useful stress assessments using EEG markers against the serious need for adequate stress monitoring techniques.

2.5.1 Participant Recruitment and Selection

The study recruited twenty healthy volunteers (14 males, 6 females) from the University of Granada community, primarily consisting of students and staff members. Inclusion criteria included good health and the absence of any mental disorders, while exclusion criteria involved any health conditions that could potentially impact the study outcomes. Participants were recruited via email distribution lists, and ethical considerations were addressed through the informed consent process, ensuring that participants were fully informed about the study's objectives and procedures. Additionally, participants were instructed to avoid stimulants or relaxants the day before the experiment to minimize potential confounding factors.

2.5.2 Experimental Design

The experimental design had several phases underneath a structured timetable. After the placement of electrodes, every participant underwent two resting-state eyes-closed minutes with the objective to acquire baseline EEG. After that, they were exposed to the Montreal Imaging Stress Task , which is a standard paradigm for psychological stress-induction. After the stressful task, all subjects were randomly assigned to two groups: one experienced the relaxation program executed in a chromotherapy room with ambient light's colors, and the other experienced an immersive virtual reality app simulating the chromotherapy room program. Another resting state period of two minutes concluded the experiment. Participants were requested to self-perceived stress levels in four different occasions (T1-T4), adding a subjective data set to be correlated with EEG activity.

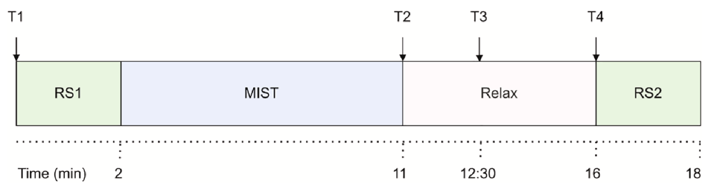


Figure 2.14: Timeline of the experimental process(18 min.)

2.5.3 EEG Data Acquisition

The study utilized the RABio w8 EEG acquisition system, developed by the University of Granada, operating at a sampling rate of 500 Hz[?]. Electrodes were placed at specific positions according to the 10–20 International System, with a focus on frontal and prefrontal positions (Fp1, Fp2, F7, and F8) for further analysis in the study. Electrodes were referenced and grounded to the left ear lobe, ensuring a standardized and consistent approach to EEG data recording.

Band	**Frequency Range(Hz)**
Delta	1-4
Theta	4-8
Alpha	8-13
Beta	13-25
Gamma	25-45

Table 2.2: Frequency bands where PSD of the EEG was obtained.

2.5.4 Preprocessing of EEG Data

The first step involved filtering the EEG signals using a zero-phase shift 2nd order Butterworth filter with bandpass between 1 and 50 Hz. The following application involved using the notion filter at 50 Hz in the removal of electric coupling. The signals are then segmented into two-second epochs and any such epochs exceeding a pre-arranged threshold of 100 μV were zeroed in order to reject artifacts. Each epoch is not only detrended but its also z-scored and then for each electrode the PSD was estimated using the periodogram using five frequency bands as follows (Delta, Theta, Alpha, Beta and Gamma). The PSD of the EEG signal at frequency bin j and electrode i was computed using:

$$PSD_{i,j} = \frac{1}{N} \sum_{k=1}^{N} |X_{i,j,k}|^2 \tag{2.1}$$

where N is the number of samples[?] in the window, and X is the DFT of the EEG signal. Then the results of the seven spectrograms were smoothed using a Savitzky-Golay filter, also taking different window lengths to assess the influence of this parameter in the performance of the classification of the degree of stress. Other steps involved in the signal processing prepared the signals for feature extraction and subsequent stress classification.

2.5.5 Feature Extraction

Feature extraction focused on obtaining EEG Power Spectral Density features from the recorded EEG signals[?]. Segmentation of EEG signals into specific time intervals or epochs allowed for the extraction and averaging of spectral features corresponding to the SPSL surveys completed by the participants. This process facilitated the construction of a feature matrix X and a target array y for subsequent stress classification tasks.

2.5.6 Classification and Model Evaluation

Some of the selected classifiers and stress classification models that took part in this research were: Logistic Regression , Support Vector Machine , Random Forest , k-Nearest Neighbors , and multi-layer perceptron . GSCV is an acronym for Grid Search Cross-Validation which was applied to determine the best combination of classifier and associated hyperparameters for the prediction of SPSL from spectral features. Selected evaluation metrics accuracy, precision, recall and F1 score[?] were used for accessing classification models performance.

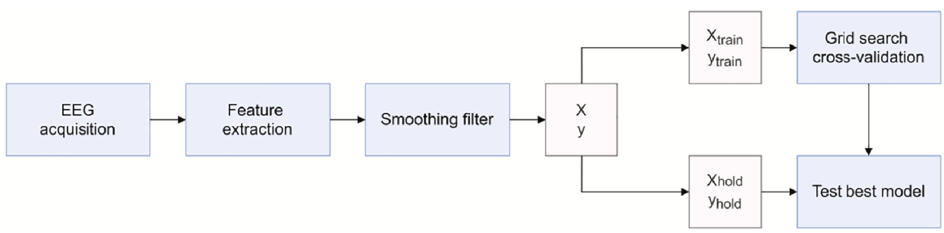


Figure 2.15: Stress classification pipeline.

2.5.7 Data Analysis and Interpretation

The results obtained during GSCV for stress classification tasks were analyzed, and performance metrics were visualized to compare the impact of different smoothing window lengths on classification performance. Comparative discussions with other studies in the literature were conducted to contextualize the findings and provide a comprehensive interpretation of the study's outcomes.

Model	**F1 Score**
LR	0.65 ± 0.06
SVM	0.84 ± 0.02
RF	0.84 ± 0.03
KNN	$0.78 \pm .04$
MLP	0.84 ± 0.02

Table 2.3: Results obtained during GSCV for the stress detection task

2.5.8 Implications and Conclusions

The study discussed the implications of its findings for the development of more accurate and reliable multi-level stress assessment models based on EEG signals. The conclusion summarized the key insights and contributions of the research, providing recommendations for future research and potential extensions of the current study.

2.6 Summary and Gaps Identified

This section provides a comprehensive summary of the discussed studies, highlighting their respective advantages and disadvantages.

2.6.1 Gaps Identified

1. Lack of detailed discussion on real-time application considerations in StressNet study.

2. Incomplete information on data preprocessing steps in Interpretable ML Approach study.

3. The sleep staging study could benefit from a more in-depth exploration of external factors influencing EEG signals.

4. The hybrid deep learning study would benefit from a more extensive comparison with other stress detection models.

5. The stress identification study would benefit from a more thorough discussion on the correlation between subjective stress perception and EEG signals.

6. Further research is needed to understand the impact of smoothing filter window length on stress classification performance.

Study Title	**Advantages**	**Disadvantages**
StressNet: LSTM-CNN Hybrid for Stress Detection	Revolutionary architecture, High accuracy (97.8 percent) Novel preprocessing technique	Lack of detailed discussion on real-time application considerations
Interpretable ML Approach to Multimodal Stress Detection	Thorough approach to stress detection, Integration of behavioral, physiological, and psychological data, Advanced ML techniques	Lack of explicit details on data preprocessing steps
Explainable Deep-Learning model to stage sleep states	Accurate sleep staging, Interpretable model	Limited discussion on external factors influencing EEG
Hybrid Deep Learning for EEG-based Stress Detection	DWT enhances feature extraction, Hybrid model captures temporal dependencies	Limited comparison with other stress detection models
Multi-level Stress Identification using EEG Signals and Smoothing Filters	Investigates smoothing filter impact, Comprehensive preprocessing steps	Limited discussion on subjective stress perception correlation

Table 2.4: Summary of Studies

Chapter 3

Requirements

3.1 Hardware and Software Requirements

3.1.1 Hardware

- 1: Graphics Processing Unit
  - Utilize Google Colab's GPU runtime T4 for accelerated deep learning computations.
- 2: Storage:
  - Utilize Google Drive for storing datasets,consider using SSD-based storage for faster data access during training.

3.1.2 Software

- 1: Signal Processing Software
  - We implemented signal processing algorithms for filtering and preprocessing of EEG data.
  - We used software tools like Python with libraries such as NumPy, and MNE for signal processing.
- 2: Stress Detection Model
  - We develop a stress detection Model based on the processed EEG data.
  - ML libraries such as TensorFlow and Keras were used for building and training stress detection models.
- 3: Interpretability using GRAD-CAM

  - We implemented GRAD-CAM for interpretability.
  - We used deep learning frameworks Keras and TensorFlow to integrate GRAD-CAM into our model.
- 4: UI
  - We developed a UI to display post-processed EEG data for better understanding.
  - We included stress detection results and interpretation information using GRAD-CAM.

3.2 Functional Requirements

- **Signal Processing:**
  - Implemented signal processing algorithms, using tools such as Python (NumPy, SciPy, MNE) for preprocessing EEG data. We divided the data into two second segments and standardization was done on the data.
- **Model for Detection of Stress:**
  - Formulated and implemented a stress detection CNN-Model based on processed EEG data with the aid of machine learning libraries tensorFlow and keras.
- **Interpretability using GRAD-CAM:**
  - We made the stress detection using CNN and deep learning frameworks TensorFlow and Keras interpretable using GRAD-CAM. It allows the users to interpret the features of the stress that have been used by the model in its decision through the visualization done by GRAD-CAM.

3.3 Summary of the chapter

In conclusion, the designing of this stress detection system has leveraged the power of advanced hardware and software elements to come up with a robust and flexible solution. Our work includes implementing signal processing algorithms for EEG data using Python tools like NumPy, SciPy, and MNE. We divided the data into two-second segments and standardized it. For stress detection, we formulated and implemented a CNN-based model using TensorFlow and Keras. This model leverages processed EEG data for detecting stress.

Additionally, we made the stress detection model interpretable using GRAD-CAM, a technique that visualizes the features utilized by the model in its decision-making process. This allows users to understand which features contribute to the model's stress detection predictions.

Chapter 4

System Design

Stress has become an increasingly prevalent concern in today's fast-paced world, impacting individuals across various facets of life. This chapter delves into the meticulous design considerations undertaken for our project, focusing on the development of a robust system for stress detection from EEG signals.

4.1 Architectural Diagram of the System

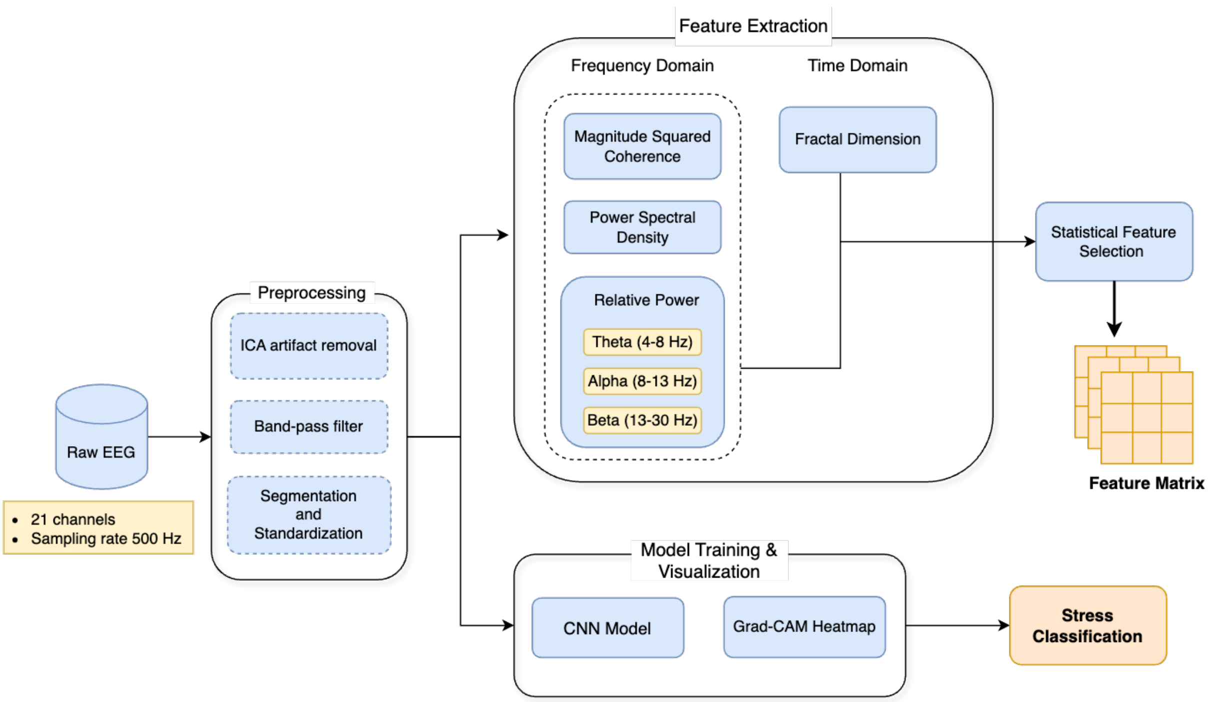


Figure 4.1: Architecture Diagram of the Stress Detection System.

The designed system works in a sequential way, starting with the collection of EEG data from an EEG cap. These signals provide the raw input to our stress detection system, recording electrical activity from the brain. Before going into CNN model training, a critical preprocessing step is performed to remove noise and assure the reliability of upcoming research.

We used a high-pass filter and power notch filtering in the preprocessing stage to enhance the quality of the EEG signal. Furthermore, Independent Component Analysis was performed in order to remove any artifacts from the EEG input. The EEG signal was segmented into overlapping segments and standardized using standard scaler.This preprocessing stage is essential to improving the signal's quality, which raises the accuracy of stress detection.

Following the preprocessing stage, we created a Convolutional Neural Network model that was especially designed to distinguish between states of tension and relaxation. This CNN model was designed to analyze the preprocessed EEG data and make accurate predictions regarding the individual's current state of stress or relaxation. Through the utilization of convolutional layers hierarchical features, the CNN model attempted to identify minute patterns in the EEG data that corresponded to either stress or relaxed. This was a critical phase in the experiment as the accuracy and dependability of the stress categorization procedure were directly impacted by the CNN model's efficiency.

Gradient-weighted Class Activation Mapping has been added into our model to improve interpretability and transparency for explainable AI. Grad-CAM identifies areas in the input EEG signals that strongly influence the stress categorization choice, providing insight into the model's decision-making process. This characteristic is useful in making the system transparent and trustworthy, particularly in critical situations where interpretability is crucial.

In summary, the stress detection model we designed integrates preprocessing, CNN-based model, and Grad-CAM for explainable AI. This comprehensive approach ensures the development of a robust and interpretable system for accurately detecting stress from EEG signals.

4.2 Sequence Diagram

Figure 4.2 shows the UML sequence diagram.This UML sequence diagram depicts the interaction flow during the stress detection process in a system that uses EEG data.

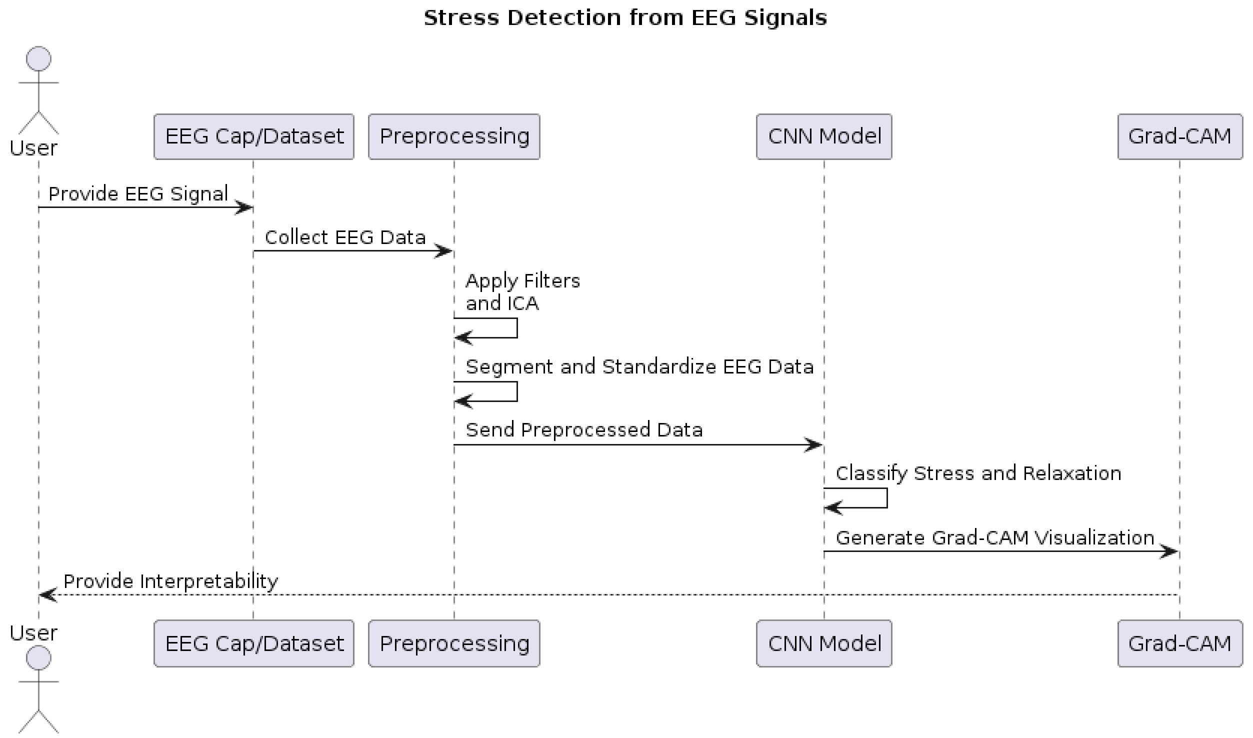


Figure 4.2: Sequence Diagram of the System.

4.3 Module Division

4.3.1 Data Preprocessing Module

To ensure the reliability of our EEG data for subsequent analyses, we implemented a meticulous preprocessing pipeline. Initially, we applied a high-pass filter with a 30 Hz cut-off frequency and a power notch filter at 50 Hz to remove unwanted noise from the EEG signals. Additionally, Independent Component Analysis was utilized to identify and eliminate artifacts such as eye blinks, muscle activity, and heart pulsations overlapping with the EEG recordings.

Following the application of filters and ICA, the continuous EEG data from each electrode was segmented into overlapping frames, each consisting of 500 samples. This windowing approach provided high temporal resolution, essential for capturing transient changes in brain activity during stressful states. Subsequently, the segmented EEG data underwent standardization using the standard scaler formula:

$$x_{\text{standardized}} = \frac{x - \mu}{\sigma}$$

where x is the original data, μ is the mean of the data, and σ is the standard deviation of the data.

Throughout the preprocessing pipeline, careful attention was paid to potential artifacts, including power line noise and muscular activity, which were meticulously identified and removed. This comprehensive preprocessing approach ensured that our EEG data was clean, reliable, and ready for accurate subsequent analyses, particularly those aimed at understanding brain activity during stressed states.

4.3.2 Classification Module

The Convolutional Neural Network module serves as the core component of our stress detection system, responsible for analyzing preprocessed EEG data and making accurate predictions regarding an individual's stress or relaxation state. The CNN model architecture is designed to effectively capture spatial and temporal patterns within the EEG signals, enabling robust classification performance.

The CNN model architecture consists of multiple layers, starting with convolutional layers that extract hierarchical features from the segmented EEG signals. The first convolutional layer consists of 256 filters with a kernel size of 9 and utilizes a rectified linear unit activation function to introduce non-linearity. This is followed by a max-pooling layer to downsample the feature maps and reduce computational complexity. A dropout layer is then applied to prevent overfitting by randomly deactivating a fraction of the neurons.

Subsequently, a second convolutional layer with 512 filters and the same kernel size and activation function is added to further extract intricate features from the EEG data. Again, max-pooling and dropout layers are employed for feature reduction and regularization, respectively. The flattened output is then passed through a fully connected layer with 512 neurons and ReLU activation, facilitating the integration of extracted features for classification.

Finally, the output layer consists of neurons corresponding to the number of classes (e.g., stressed and relaxed), with a softmax activation function to produce probability scores for each class. This enables the model to make predictions based on the likelihood of an individual belonging to each class.

As illustrated in Figure 4.3, the CNN model architecture consists of multiple layers, including convolutional layers, max-pooling layers, fully connected layers, and a softmax

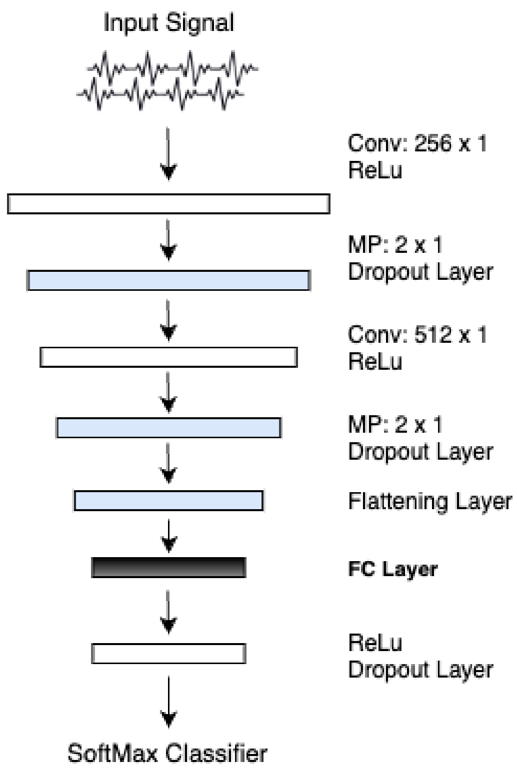


Figure 4.3: CNN Model Architecture

layer.

4.3.3 Explainable AI

The Explainable AI Module, leveraging Gradient-weighted Class Activation Mapping, enhances the interpretability of the stress detection system by providing visual insights into the decision-making process. Grad-CAM meticulously identifies key locations within the input EEG data that exert significant influence on the neural network's stress categorization decisions. By assigning importance rankings to different elements of the input data, Grad-CAM enables users and practitioners to discern which aspects and regions of brain activity play a pivotal role in determining stress outcomes [7].

This interpretability feature holds paramount importance, especially in applications where transparency and understanding of the model's decisions are crucial. It empowers users with a clearer and more reliable comprehension of how the AI system reaches its conclusions within the context of stress detection using EEG data. By visualizing the salient regions of the EEG signals, Grad-CAM facilitates not only the validation of the model's outputs but also the identification of relevant physiological patterns associated with stress. Such insights enable informed decision-making and foster trust in the AI system's capabilities, ultimately enhancing its utility and effectiveness in real-world scenarios.

4.4 Work Schedule - Gantt Chart

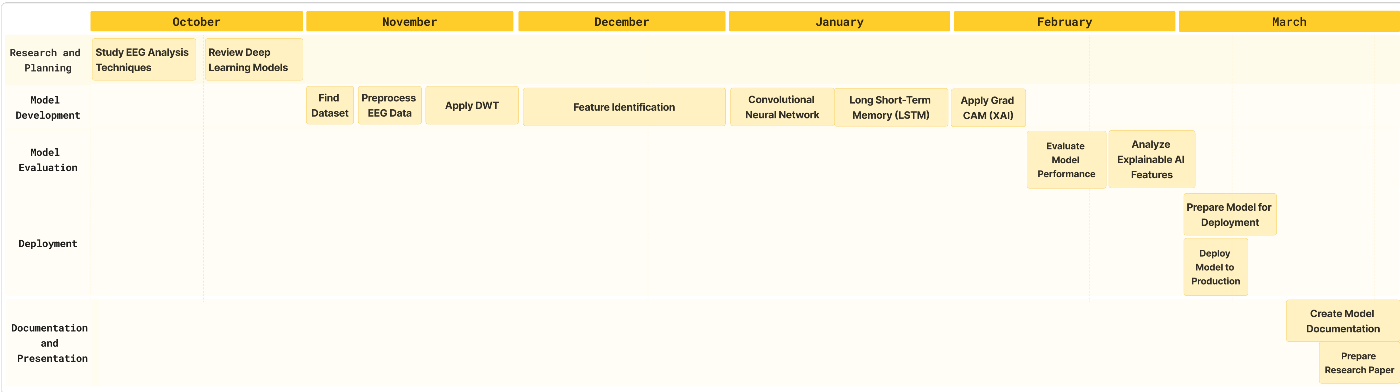


Figure 4.4: Gantt Chart

4.5 Conclusion

In the System Design chapter, we presented a detailed architecture for the stress detection system, covering everything from EEG signal collecting to interpretable decision-making. The modular architecture, which includes components such as EEG signal acquisition, preprocessing, feature extraction, CNN-based feature selection and Explainable AI Modules, offers a methodical and successful approach to stress detection. The combination of modern signal processing techniques, neural network topologies, and explainable AI methodology demonstrates the system's capacity to detect nuanced patterns in EEG data. This well-structured system architecture establishes the groundwork for the following implementation, testing, and optimization phases, indicating a comprehensive and transparent solution for stress detection using EEG data.

Chapter 5

System Implementation

In this chapter, we delve into the detailed implementation of our stress detection system, which encompasses the development of algorithms, methodologies, and user interface designs. Building upon the foundation laid in the previous chapters, we outline the steps taken to bring our project from concept to reality. Through this chapter, readers will gain a comprehensive understanding of how our stress detection system was implemented, from data processing to user interaction.

5.1 Datasets Identified

The dataset used in this study consists of EEG recordings stored in European Data Format . The dataset comprises 36 subjects before and during the performance of mental arithmetic tasks. The EEGs obtained from PhysioNet [8][9] were recorded monopolarly with the Neurocom EEG 23-channel equipment (Ukraine, XAI-MEDICA). The silver/silver chloride electrodes were put to the scalp in accordance with the International 10/20 system. All electrodes were referenced to the interconnected ear reference electrodes. The arithmetic challenge involved the serial subtraction of two integers. Each trial began with the communication of four-digit (minuend) and two-digit (subtrahend) integers (for example, 3141 and 42).

5.2 Algorithm

In this section, we outline the proposed methodologies and algorithms employed in our work to develop a stress detection system using EEG data. The algorithm presented here, named "EEG Data Processing and Analysis," serves as a comprehensive guide to the various stages involved in the processing and analysis of EEG signals.

Algorithm 1 EEG Data Processing and Analysis

```
Input: Raw EEG dataset
Output: Processed EEG data, feature matrix, CNN model
Preprocessing:
Remove artifacts from EEG signals
Apply filtering techniques to remove noise
Segment EEG signals into appropriate time windows
Standardize segmented EEG data
Feature Extraction:
Compute relative theta power for each EEG segment
Compute relative alpha power for each EEG segment
Calculate magnitude squared coherence between EEG channels
Determine Higuchi fractal dimension for each EEG segment
Feature Selection:
Select top five electrodes for each feature
Model Development:
Construct feature matrix from selected electrodes
Split dataset into training and testing sets
Train a Convolutional Neural Network (CNN) model
Interpretability Analysis:
Implement Grad-CAM within CNN model
Analyze areas highlighted by Grad-CAM
Results Interpretation:
Investigate relationships between highlighted areas and features
Determine brain regions and neural patterns associated with stress states
Output:
Processed EEG data, feature matrix, trained CNN model
```

5.3 User Interface Design

The user interface design (wireframe designs) is depicted in this section.

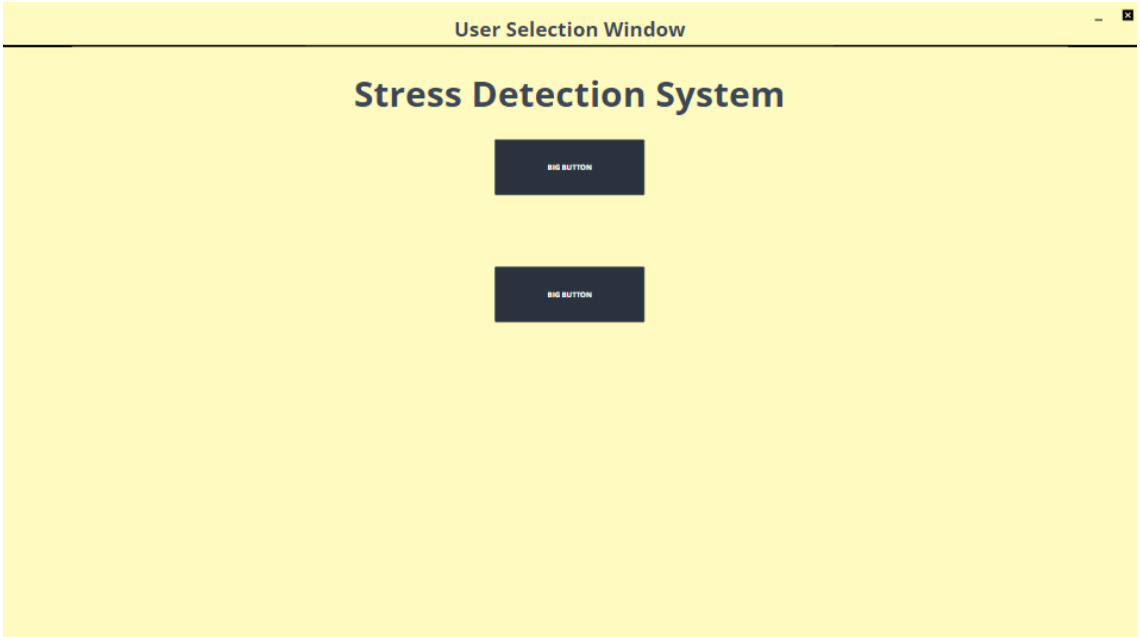


Figure 5.1: User Selection window Wireframe

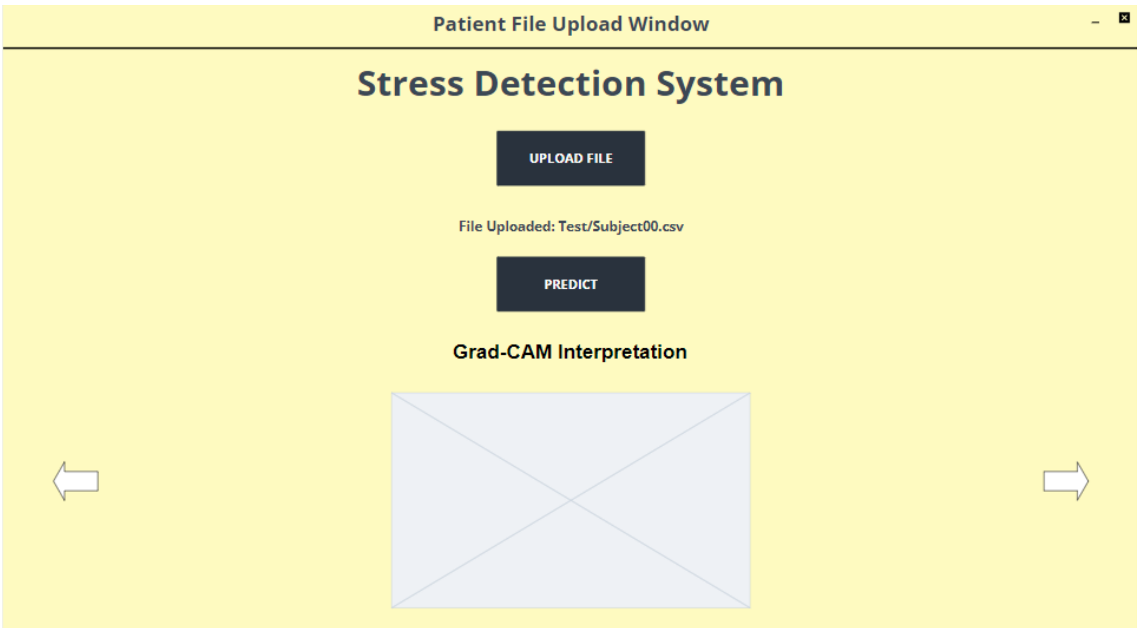


Figure 5.2: Patient File Upload Wireframe

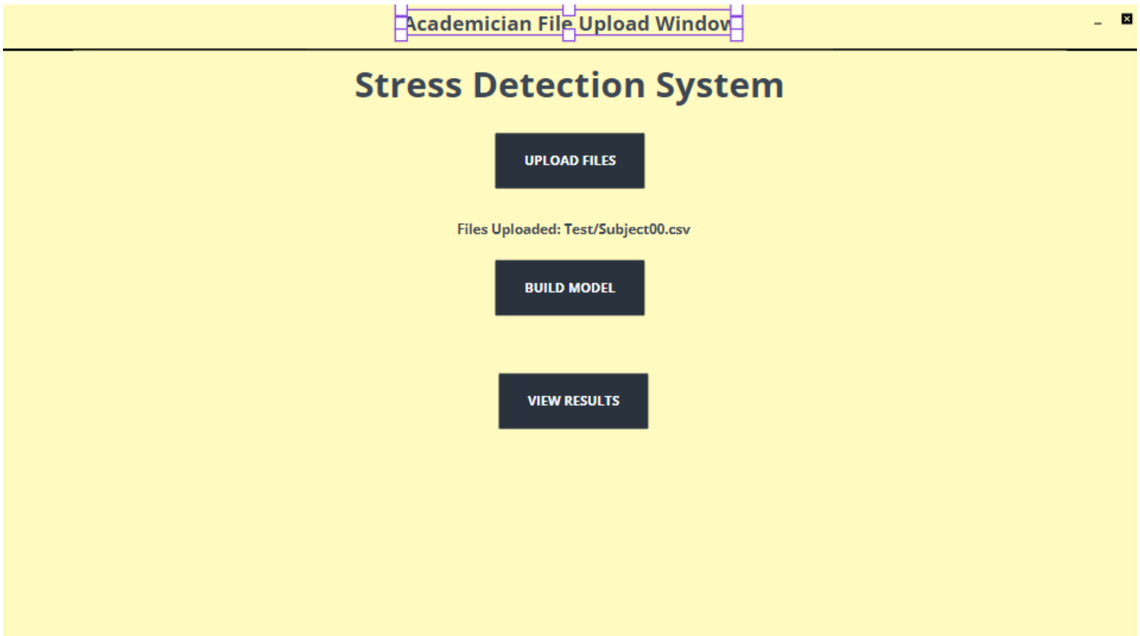


Figure 5.3: Academician File Upload Wireframe

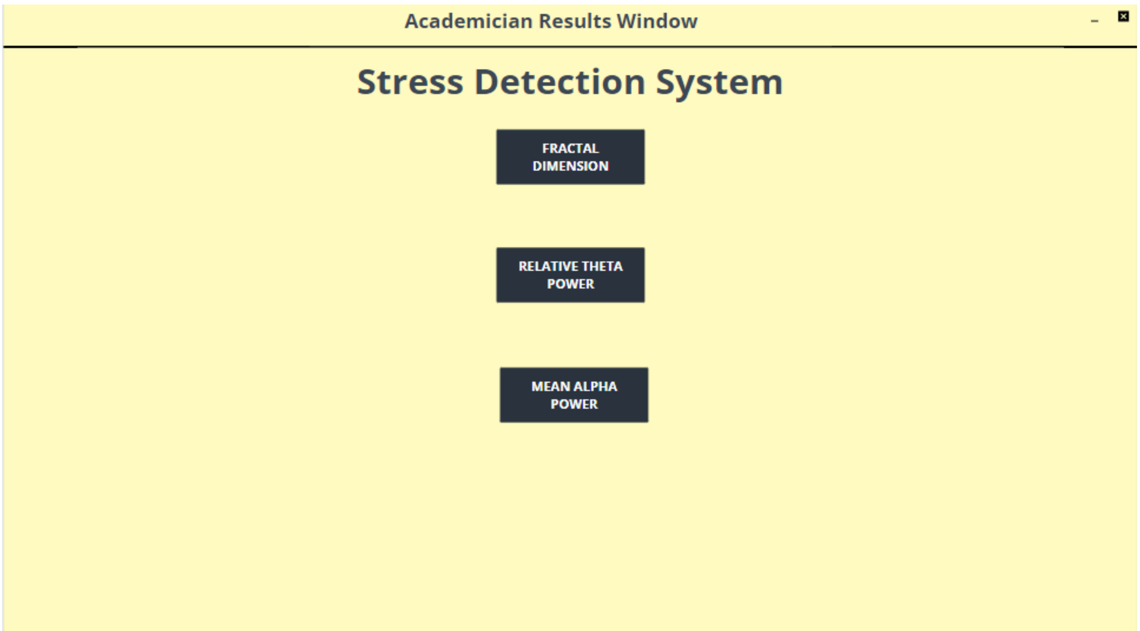


Figure 5.4: Academician Results Wireframe

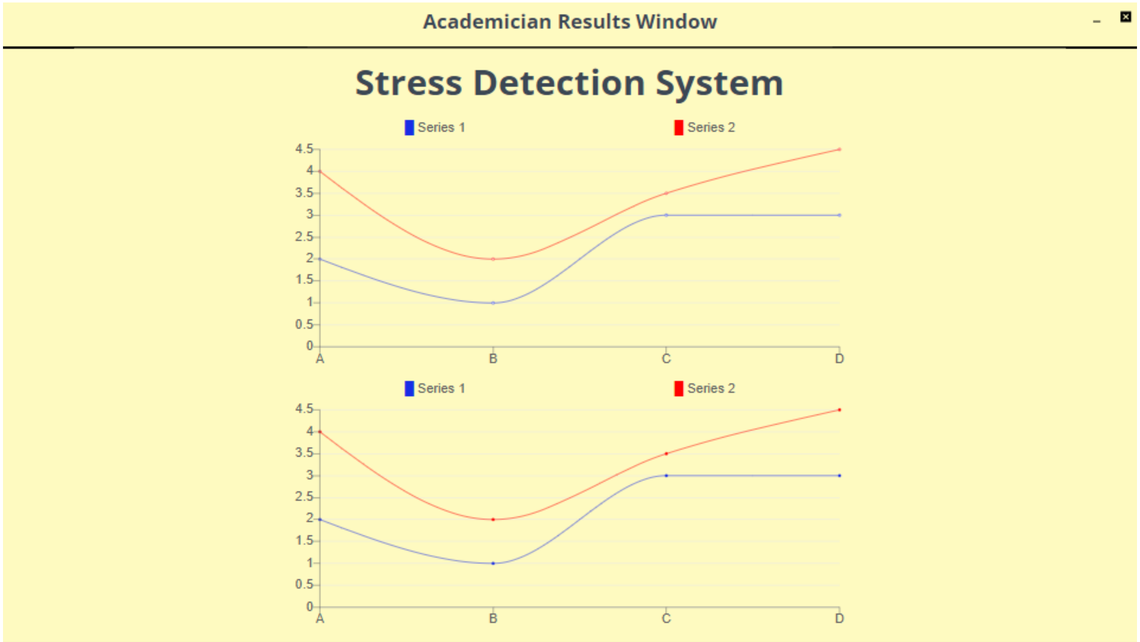


Figure 5.5: Fractal Dimensions Graphical Representation Wireframe

5.4 Description of Implementation Strategies

In our implementation, we utilized the 'pyedflib' library to handle the reading of EDF (European Data Format) files, which are commonly used for storing EEG recordings. This library provided us with the necessary functionality to efficiently parse and extract data from EDF files. Additionally, we employed 'pyedflib' to facilitate the conversion of EDF files into CSV (Comma-Separated Values) format, which is a widely used tabular data format suitable for further processing and analysis. By leveraging the capabilities of 'pyedflib', we were able to seamlessly handle EEG data stored in the EDF format and convert it into a more accessible and versatile CSV format for subsequent processing steps in our project.

The CNN model tailored for stress detection takes the input shape, typically representing the shape of EEG signals, and the number of output classes, which is set to 2 for binary classification of stress and relaxation. The model comprises two convolutional layers, each employing ReLU activation functions and followed by max-pooling layers to downsample feature maps. Dropout layers are inserted after each max-pooling layer to mitigate overfitting. A Flatten layer converts the output into a 1D array, preparing it for fully connected layers. These layers include one with 512 units, ReLU activation, and L2 regularization. The output layer, consisting of units equal to the number of classes, utilizes softmax activation to generate class probabilities. L2 regularization is applied throughout the model to prevent overfitting. Overall, this architecture effectively captures spatial and temporal patterns in EEG signals, facilitating accurate stress classification.

In evaluating our work, we leveraged a variety of methods within the Python programming language to comprehensively assess the performance and efficacy of our stress detection system based on EEG data. Key evaluation techniques included the utilization of standard model evaluation metrics such as accuracy, precision, recall (sensitivity), specificity, and F1 score, providing quantitative measures of our system's classification performance. Additionally, we employed cross-validation methodologies, such as k-fold cross-validation, to gauge the model's generalization capability across different data partitions. Confusion matrix analysis offered further insights into classification performance by visualizing true positive, true negative, false positive, and false negative predictions. ROC curve analysis allowed us to evaluate the discriminatory power of the model and determine an optimal decision threshold. Visualizations, including learning curves, ROC curves, and confusion matrices, aided in the interpretation of results and facilitated communication of findings.

5.5 Conclusion

In this chapter, we provided a detailed overview of the implementation of our stress detection system, covering various aspects from data preprocessing to user interface design. We began by discussing the datasets identified for our study, which consisted of EEG recordings obtained from PhysioNet and recorded using the Neurocom EEG 23-channel equipment. We outlined the preprocessing steps and feature extraction techniques employed to analyze the EEG signals, including the computation of relative theta power, relative alpha power, coherence between EEG channels, and Higuchi fractal dimension. Our algorithm, "EEG Data Processing and Analysis," encapsulates these methodologies in a systematic framework.

Furthermore, we delved into the design of the user interface, presenting wireframe designs for key components such as user selection, file upload for patients and academicians, and graphical representation of results. These wireframes offer a glimpse into the user experience of interacting with our stress detection system.

In conclusion, this chapter provides a comprehensive overview of the steps taken to implement our stress detection system, demonstrating the integration of various methodologies and algorithms to achieve our research objectives. The insights gained from this implementation process lay the foundation for the subsequent evaluation and discussion of our system's performance and implications.

Chapter 6

Results and Discussions

In this chapter, we present the results of our project and engage in discussions surrounding them. We provide an overview of the outcomes, including quantitative results such as learning curves, confusion matrices, and precision-recall values. Additionally, we showcase graphical analyses, including ROC curves and Grad-CAM overlays on input images. Furthermore, we discuss the functionality and user interface of the developed GUI, highlighting its two user modes for patients and academicians. Finally, we offer insights and interpretations of the results, exploring their implications and potential future directions.

6.1 Overview

In this section, we present the overall outcomes of our project. We trained the CNN model for 100 epochs, achieving an accuracy of 84.6 %. The training and validation loss and accuracy were visualized through plotted graphs. Additionally, we generated ROC curves and confusion matrices to evaluate the model's performance. Furthermore, we calculated metrics such as sensitivity, specificity, precision, and F1 score to assess the model's effectiveness in stress detection.

6.2 Testing

In this section, screenshots of the system's graphical user interface are provided. The GUI includes a user selection window where users can choose between the "Patient" and "Academician" modes. In the "Patient" mode, users can upload their EEG file to obtain the prediction result. In the "Academician" mode, users can upload datasets to analyze features such as relative theta power, Higuchi Fractal Dimension, and mean alpha power. The results are presented graphically for easier interpretation.

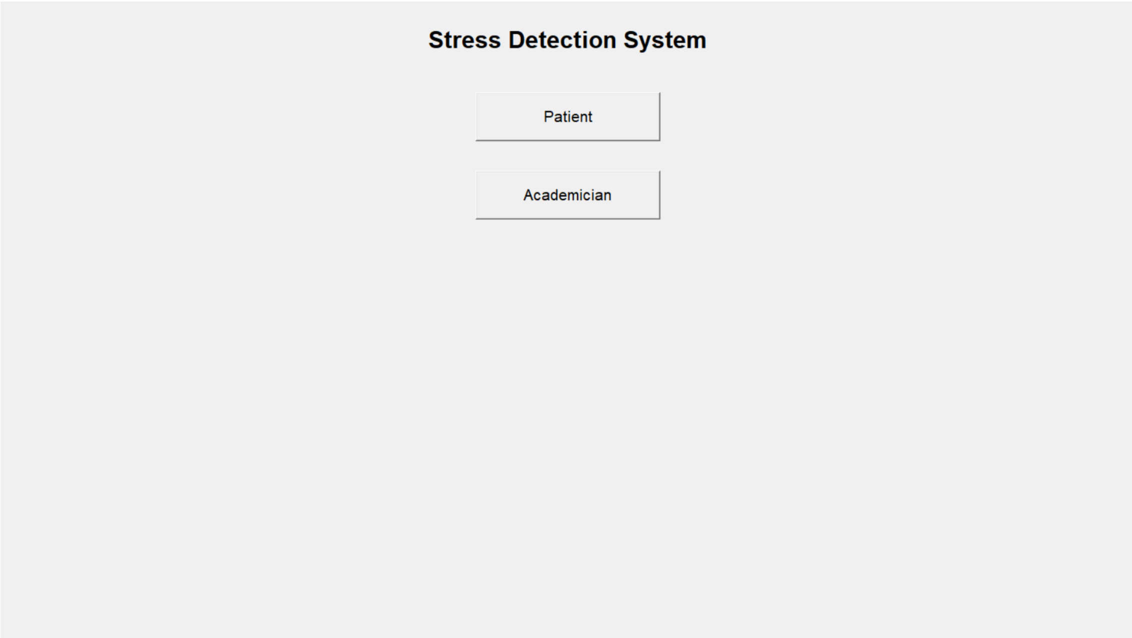


Figure 6.1: User Selection window

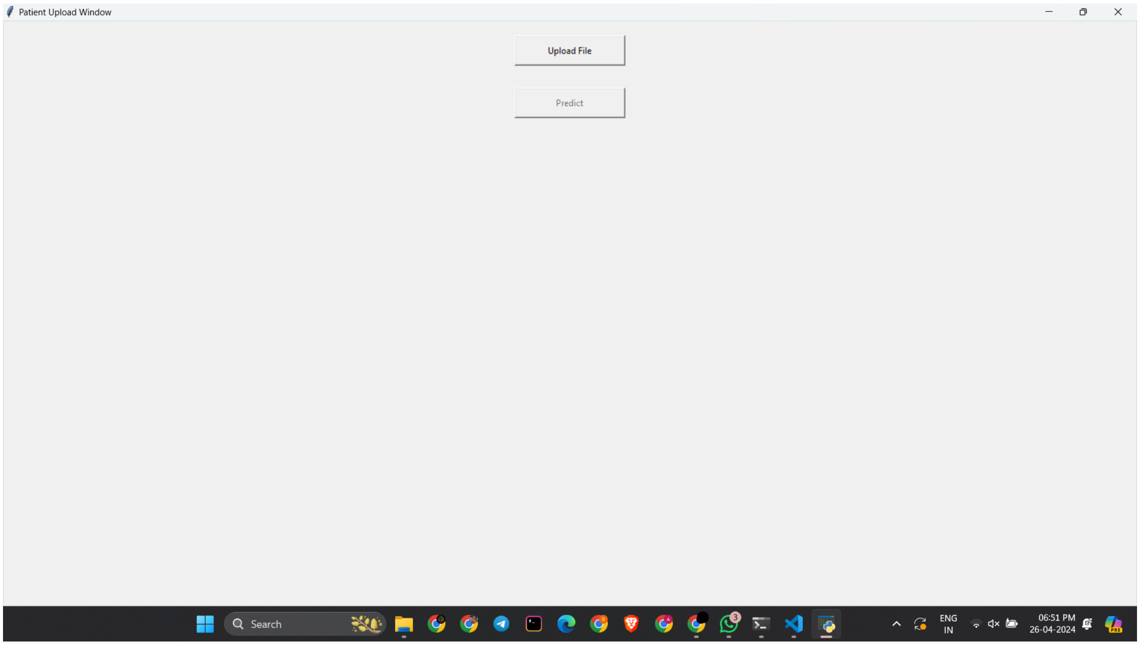


Figure 6.2: Patient File upload window

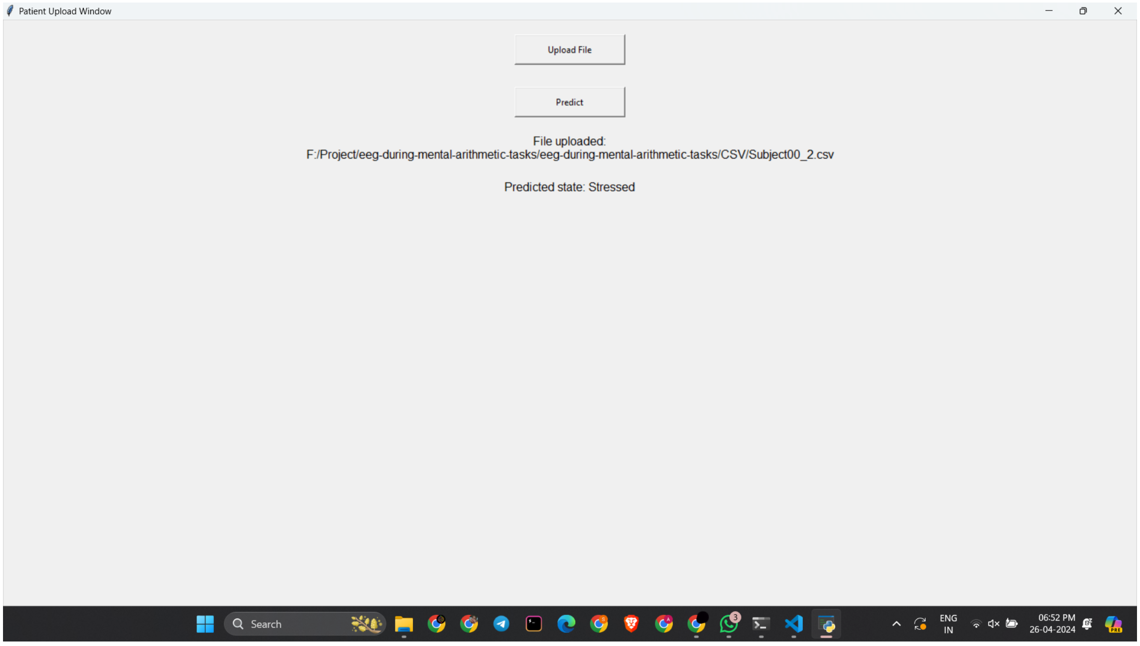


Figure 6.3: Prediction result

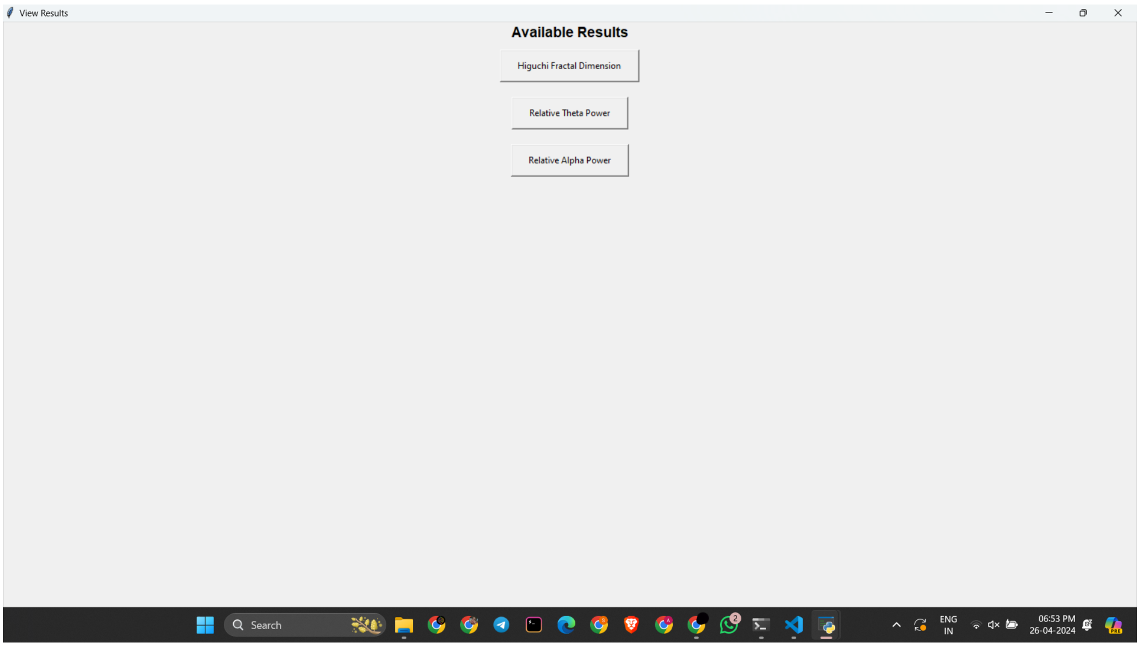


Figure 6.4: Academician Window

Figure 6.5: Result of Relative Theta power

6.3 Features

This section provides details on features such as the Relative Power of Alpha, Relative Power of Theta, Higuchi Fractal Dimension, and Magnitude Squared Coherence, along with the corresponding top five electrodes where these features are identified.

These metrics offer valuable insights into the complexity and connectivity patterns of brain activity, which are crucial in understanding neurological responses to various stimuli or conditions. Furthermore, the identification of the top electrodes associated with each feature adds granularity to the analysis, highlighting specific brain regions or neural networks that may play a significant role in the observed patterns.

6.3.1 Relative Power of theta

As depicted in Table 6.1, we distinguished the relative power of theta in both stressed and normal datasets, observing a greater relative power of theta in the stressed data. Furthermore, we noted that the Fz and Fp1 electrodes exhibited the most significant contrast in relative power of theta between states of stress and relaxation.

Electrode	Average Difference
Fz	0.06372
Fp1	0.06345
Fp2	0.05747
F4	0.05404
F3	0.05261
F8	0.04817
F7	0.04332
P3	0.03651
C3	0.03466
Pz	0.03393
Cz	0.03328
C4	0.02810
O1	0.02678
P4	0.02102
T3	0.01955
T5	0.01552
O2	0.01134
T6	0.00152
T4	0.00138

Table 6.1: The electrodes exhibiting the greatest differences between stressed and normal data for relative power of theta.

6.3.2 Power Spectral Density

Figure 6.6 presents the heat map illustrating the Power Spectral Density during the relaxed and the stressed states of four random subjects. The analysis of the PSD heat maps revealed minimal changes in the alpha band between relaxed and stressed states. This aligns with previous research suggesting that alpha activity is primarily associated with a state of wakeful relaxation. When individuals are awake but not actively engaged, such as during meditation or day dreaming, alpha waves become more prominent.

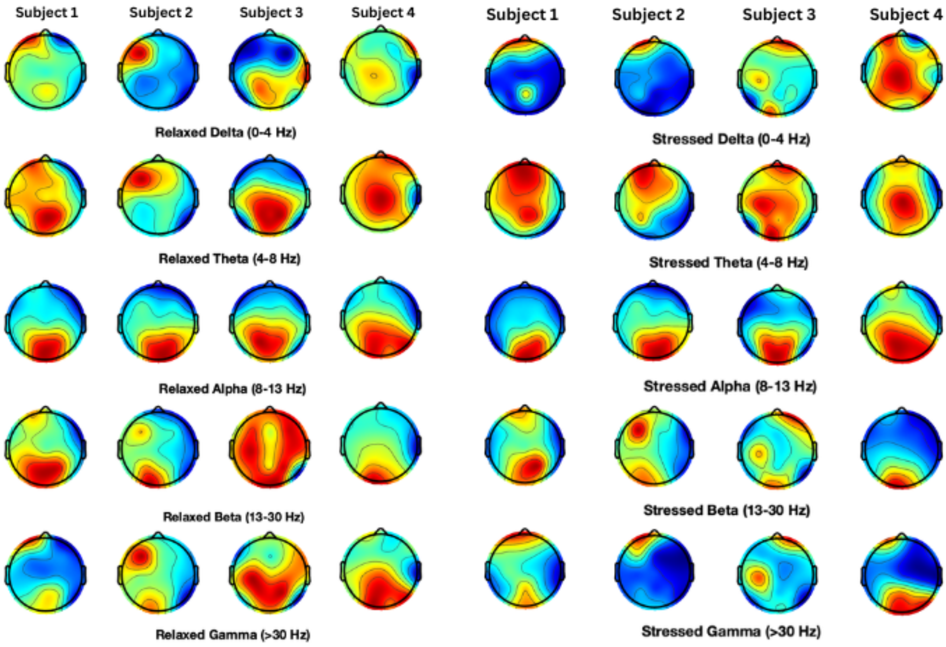


Figure 6.6: Comparison of Relaxed and Stressed States for 4 Subjects.

In contrast, the theta band, the frontal and parietal lobes displayed a significant increase in theta activity (reddish-brown hues) during the stressed state compared to the relaxed state, suggesting heightened cognitive processing and mental workload in the stressed condition.

Finally, the Beta band, associated with motor activity, exhibited a decrease in power (more prominent blue areas) during the stressed state compared to the relaxed state. The occipital region appears to be having more power during the stressed state.

6.3.3 Relative power of alpha

Our analysis, as presented in Table 6.2, revealed the difference between the mean alpha power for stressed and normal data, highlighting a reduced mean alpha power for the stressed data. We have observed that O1 and P3 electrodes show the highest difference for relative power of alpha between stressed and relaxed states.

Electrode	Average Difference
O1	0.09532
P3	0.09228
Pz	0.09163
Fp2	0.08227
Fp1	0.08163
P4	0.08105
T5	0.07565
O2	0.07195
T6	0.06733
F7	0.06722
F4	0.06585
F8	0.06566
Fz	0.06565
F3	0.06028
C3	0.05708
C4	0.05515
T3	0.05390
Cz	0.05221
T4	0.05109

Table 6.2: The electrodes exhibiting the greatest differences between stressed and normal data for relative power of alpha.

6.3.4 Fractal Dimension

Table 6.3 displays the electrodes with the absolute average difference for relaxed and stressed data. Frontal electrodes exhibit the maximum difference between the values of the relaxed and stressed states. The average values for the 36 patients were calculated for both stressed and relaxed conditions, and their absolute differences were then consolidated into a tabular format.

Electrode	Average Difference
Fp1	0.03893
F8	0.03443
Fp2	0.02904
F7	0.02001
F4	0.01947
P3	0.01912
F3	0.01850
Fz	0.01613
O2	0.01559
Cz	0.01526
P4	0.01525
C3	0.01509
Pz	0.01480
O1	0.01473
T5	0.01316
C4	0.00779
T6	0.00732
T3	0.00434
T4	0.00303

Table 6.3: Electrodes exhibiting absolute differences in Higuchi Fractal Dimension values between mental arithmetic tasks and relaxed state.

6.3.5 Magnitude Squared Coherence

This finding, as shown in Table 6.4, suggests that frontal regions might act as key orchestrators of stress responses, demonstrating enhanced coordination during stressful situations.

Electrode	Average Difference
Fp1	0.04323
Fz	0.02678
T5	0.01656
F8	0.01559
F4	0.01477
Cz	0.01455
F7	0.01213
T4	0.01026
O1	0.00895
C4	0.00853
Fp2	0.03554
O2	0.01920
Pz	0.01560
T3	0.01524
P3	0.01462
P4	0.01264
F3	0.01037
T6	0.01000
C3	0.00869

Table 6.4: Electrodes exhibiting significant average MSC differences between stressed and relaxed states.

6.4 Quantitative Results

The table 6.5 presents the evaluation metrics for the trained model. The metrics include test loss, test accuracy, sensitivity recall, specificity, precision positive predictive value, and F1 score. These metrics provide insights into the performance of the model in classifying stress levels based on EEG signals.

Table 6.5 provides a summary of the evaluation metrics for the trained model. The test loss is reported as 0.6345, indicating the average loss over the test dataset. The

Metric	**Value**
Test Loss	0.6345
Test Accuracy	0.8461
Sensitivity Recall	0.8365
Specificity	0.8549
Precision Positive Predictive Value	0.8426
F1 Score	0.8396

Table 6.5: Model Evaluation Metrics

test accuracy achieved by the model is 0.8461, representing the proportion of correctly classified samples in the test set. The sensitivity recall value is 0.8365, indicating the proportion of true positive predictions among all actual positive instances. The specificity value is 0.8549, representing the proportion of true negative predictions among all actual negative instances. The precision positive predictive value is reported as 0.8426, indicating the proportion of true positive predictions among all positive predictions made by the model. Finally, the F1 score, a harmonic mean of precision and recall, is calculated as 0.8396, providing a balanced measure of the model's performance.

6.5 Graphical Analysis

In this section, the graphical analysis of the project is presented, featuring three figures. Figure 6.9 depicts the learning curve, showcasing the training and validation loss and accuracy over epochs. Figure 6.8 illustrates the confusion matrix, providing insights into the model's performance in classifying different classes and ROC curve, demonstrating the trade-off between true positive rate and false positive rate across different thresholds.

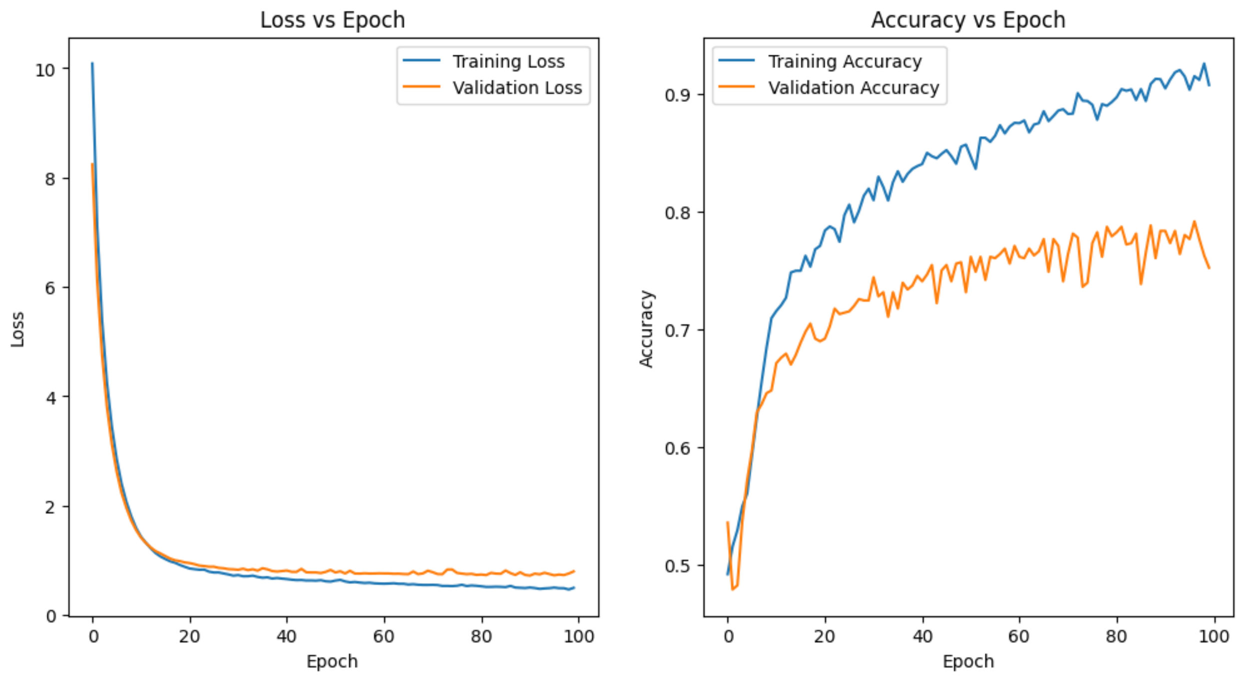
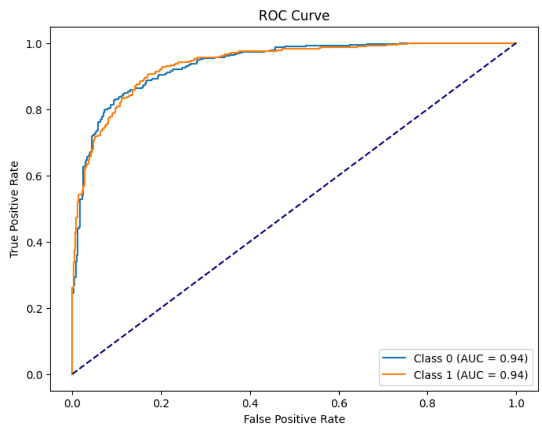
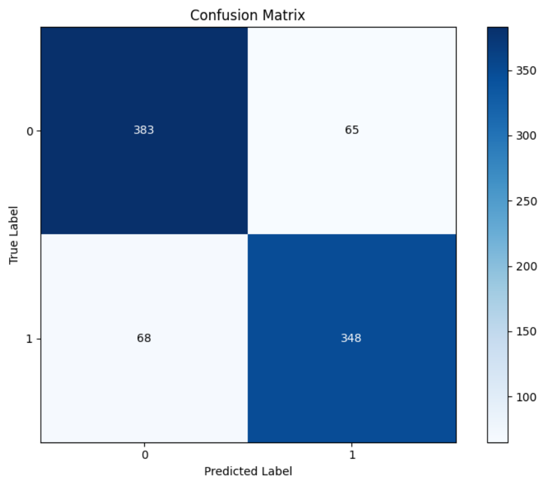


Figure 6.7: Learning rate of the model



(a) ROC curve of the model



(b) Confusion matrix of the model

Figure 6.8: ROC curve and confusion matrix of the model

6.6 Grad-CAM

In this section, we discuss about the output of Grad-CAM after our input is passed.The region in red represents the region with high importance given for obtaining the result. The region in blue represents region which was given least importance while obtaining result from our CNN model. The black lines represent our eeg signal.

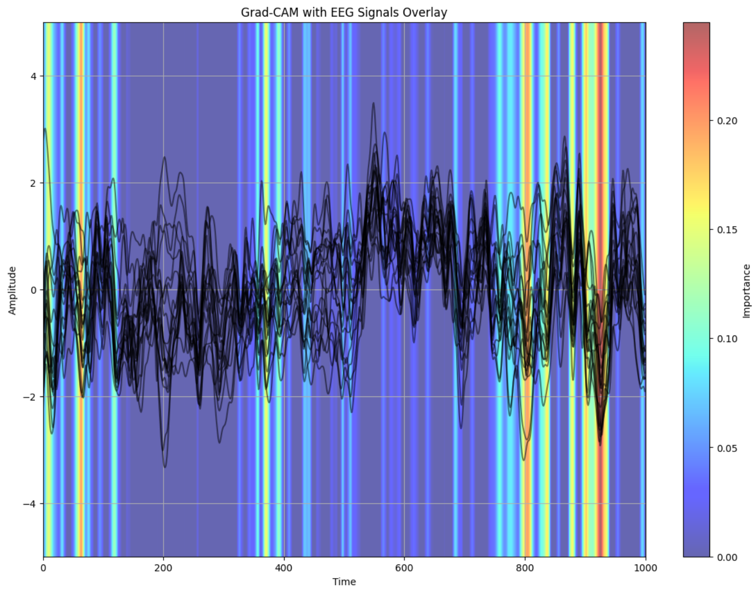


Figure 6.9: Output of the Grad-CAM model

6.7 Summary

In summary, the "Results and Discussions" chapter presents a comprehensive evaluation of the stress detection system developed in this project. The chapter begins with an overview of the outcomes, including a description of the end results, quantitative metrics, and further analysis. The training process of the Convolutional Neural Network model is detailed, highlighting its performance metrics such as accuracy and loss. Additionally, graphical representations including the learning curve, confusion matrix, and ROC curve provide visual insights into the model's performance and classification capabilities. The GUI screenshots showcase the user interface functionality, distinguishing between user roles and their corresponding interactions with the system. Overall, the chapter offers a comprehensive examination of the system's efficacy in detecting stress from EEG signals, providing valuable insights for future improvements and applications.

Chapter 7

Conclusion

7.1 Conclusion

Conclusively, the integration of Convolutional Neural Network , and Grad CAM in our stress detection system poses a state-of-the-art approach for early detection and mitigation increase in stress level. With this, we tap into the potentials of signal processing and deep learning. We develop a formidable technique that extracts crucial information from EEG signals to impact and work towards improved cognition functions as well as community resilience [8].

7.2 Future Scope

When this advanced methodology is deployed, it ensures that our stress detection system doesn't only respond on time to such elevated stress but also facilitate a general and well-being. Leverage the insights of these data to drive informed proactive interventions through sophisticated neural network architectures. This is not only important at the personal level where increased cognitive processing will positively influence various issues in life but extends at the community level in a way identifying communal contribution and collective resilience towards social well-being. Inclusion of these technologies is not only a big step in amplification of stress detection, but also in the illustration of how transformational impacts on mental health can be obtained across various atmospheres.

Its success makes the project have its potential not only in revolutionizing individual being but also considering the positive impact on academic, professional, and personal Additional physiological signals or contextual information through multimodal data sources may cross-check each other and help to refine the accuracy of stress-detection [9]. The adaptive learning mechanisms are interesting to be explored so that stress detection models adapt to the personal life of an individual user over time. Furthermore, collaboration with psychologists and thinking over the user-centered principles will guarantee the bona fide viability and ethical soundness of a system in a real world life. With research ongoing to develop novel signal processing techniques, and with improvements taking place in the field of neural network architectures, stress detection methodologies can be expected to become even more accurate and effective than they already are, thereby reinforcing the importance of this project in the domain of health technology [2].

7.3 Summary of the chapter

The early detection of stress system through integrating Convolutional Neural Network and Grad CAM represents a state-of-the-art technique of early detection of stress. This innovative combination will help exploit the signal processing and the deep learning to mine the crucial information from the EEG signals which will offer potential benefits for the cognitive functions and also the community resilience. The success of the project promises to revolutionize an individual's well-being and underscores its positive influence on academic, professional, and personal life. Looking into the future, possibilities in adapting to the system, focus on user-centered principles and continuously advancing in such growing fields as signal processing and neural network architectures leave the system as one of the key players for the future health technology landscape.

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medical image analysis," *arXiv preprint arXiv:2107.10912*, 2023. [Online]. Available: https://arxiv.org/abs/2107.10912

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Appendix A: Presentation

Stress Detection from EEG Signal

100% Evaluation

Project Guide : Dr. Sminu Izudheen
Anantha Krishnan G | Anjoe S Nambadan | Ashwin Saji | Chackochan Sanjai

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Problem Definition

- In today's world, chronic stress not only jeopardizes individual health but also undermines workplace productivity and societal well-being,
- Existing methods heavily **rely on subjective human expertise, introducing the potential for errors, and can be very time consuming.**
- Our goal is to develop an efficient and accurate stress detection system that uses multiple features of EEG data.
- The proposed solution incorporates explainability to provide transparent insights into the decision-making process, ensuring interpretability and reducing dependence on manual analysis.

Objective

The project aims to explore EEG frequency domain features, develop a CNN model for stress classification, and validate its effectiveness for real-time stress monitoring and intervention.

Novelty

- **Comprehensive Feature Set:** We employ a diverse range of features such as relative theta and alpha power, Higuchi fractal dimension, and magnitude square coherence. This multifaceted approach offers a more comprehensive understanding of the complex neural signatures associated with stress, enhancing the sensitivity and specificity of our detection system.

- **Transparency and Interpretability:** We prioritize transparency in our methodologies and decision-making processes.

Scope

- **Healthcare and Clinical Applications:** The stress detection model can be adapted for clinical use, aiding healthcare professionals in diagnosing and treating stress-related conditions. This can lead to more effective healthcare interventions and improved patient outcomes.

- **Mental Health Support:** Early stress detection can lead to timely interventions and support for individuals experiencing stress. By identifying stress at an early stage, this project can help people manage their mental health effectively.

- **Enhanced Productivity:** Stress can diminish productivity in various settings, including workplaces and educational institutions. This project can contribute to improved productivity and efficiency by identifying and addressing stress factors.

Literature Survey

Title	Methodology
B. Mahesh, T. Hassan, E. Prassler and J. -U. Garbas, "Requirements for a Reference Dataset for Multimodal Human Stress Detection," 2019 IEEE International Conference on Pervasive Computing and Communications Workshops (PerCom Workshops), Kyoto, Japan, 2019, pp. 492-498, doi: 10.1109/PERCOMW.2019.8730884.	This paper proposes a set of requirements to support the establishment of a reference dataset for multimodal human stress detection. The requirements cover person-dependent and technical aspects such as selection of sample population, choice of stress stimuli, inclusion of multiple stress modalities, selection of annotation methods, and selection of data acquisition devices.
Yao, Y., Papakostas, M., Burzo, M., Abouelenien, M. and Mihalcea, R., 2021. Muser: Multimodal stress detection using emotion recognition as an auxiliary task. arXiv preprint arXiv:2105.08146.	A transformer-based model architecture and a novel multi-task learning algorithm with speed-based dynamic sampling strategy.

Title	Methodology
Radhika, K. and Oruganti, V.R.M., 2021, January. Deep multimodal fusion for subject-independent stress detection. In 2021 11th International Conference on Cloud Computing, Data Science & Engineering (Confluence) (pp. 105-109). IEEE.	Explores how to combine ECG and EDA signals using convolutional neural networks (CNNs) to detect subject-independent stress levels.The paper uses tsfresh to extract time and frequency domain features from raw ECG and EDA data, and applies recursive feature elimination (RFE) to select 50 relevant features for each modality.
Naegelin, M., Weibel, R.P., Kerr, J.I., Schinazi, V.R., La Marca, R., von Wangenheim, F., Hoelscher, C. and Ferrario, A., 2023. An interpretable machine learning approach to multimodal stress detection in a simulated office environment. Journal of Biomedical Informatics, 139, p.104299.	Proposes a machine learning approach to detect stress levels in a simulated office environment based on multimodal data from mouse, keyboard and heart rate variability sensors.

Title	Methodology
Gedam, S. and Paul, S., 2021. A review on mental stress detection using wearable sensors and machine learning techniques. IEEE Access, 9, pp.84045-84066.	This paper investigates the stress detection approaches adopted in accordance with the sensory devices such as wearable sensors, Electrocardiogram (ECG), Electroencephalography (EEG), and Photoplethysmography (PPG), and also depending on various environments. The stressors, techniques, results, advantages, limitations, and issues for each study are highlighted and expected to provide a path for future research studies.

Title	Methodology
Vaquerizo-Villar, F., Gutiérrez-Tobal, G.C., Calvo, E., Álvarez, D., Kheirandish-Gozal, L., Del Campo, F., Gozal, D. and Hornero, R., 2023. An explainable deep-learning model to stage sleep states in children and propose novel EEG-related patterns in sleep apnea. Computers in Biology and Medicine, 165, p.107419.	This paper employs a single-channel electroencephalogram (EEG) to classify sleep stages, incorporating convolutional neural networks (CNN) and CNN Inception architectures. The inclusion of the Grad-CAM algorithm enhances the model's interpretability, bringing explainable artificial intelligence (XAI) into the framework.
Partamian, H., Khnaisser, F., Mansour, M., Mahmoud, R. and Karameh, H.H.F., 2021. A deep model for eeg seizure detection with explainable ai using connectivity features. In International Conference on Biomedical Engineering and Science (BIOEN 2021) doi (Vol. 10).	The seizure detection method described in the study utilizes a deep neural network with connectivity features derived from EEG data to classify seizures, while also providing feature relevance for explainable AI using CAM method.

Title	Methodology
Nazari, M., Kluge, A., Apostolova, I., Klutmann, S., Kimiaei, S., Schroeder, M. and Buchert, R., 2022. **Explainable AI to improve acceptance of convolutional neural networks for automatic classification of dopamine transporter SPECT in the diagnosis of clinically uncertain parkinsonian syndromes.** European journal of nuclear medicine and molecular imaging, pp.1-11. Vancouver	This study demonstrates the effectiveness of layer-wise relevance propagation (LRP) in providing interpretable explanations for CNN-based dopamine transporter(DAT-SPECT) classification, with notable focus on the putamen as the most relevant brain region in cases of reduced DAT-SPECT.
Van der Velden, B.H., Kuijf, H.J., Gilhuijs, K.G. and Viergever, M.A., 2022. **Explainable artificial intelligence (XAI) in deep learning-based medical image analysis.** Medical Image Analysis, 79, p.102470.	This survey discusses the increasing need for making deep learning-based medical image analysis understandable, categorizes XAI methods, and organizes related papers by their approach and anatomical focus, and offers insights into the future of explainable AI in this medical field.

Title	Methodology
Loh, H.W., Ooi, C.P., Seoni, S., Barua, P.D., Molinari, F. and Acharya, U.R., 2022. **Application of explainable artificial intelligence for healthcare: A systematic review of the last decade (2011–2022)**. Computer Methods and Programs in Biomedicine, p.107161.	Compares the different XAI techniques like CAM, SHAP, LRP, Grad-CAM in healthcare.

Title	Methodology
Mane, S.A.M. and Shinde, A., 2023. **StressNet: Hybrid model of LSTM and CNN for stress detection from electroencephalogram signal (EEG).** Results in Control and Optimization, 11, p.100231.	The methodology involved decomposing EEG signals into alpha, beta, and theta signals, generating azimuthal projection-based images, passing these images through a two-dimensional convolutional neural network (CNN) for feature extraction, and a long short-term memory (LSTM) network to capture temporal dynamics, and finally classifying the features into stress or normal classes using fully connected layers in the StressNet model.
Bhatnagar, S., Khandelwal, S., Jain, S. and Vyawahare, H., 2023. **A deep learning approach for assessing stress levels in patients using electroencephalogram signals** Decision Analytics Journal, 7, p.100211.	The methodology involved using a compact convolutional neural network, to analyze electroencephalogram signals from frontal and temporal positions within the 8-16 Hz alpha band, achieving a 99.45% accuracy for stress level detection .

Title	Methodology
Roy, B., Malviya, L., Kumar, R., Mal, S., Kumar, A., Bhowmik, T. and Hu, J.W., 2023. **Hybrid Deep Learning Approach for Stress Detection Using Decomposed EEG Signals.** Diagnostics, 13(11), p.1936.	The methodology involved the application of a hybrid deep learning approach, combining discrete wavelet transform (DWT)-based CNN for feature extraction from multichannel EEG recordings and identifying stress using bidirectional long short-term memory (BiLSTM) and two layers of gated recurrent unit (GRU) networks.
Katmah, R., Al-Shargie, F., Tariq, U., Babiloni, F., Al-Mughairbi, F. and Al-Nashash, H., 2021. **A review on mental stress assessment methods using EEG signals.** Sensors, 21(15), p.5043.	The methodology involves a comprehensive review of existing EEG signal analysis methods related to the assessment of mental stress, highlighting variations in data analysis methods and identifying key factors contributing to contradictory results, and proposing deep learning approaches to enhance the accuracy of mental stress level assessment.

Title	Methodology
Immanuel, R.R. and Sangeetha, S.K.B., 2022. **Recognition of emotion with deep learning using EEG signals-the next big wave for stress management in this covid-19 outbreak**. Periodico di Mineralogia, 91(5).	The methodology involves adopting a deep learning approach for emotion recognition, particularly stress, utilizing Electroencephalogram (EEG) signals as the primary input source due to their rich information content, focusing on various deep learning architectures applied to EEG inputs, comparing their performance, and highlighting the superiority of a Convolutional Neural Network (CNN) classifier.

Title	Methodology
Malviya, L. and Mal, S., 2022. **A novel technique for stress detection from EEG signal using hybrid deep learning model.** *Neural Computing and Applications*, 34(22), pp.19819-19830.	Preprocessing EEG signals by removing noise, decomposing them using Discrete Wavelet Transform (DWT), applying Convolutional Neural Network (CNN) for automatic feature selection on the decomposed signals, and ultimately utilizing Bidirectional Long Short-Term Memory (BLSTM) for classifying stress levels, achieving a high classification accuracy.
García-Martínez, B., Fernández-Caballero, A., Alcaraz, R. and Martínez-Rodrigo, A., 2021. **Assessment of dispersion patterns for negative stress detection from electroencephalographic signals.** Pattern Recognition, 119, p.108094.	It involves the application of three entropy metrics, including regularity-based quadratic sample entropy (QSampEn), symbolic amplitude-aware permutation entropy (AAPE), and dispersion entropy (DispEn), for the detection of distress from physiological signals.

Title	Methodology
Perez-Valero, E., Lopez-Gordo, M.A. and Vaquero-Blasco, M.A., 2021. **EEG-based multi-level stress classification with and without smoothing filter.** Biomedical Signal Processing and Control, 69, p.102881.	It involves recording EEG data during a stress-relax session, estimating EEG power spectral density (PSD) from the data, and using participant-reported stress levels as labels for classification.
Arsalan, A. and Majid, M., 2022. **A study on multi-class anxiety detection using wearable EEG headband.** Journal of Ambient Intelligence and Humanized Computing, 13(12), pp.5739-5749.	Recording resting-state EEG data from 65 participants, labeling the data into two and three classes of anxiety using trait anxiety scores, applying onboard noise cancellation, selecting EEG channels based on statistical tests, extracting five time-domain features, and using a wrapper method for feature selection.

Title	Methodology
Salankar, N. and Qaisar, S.M., 2022. **EEG based stress classification by using difference plots of variational modes and machine learning**. Journal of Ambient Intelligence and Humanized Computing, pp.1-14.	Processing multichannel EEG signals using Empirical Mode Decomposition (EMD) and Variational Mode Decomposition (VMD) to extract Intrinsic Mode Functions (IMFs) and Modes, followed by generating second order difference plots (SODPs) for each IMF and Mode.

Proposed Method

Step 1 Obtain EEG dataset containing recordings of subjects' brain activity before and during a mental arithmetic task from PhysioNet.

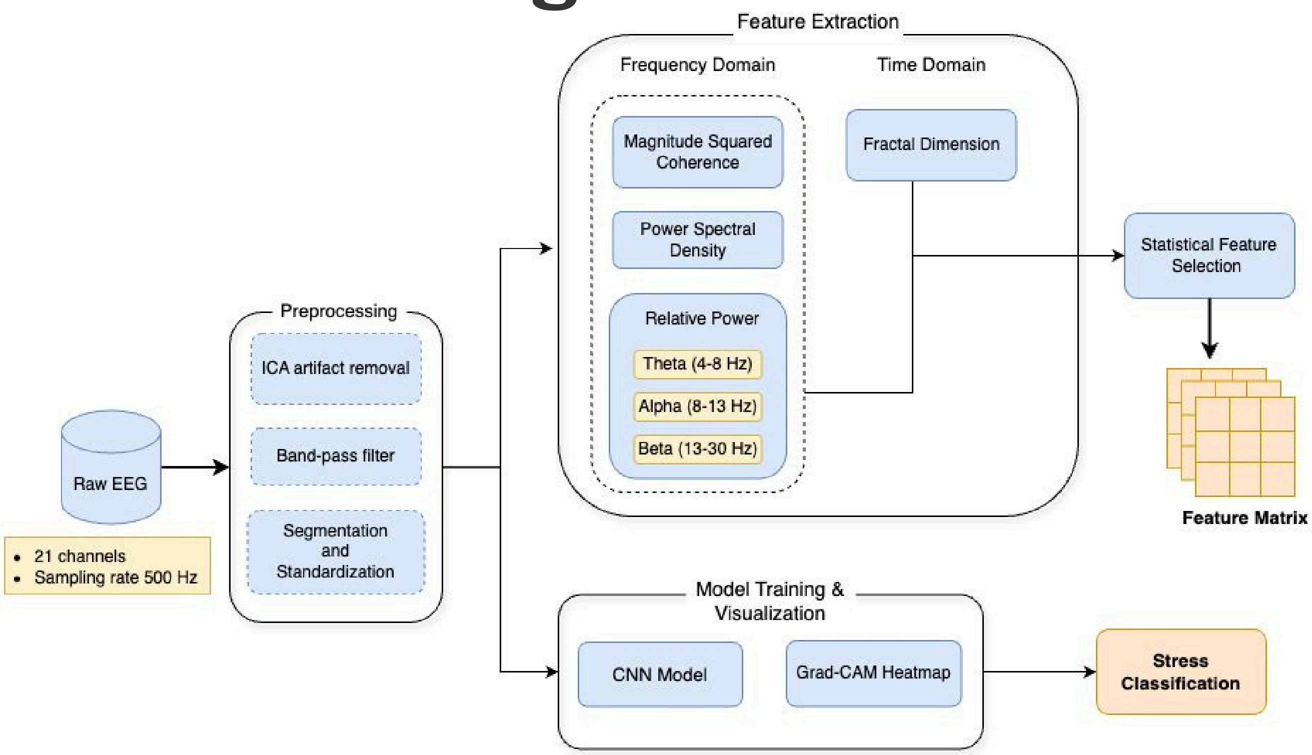
Step 2
- Artifact Removal: Eliminate noise and artifacts from EEG signals.
- Filtering: Apply a 50-Hz power notch filter and a high-pass filter (30 Hz) to remove unwanted frequencies.
- Conversion to CSV: Convert EEG data files from EDF to CSV format for easier processing.
- Channel Selection: Choose relevant EEG channels for analysis.
- Segmentation & Standardization: Divide EEG recordings into 2-second segments with a 1-second overlap, then standardize using Z-score normalization for consistent feature scaling.

Step 3
- Extract features such as relative theta power, relative alpha power, magnitude squared coherence, and Higuchi fractal dimension from preprocessed EEG data.
- Create a feature matrix comprising the top five electrodes for each extracted feature.

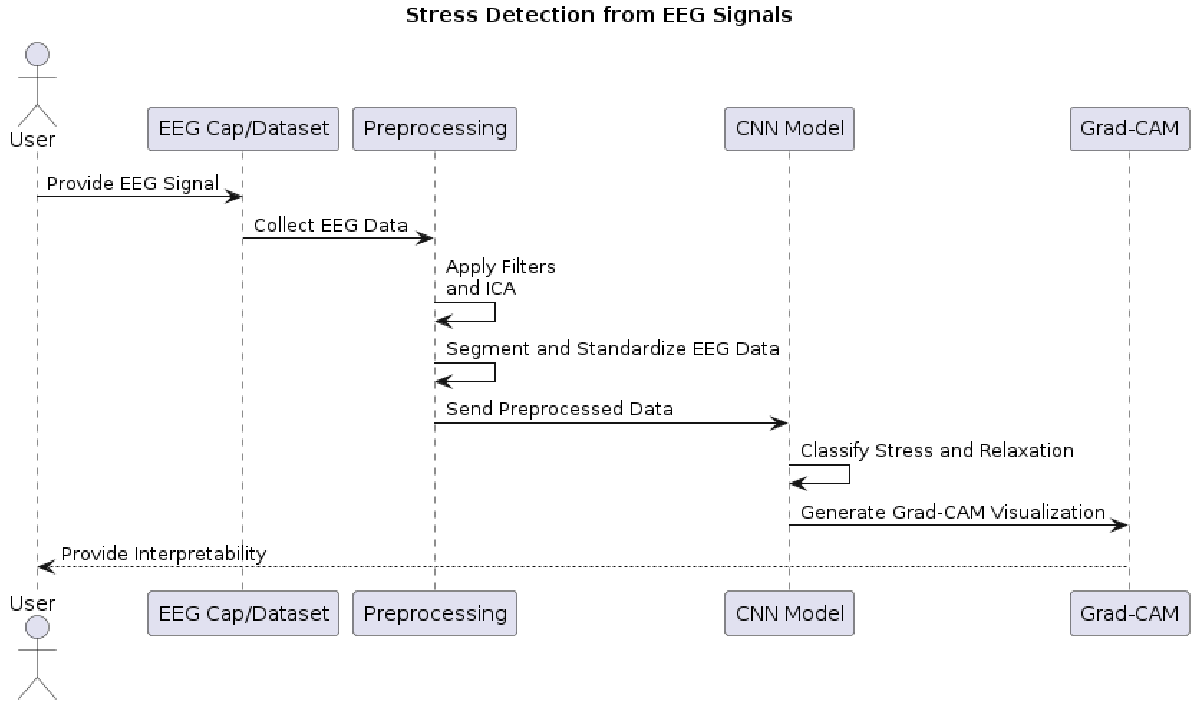
Step 4
- Develop a CNN model architecture for classifying EEG signals.
- Design the model to take preprocessed EEG signals as input and classify them into relaxed and stressed states.

Step 5
- Implement Explainable AI to provide interpretability for the model. In this project we plan to use Grad-CAM.

Architecture Diagram



Sequence Diagram



Modules

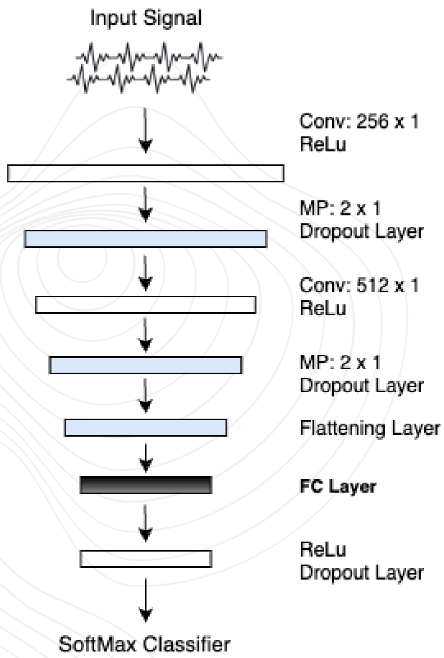
Data Preprocessing Module

- Artifact Removal: Eliminate noise and artifacts from the EEG signals.
- Filtering: Apply a 50-Hz power notch filter and a high-pass filter (30 Hz) to remove unwanted frequencies.
- Conversion to CSV: Convert EEG data files from EDF to CSV format for easier processing.
- Channel Selection: Choose relevant EEG channels for analysis (e.g., EEG Fp1, EEG Fp2, EEG F3, EEG F4, etc.).
- Segmentation: Divide EEG recordings into 2-second segments with a 1-second overlap to capture temporal dynamics.
- Standardization: Standardize segmented EEG windows using techniques like Z-score normalization for consistent feature scaling.

Modules

Classification Module

- Convolutional Neural Network (CNN) architecture
- ReLU activation functions for introducing non-linearity
- Max-pooling layers for downsampling and translational invariance
- Flattening and dense layers for learning high-level representations
- Dropout layers to prevent overfitting
- Softmax output layer for probability distribution over classes
- Training with labeled EEG data using appropriate loss function and optimizer



Modules

XAI module

- The system uses Gradient Class Activation Mapping (Grad-CAM) to provide interpretation of the model.

- Grad-CAM is the widely used algorithm for XAI in deep learning models.

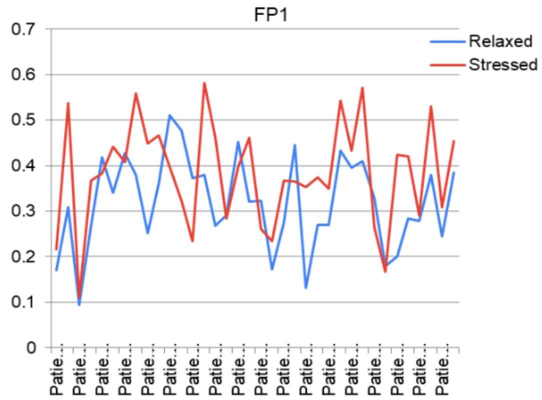
Feed the image to CNN → **Compute the gradients of the target class with respect to the final layer** → **Perform global average pooling on the gradients** → **Multiply each channel of the final convolutional layer by its corresponding gradient** → **Sum the channels to obtain the heatmap** → **Normalize the heatmap** → **Overlay the heatmap on the original image** → **Visualize the result**

Relative Power

Relative Power is a normalized metric that indicates the proportion of total power inside a certain frequency band relative to total power across all frequency bands.

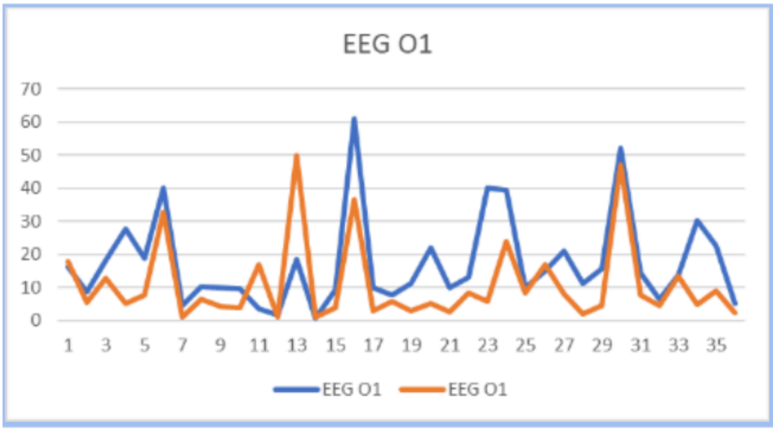
Relative Power(f) = Power(f)/Total Power

Electrode	Avg. Difference
EEG Fz	0.063722139
EEG Fp1	0.063452659
EEG Fp2	0.057475287
EEG F4	0.054041367
EEG F3	0.052619234



Relative Alpha Power

Electrode	Average Difference
EEG O1	6.536894
EEG Pz	5.911126
EEG O2	5.330551
EEG P4	5.04442
EEG P3	5.025135



Magnitude Square Coherence(MSC)

The Mean Square Coherence (MSC) metric is utilized for quantifying the degree of coherence between electrode pairs.

For each electrode pair, the Mean Square Coherence (MSC) was computed using

$$MSC(f) = \frac{|S_{xy}(f)|^2}{S_{xx}(f) \cdot S_{yy}(f)}$$

Cross-Spectral Density (CSD)

$$S_{xy}(f) = \mathrm{FFT}(x(t)) \cdot \mathrm{FFT}(y(t))^*$$

Here, * denotes the complex conjugate.

The cross-spectral density is the Fourier transform of the cross-correlation function.

Auto-Spectral Density (ASD)

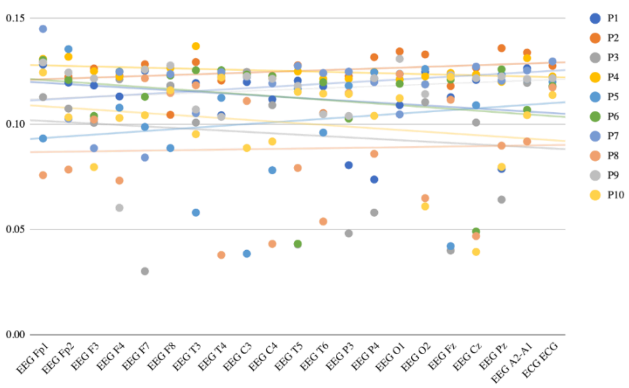
$$S_{xx}(f) = \mathrm{FFT}(x(t)) \cdot \mathrm{FFT}(x(t))^*$$
$$S_{yy}(f) = \mathrm{FFT}(y(t)) \cdot \mathrm{FFT}(y(t))^*$$

Magnitude Square Coherence(MSC)

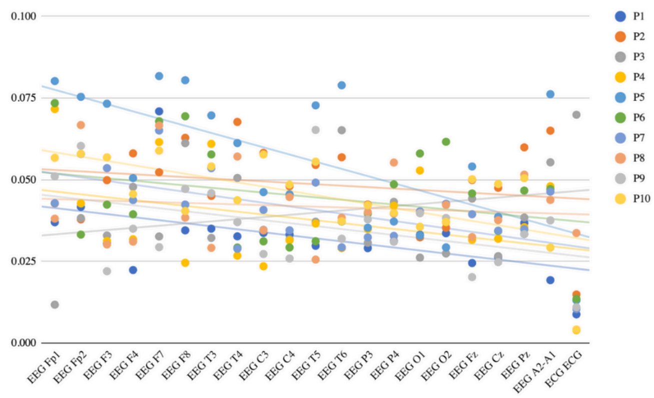
Electrode	Average Difference
EEG Fp1	0.04323056015
EEG Fp2	0.0355412495
EEG Fz	0.02678434222
EEG O2	0.01920531371
EEG T5	0.01656999456
EEG Pz	0.01560168745
EEG F8	0.01559783324
EEG T3	0.01524334103

EEG F4	0.0147729509
EEG P3	0.01462284824
EEG Cz	0.01455014482
EEG P4	0.01264431451
EEG F7	0.01213520157
EEG F3	0.01037110264
EEG T4	0.0102630367
EEG T6	0.01000507485
EEG O1	0.008951363365
EEG C3	0.008691283312
EEG C4	0.008538318305

Magnitude Square Coherence(MSC)



Stressed State



Relaxed State

In the stressed state, the trend lines appeared consistently straight and unvarying, falling within the range of 0.1 to 0.15. This suggests a more uniform and predictable pattern of MSC variability among subjects during periods of stress.

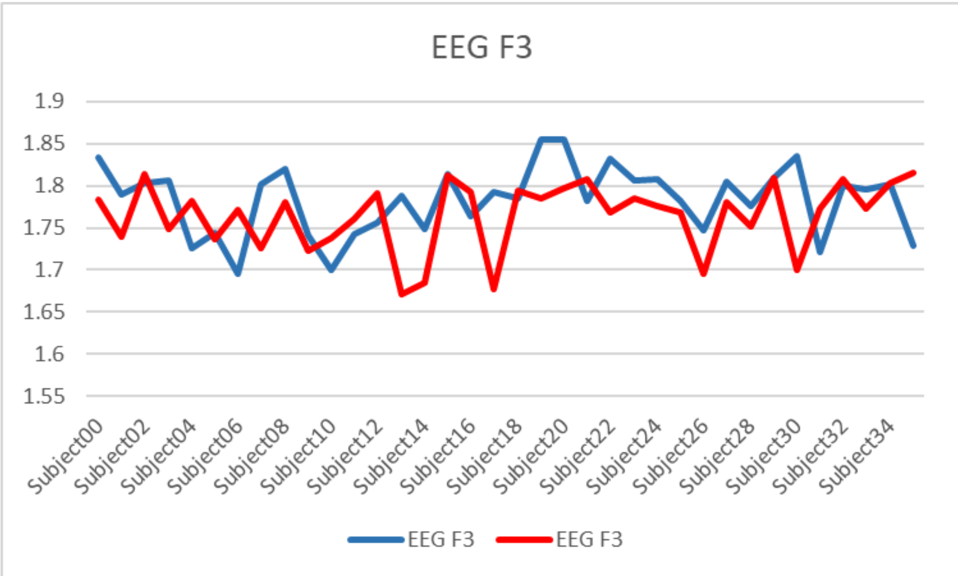
Higuchi Fractal Dimension

- The Higuchi Fractal Dimension (HFD) is a mathematical metric used to assess the complexity or irregularity within a curve or time series data.

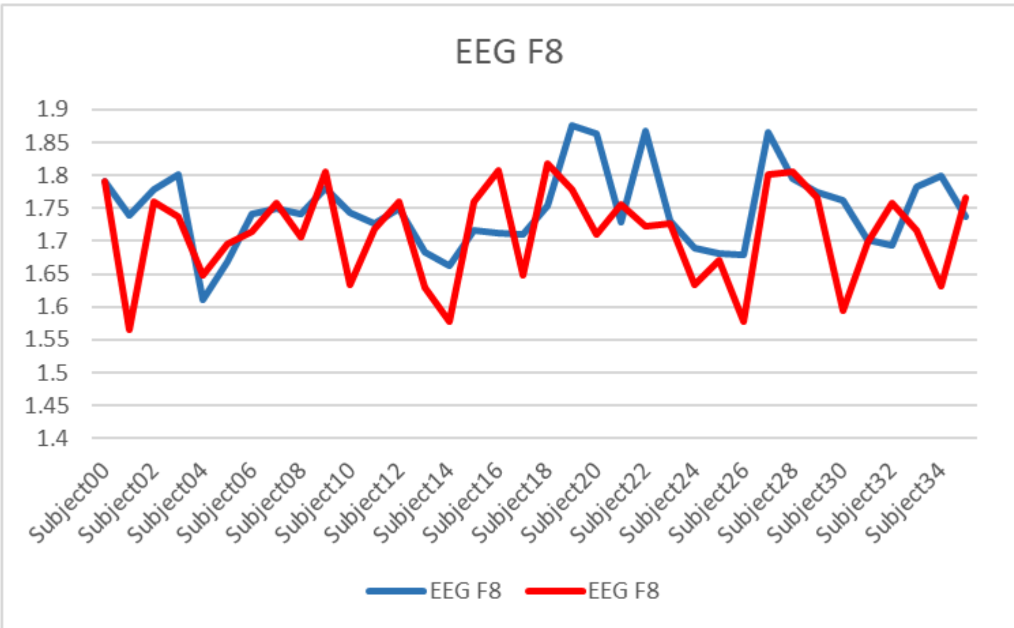
Electrode	Average Difference
EEG Fp1	0.03894
EEG F8	0.03444
EEG Fp2	0.02904
EEG F7	0.02001
EEG F4	0.02001

$$D_k = \frac{\log(N)}{\log(N/kL(k))}$$

Higuchi Fractal Dimension

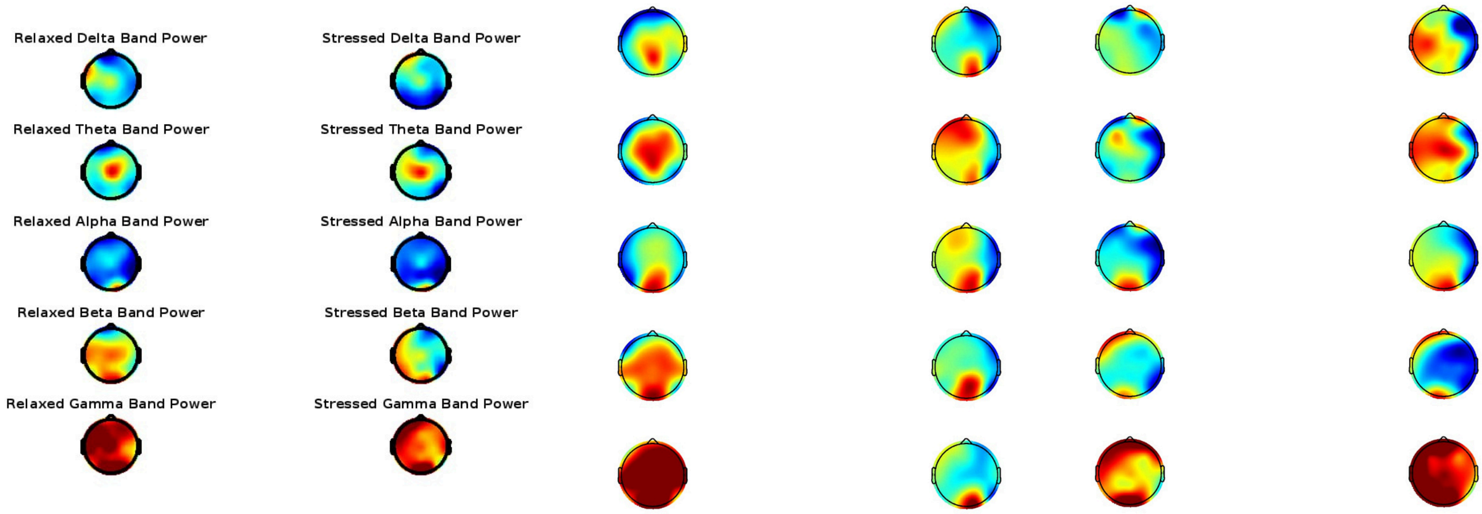


Higuchi Fractal Dimension



Power Spectral Density

- Revealshow signal power is distributed across different frequencies.
- In **Theta** Band the spread is more from the direction of frontal part to left hemisphere.
- In **Beta** Band intensity reduces from left to right hemisphere.



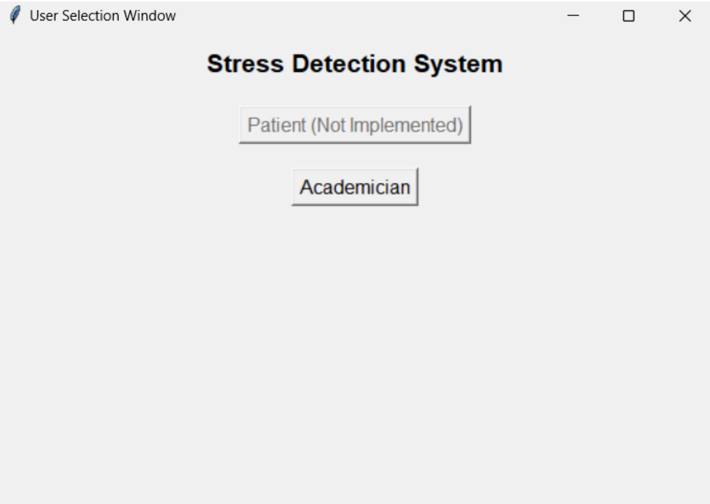
GUI

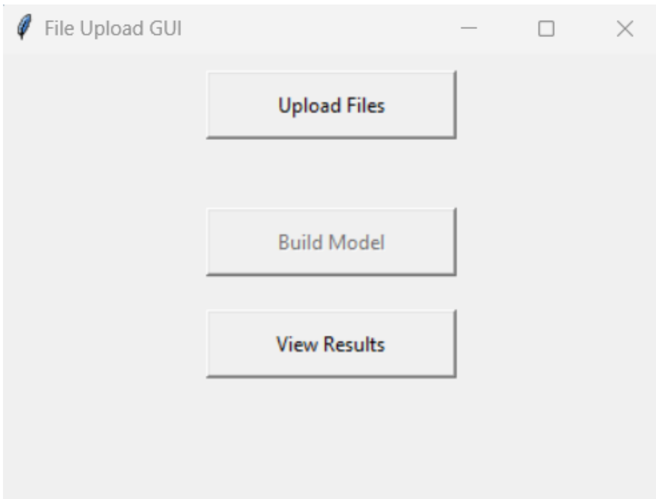
- Developed a Graphical User Interface (GUI) that simplifies the feature extraction process for stress detection.

- **Academician Interface:** Offers advanced functionalities for academicians, including file uploading, and feature extraction tools

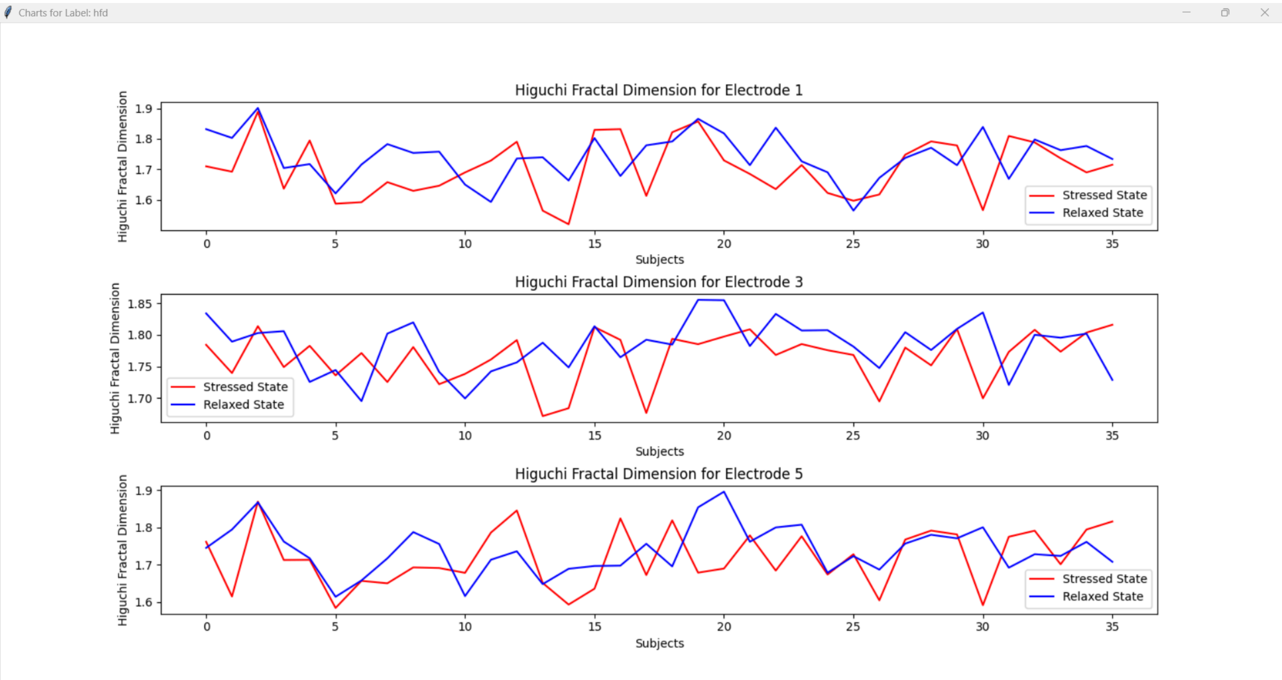
- **Graphical Result Visualization:** Presents the results of model analyses in a graphical format within the GUI, enabling academicians to visualize key insights and trends derived from the data.

GUI


User Selection Window
Stress Detection System
Patient (Not Implemented)
Academician


File Upload GUI
Upload Files
Build Model
View Results

GUI


Charts for Label: hfd
Higuchi Fractal Dimension for Electrode 1
Higuchi Fractal Dimension
Subjects
Stressed State
Relaxed State
Higuchi Fractal Dimension for Electrode 3
Higuchi Fractal Dimension
Subjects
Stressed State
Relaxed State
Higuchi Fractal Dimension for Electrode 5
Higuchi Fractal Dimension
Subjects
Stressed State
Relaxed State

CNN model

Data Preparation

- EEG data loaded from EDF files in Google Drive.
- Categorized into healthy (control) and patient groups.

Data Processing

- MNE library used for reading and preprocessing.
- Bandpass filter applied (0-60 Hz).
- Data segmented into 1-second epochs.

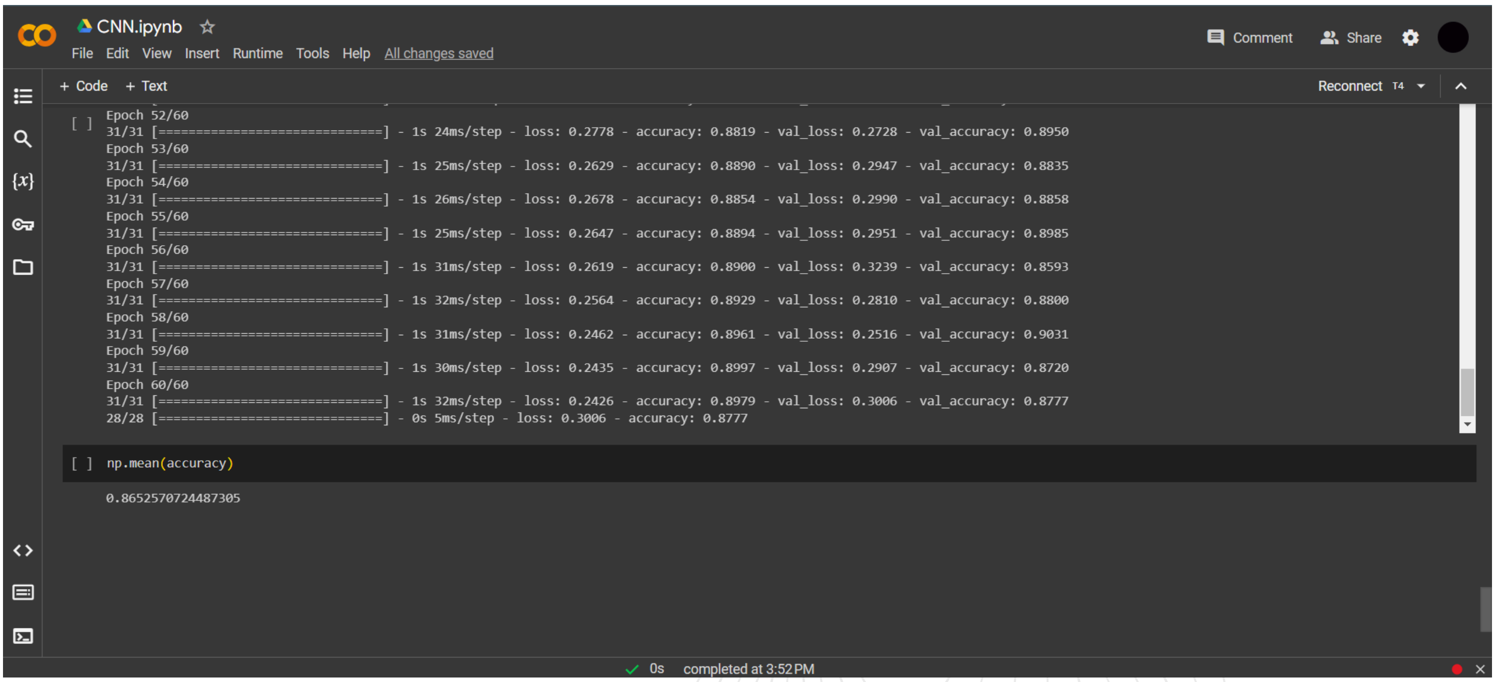
Organization

- Arrays created for control and patient epochs.
- Labels assigned (0 for control, 1 for patients).
- Data grouped for analysis.

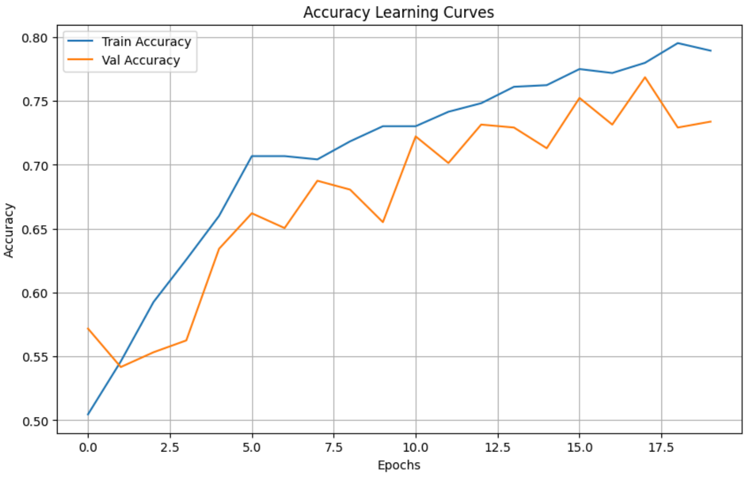
Model Architecture

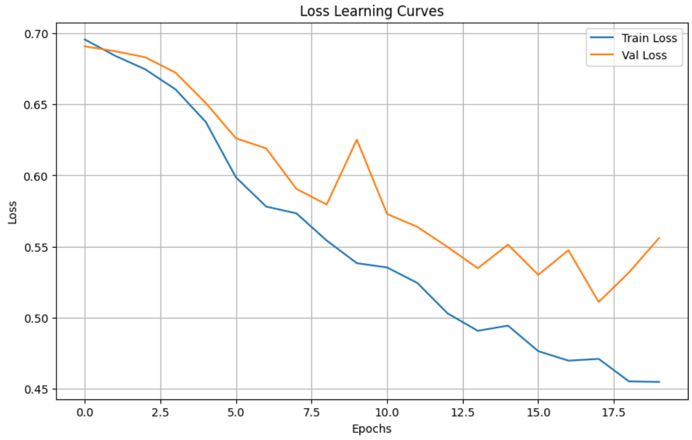
- CNN model designed for stress detection.
- Conv1D layers with normalization, pooling, and dropout.
- Ends with global pooling and sigmoid activation.

CNN model

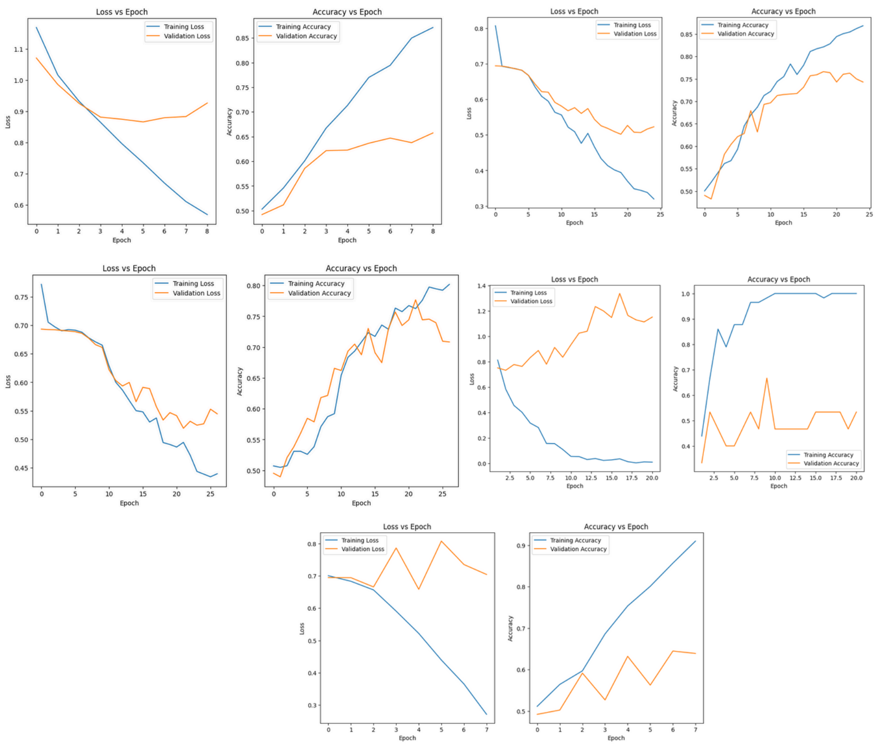


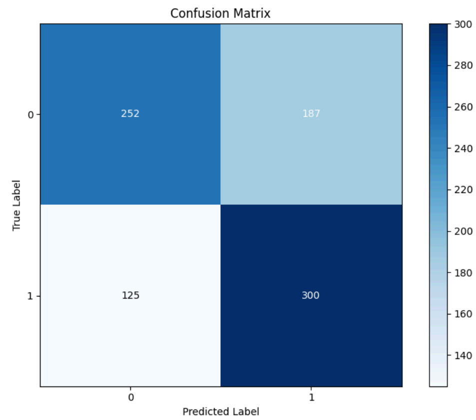
CNN model

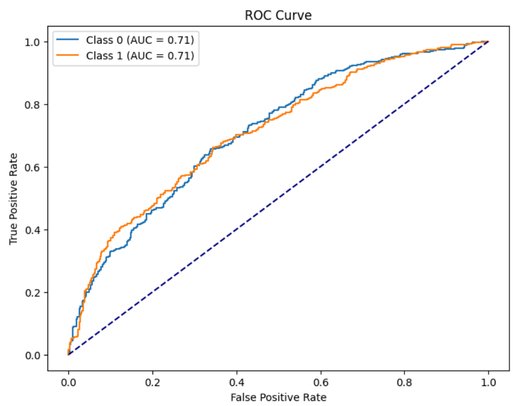




CNN







CNN

Data Preparation:

- Loaded EEG data from CSV files stored in a specified directory.
- Separate data into relaxed and stressed categories based on file naming conventions.
- Preprocess the data by segmenting it into windows and performing standardization.

Convolutional Layers:

- Two convolutional layers are employed for feature extraction.
- Each Conv1D layer applies a 1-dimensional convolution operation to the input data.
- The first convolutional layer consists of 64 filters of size 5, preserving the input shape by using 'same' padding.
- The second convolutional layer consists of 128 filters of size 5, with the same padding.

CNN

Activation Function:

- Rectified Linear Unit (ReLU) activation functions are applied after each convolutional layer.
- ReLU introduces non-linearity, enabling the model to learn complex patterns and improve its expressive power.

Pooling Layers:

- MaxPooling1D layers are used for down-sampling, reducing spatial dimensions while retaining essential features.
- Each MaxPooling1D layer pools the maximum value within a window of size 2, effectively reducing the feature map size by half.

Dropout Regularization:

- Dropout layers are incorporated to prevent overfitting during training.
- Dropout randomly drops a fraction of units during training iterations, encouraging the model to learn more robust and generalizable features.

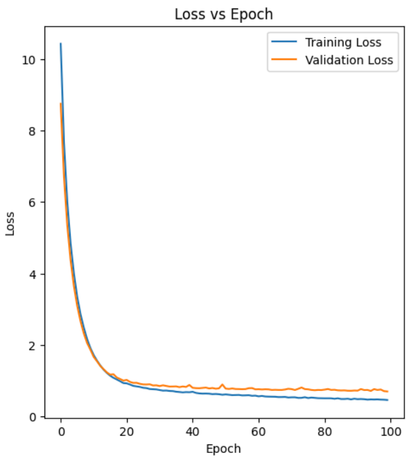
CNN

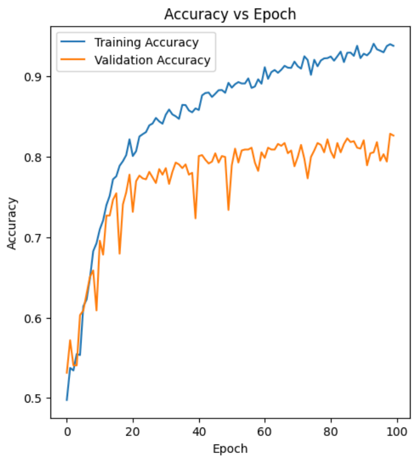
Output Layer:

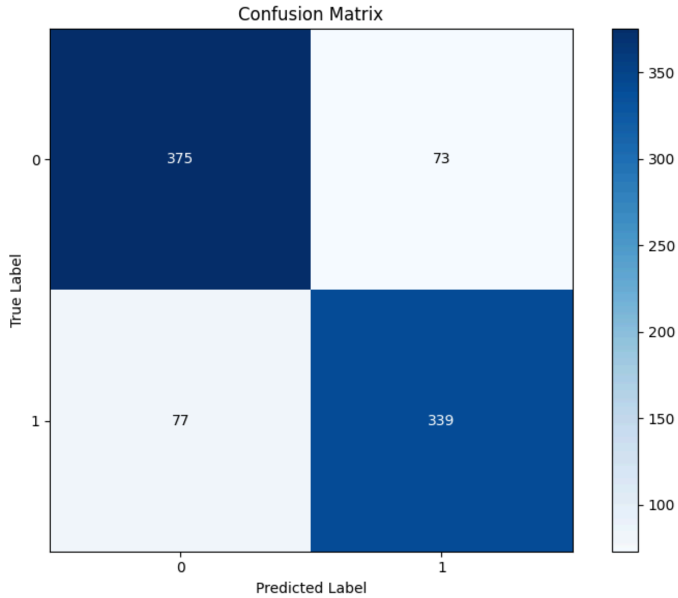
- The output layer comprises Dense layer with softmax activation, facilitating classification into two classes (relaxed or stressed).
- Softmax activation ensures that the predicted probabilities sum up to one, providing class probabilities for decision-making.

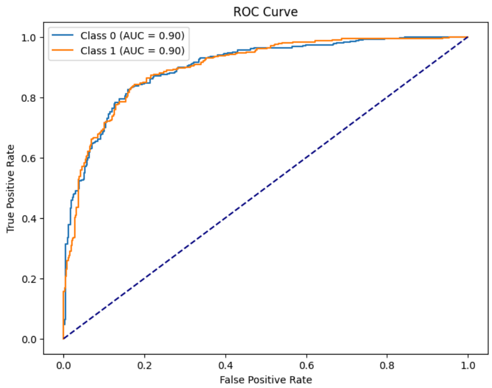
Final Loss: 0.6765547
Final Accuracy: 0.8113425

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv1d (Conv1D)             (None, 1000, 64)          6464

 re_lu (ReLU)                (None, 1000, 64)          0

 max_pooling1d (MaxPooling1  (None, 500, 64)           0
 D)

 dropout (Dropout)           (None, 500, 64)           0

 conv1d_1 (Conv1D)           (None, 500, 128)          41088

 re_lu_1 (ReLU)              (None, 500, 128)          0

 max_pooling1d_1 (MaxPoolin  (None, 250, 128)          0
 g1D)

 dropout_1 (Dropout)         (None, 250, 128)          0

 flatten (Flatten)           (None, 32000)             0

 dense (Dense)               (None, 512)               16384512

 re_lu_2 (ReLU)              (None, 512)               0

 dropout_2 (Dropout)         (None, 512)               0

 dense_1 (Dense)             (None, 2)                 1026

=================================================================
Total params: 16433090 (62.69 MB)
Trainable params: 16433090 (62.69 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```



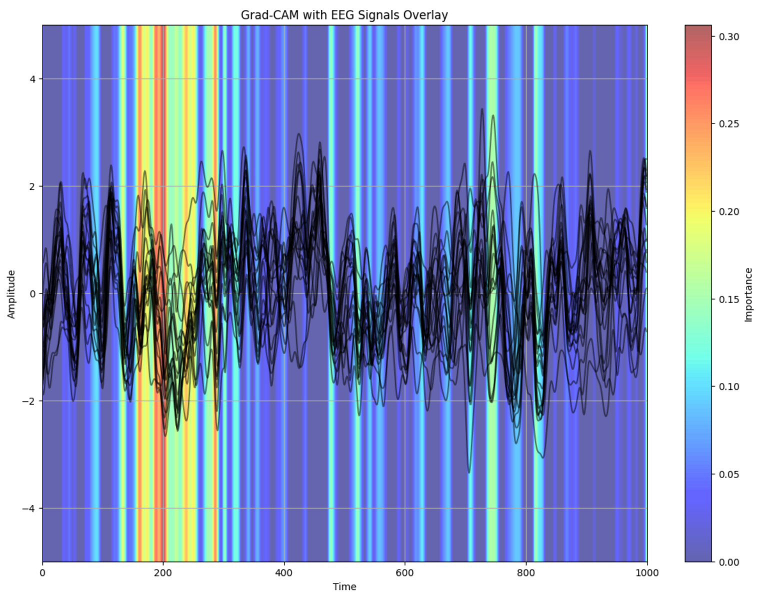




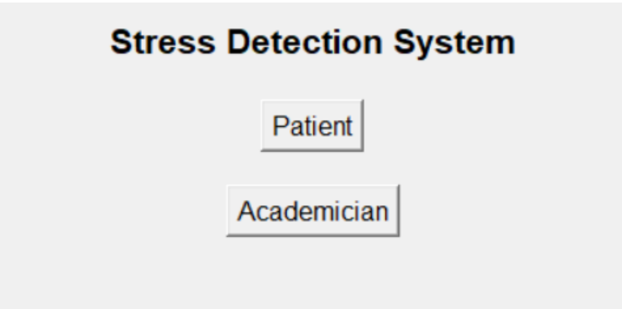


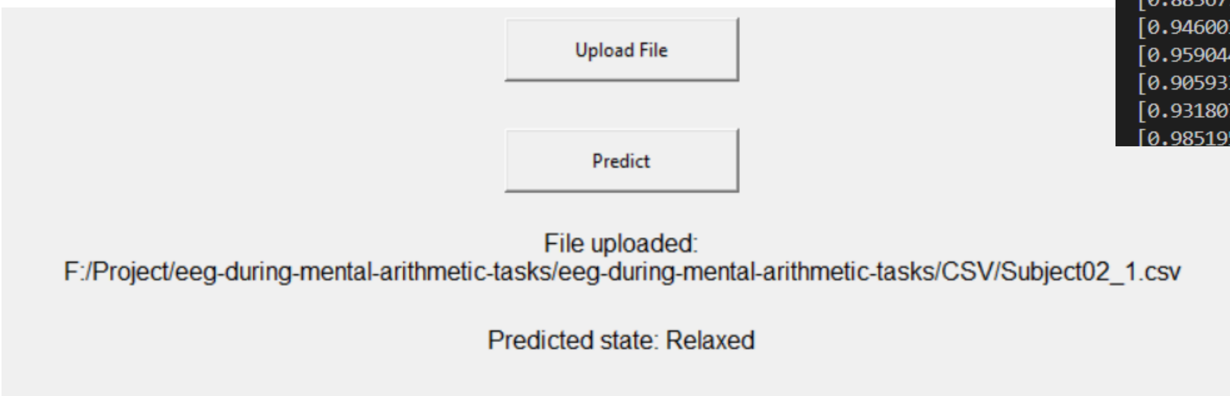
Grad-CAM

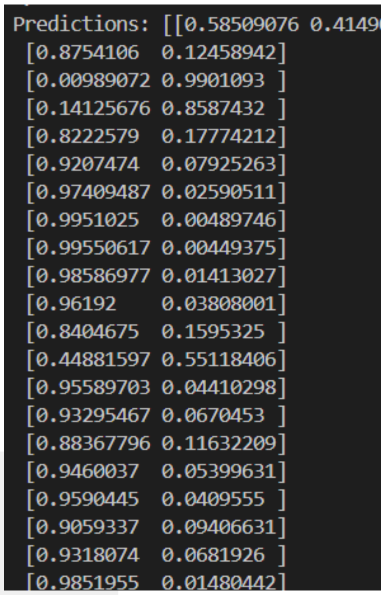
The region in red represents the region with high importance given for obtaining the result. The region in blue represents region which was given least importance while obtaining result from our CNN model. The black lines represent our eeg signal.



GUI







Task Distribution

<u>Feature Extraction</u>

- Compare PSD values for corresponding frames.
- Find mean and peak values of alpha, beta, theta and delta band PSD values.

<u>Machine Learning</u>

- Try different machine learning algorithms and find feature relevance.

<u>Feature Extraction</u>

- Find Higuchi Fractral Dimenison values for all the channels of EEG data.
- Combine the features and normalize them
- Find relevance of features.

<u>Convolutional Neural Network (CNN) & GUI</u>

- Make a CNN model taking EEG signal as input.
- Integrate the model with GUI

Data Preprocessing and Feature Extraction

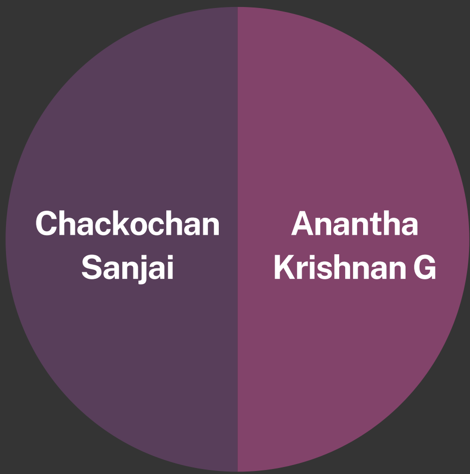
- Work on feature extraction from EEG signals .

Relative value of Theta

- Find relative value of theta power of all patients.

Relative value of Alpha

- Find relative value of alpha power of alpha of all patients.



Deep Learning Model Development and Feature extraction

- Collaborate on data preprocessing tasks and feature extraction.

Feature Extraction

- Find Magnitude Sqare Coherence(MSC) values for EEG data.
- Obtain infernece from the MSC values calculated.

GUI

- Create the GUI for stress detection.

Conclusion

- We have **focused on the frequency domain** and found features of EEG signals across different brain regions during both stressed and relaxed states which are not visible to the naked eye.

- The utilization of advanced analysis methods, including Magnitude Square Coherence (MSC) and Power Spectral Analysis, allowed for a detailed exploration of EEG data obtained from 35 patients. The results revealed distinct patterns in mean alpha power, relative power of theta, Higuchi Fractal Dimension, and MSC values during stressed and relaxed states.

- EEG signals act as valuable indicators for understanding and addressing cognitive and emotional states, particularly stress. It yields significant insights into brain dynamics during stress, revealing distinct patterns.

Status of paper

- The manuscript has been finalized and has to been send to the **"Health Data Sciences"** journal.

Mental Stress Assessment using EEG Signals

Sminu Izudheen[1], Harsha A.[2], Anantha Krishnan G[1], Anjoe S Nambadan[1], Ashwin Saji[1], Chackochan Sanjai[1]
[1]*Department of Computer Science & Engineering*
[2]*Department of Electronics & Communication Engineering*
Rajagiri School of Engineering & Technology, Kochi, India

Stress, something we all grapple with at some point, deserves closer attention to understand its effects on mental and physical health. Electroencephalography(EEG) technique can be used to identify this brain activity via its electrical bio-signals. The study proposes neuroscience tools like Magnitude Squared Coherence (MSC), Relative Power, Fractal Dimension and Power Spectral Density (PSD) analysis to get a peek into how our brains handle stress. The research involved 36 participants who underwent EEG recordings before and during mental arithmetic tasks, simulating a stressful situation. The findings underscore significant alterations in brain connectivity patterns during stressful episodes, with a notable emphasis on heightened connectivity in frontal regions. Interestingly, MSC analysis suggested the profound use of frontal parts of the brain, during stress, implying the importance of the region during stress. This uniformity suggests a common neural response pattern to stress, possibly reflecting an activation of a fundamental stress circuitry in the brain, resonating with the notion that stress might trigger a standardized neural response across individuals. Moreover, the analysis of Power Spectral Density and Relative Power reveals distinctive shifts in theta and alpha band activity, suggesting increased cognitive engagement and reduced cortical inhibition during stressful arithmetic tasks. Finally, the study explored the complexity of brain activity using Fractal Dimension. Lower Fractal Dimension values were observed during stress compared to the relaxed state, indicating a more regular and predictable pattern of brain activity under stress.

Index Terms— **index terms separated by semicolon**

1. Introduction

Stress is described as a state of anxiety or mental tension caused by challenging circumstances. Stress is a natural human response that prompts us to face difficulties and risks in our lives. Human body is designed to experience and react to stress and everyone experiences it to some extent. A little bit of stress is good and helps us in doing daily activities. Too much stress can cause mental and physical health problems.

Stress can be positive known as "eustress" and negative known as "distress". Distress can lead to physical symptoms such as lack of sleep, headache, upset stomach, chest pain, increased blood pressure, depression and anxiety. According to the World Health Organization (WHO), stress is a global epidemic, and it is estimated that around 300 million people worldwide suffer from depression. Every year, an estimated 12 billion working days are lost globally due to depression and anxiety, costing the economy $1 trillion USD in lost productivity.

To tackle this issue, several research works for stress detection have taken place. In fact, Mara Naegelin et al. (2023) [1] analyzes data from unobtrusive sources like keyboard use, mouse movements, and heart rate variability. The findings demonstrate that interpretable models using keyboard and mouse features outperform those based solely on heart rate variability, suggesting these behavioral cues hold promise for stress detection in office environments. Affanni (2020) [2] proposes a wireless sensor system for stress detection that utilizes both electrocardiogram (ECG) and electrodermal activity (EDA) signals. This non-intrusive approach transmits EDA data from the hands to a central ECG sensor on the chest for combined analysis. Additionally, research in stress detection has extended to analyzing EEG data. EEG-based approaches involve analyzing the brain's electrical activity to identify patterns associated with stress, offering valuable insights into the neural correlates of stress and complementing other physiological and behavioral modalities. The article conducts an in-depth analysis of EEG data to characterize the dynamics of brain activity during mental stress conditions.

The remainder of this paper is organized as follows: Section 2 reviews already existing methodologies for Stress Detection using EEG. Section 3 offers a detailed description of the dataset used and its format. Section 4 elaborates on the methodologies used for extracting the different features outlined in this paper, and Section 5 discusses the results obtained from said features. Section 6 contains conclusions and the directions for future work.

2. Literature Review

Malviya & Mal (2022) [3] demonstrated the potential of deep learning models for stress detection with impressive accuracy. Their approach combined convolutional and recurrent neural networks to extract EEG features. Salankar & Qaisar (2023) [4] took a different approach, focusing on the dynamic shifts in brain activity. Instead of a static snapshot, they analyzed "difference plots of variational modes," akin to capturing the subtle changes in tempo and harmony as the orchestra reacts to stress. This aligns with the emphasis on MSC's ability to reveal

Greater Relaxed State Variability

Our analysis revealed contrasting patterns in the variability of synchrony across states. In the stress domain, the scatter plots showcased remarkably straight and consistent trend lines, all nestled within the tight range of 0.1 to 0.15. This intriguing observation as shown in **Fig3 and Fig4** suggests a more uniform and predictable response to stress among the first 10 subjects (P1 to P10). It's as if, under pressure, brains synchronize in a homogeneous fashion.

Figure 3 Stressed State for first 10 Subjects

Figure 4 Relaxed State for first 10 Subjects

The lack of a clear trend in the relaxed state's scatter plot suggests individual variations in brain connectivity patterns during relaxation. This aligns with Chikhi et al. (2022) [19] highlighting the subjective nature of stress perception and individual coping mechanisms.

5.2 Power Spectral Density

5.3 Relative Power

When considering stress induced by arithmetic activities, analyzing the patterns of theta and alpha power can offer insights into the brain's response to cognitive demands and emotional stress associated with such tasks. Increased theta power indicates heightened cognitive demand and effort in problem-solving, while changes in alpha power signify shifts in emotional states and attention. By examining individual differences in these activity patterns, it becomes simpler to devise strategies for stress management and optimize task performance on an individual level. Essentially, studying theta and alpha power compares the brain's adaptive mechanisms in addressing the challenges posed by arithmetic activities.

Increased Relative Theta Power during Stress

The increase in theta power observed during stressful arithmetic tasks is associated with cognitive processes such as working memory and attention, both integral to arithmetic activities. This elevation in theta power suggests heightened cognitive engagement and reflects the brain's efforts to manage the demands of solving arithmetic problems under stress.

Electrode	Average Difference
Fz	0.06372
Fp1	0.06345
Fp2	0.05747
F4	0.05404
F3	0.05261
F8	0.04817
F7	0.04332
P3	0.03651
C3	0.03466
Pz	0.03393
Cz	0.03328
C4	0.02810
O1	0.02678
P4	0.02102
T3	0.01955
T5	0.01552
O2	0.01134
T6	0.00152
T4	0.00138

Table 3 The electrodes exhibiting the greatest differences between stressed and normal data for relative power of theta.

As given in Table 3, we identified the relative power of theta for stressed and normal data, noting a higher relative power of theta for the stressed data.We have observed that Fz and Fp1 electrodes show the highest difference for relative power of theta between stressed and relaxed states.

Fig.5 compares EEG data recorded from electrode Fz under stressed and relaxed conditions for 36 subjects. Consistently, the majority of patients display higher

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Thank You

Appendix B: Vision, Mission, Programme Outcomes and Course Outcomes

Vision, Mission, Programme Outcomes and Course Outcomes

Institute Vision

To evolve into a premier technological institution, moulding eminent professionals with creative minds, innovative ideas and sound practical skill, and to shape a future where technology works for the enrichment of mankind.

Institute Mission

To impart state-of-the-art knowledge to individuals in various technological disciplines and to inculcate in them a high degree of social consciousness and human values, thereby enabling them to face the challenges of life with courage and conviction.

Department Vision

To become a centre of excellence in Computer Science and Engineering, moulding professionals catering to the research and professional needs of national and international organizations.

Department Mission

To inspire and nurture students, with up-to-date knowledge in Computer Science and Engineering, ethics, team spirit, leadership abilities, innovation and creativity to come out with solutions meeting societal needs.

Programme Outcomes (PO)

Engineering Graduates will be able to:

1. Engineering Knowledge: Apply the knowledge of mathematics, science, engineering fundamentals, and an engineering specialization to the solution of complex engineering problems.

2. Problem analysis: Identify, formulate, review research literature, and analyze complex engineering problems reaching substantiated conclusions using first principles of mathematics, natural sciences, and engineering sciences.

3. Design/development of solutions: Design solutions for complex engineering problems and design system components or processes that meet the specified needs with appropriate consideration for the public health and safety, and the cultural, societal, and environmental considerations.

4. Conduct investigations of complex problems: Use research-based knowledge including design of experiments, analysis and interpretation of data, and synthesis of the information to provide valid conclusions.

5. Modern Tool Usage: Create, select, and apply appropriate techniques, resources, and modern engineering and IT tools including prediction and modeling to complex engineering activities with an understanding of the limitations.

6. The engineer and society: Apply reasoning informed by the contextual knowledge to assess societal, health, safety, legal, and cultural issues and the consequent responsibilities relevant to the professional engineering practice.

7. Environment and sustainability: Understand the impact of the professional engineering solutions in societal and environmental contexts, and demonstrate the knowledge of, and need for sustainable development.

8. Ethics: Apply ethical principles and commit to professional ethics and responsibilities and norms of the engineering practice.

9. Individual and Team work: Function effectively as an individual, and as a member or leader in teams, and in multidisciplinary settings.

10. Communication: Communicate effectively with the engineering community and with society at large. Be able to comprehend and write effective reports documentation. Make effective presentations, and give and receive clear instructions.

11. Project management and finance: Demonstrate knowledge and understanding of engineering and management principles and apply these to one's own work, as a member and leader in a team. Manage projects in multidisciplinary environments.

12. Life-long learning: Recognize the need for, and have the preparation and ability to engage in independent and lifelong learning in the broadest context of technological change.

Programme Specific Outcomes (PSO)

A graduate of the Computer Science and Engineering Program will demonstrate:

PSO1: Computer Science Specific Skills
The ability to identify, analyze and design solutions for complex engineering problems in multidisciplinary areas by understanding the core principles and concepts of computer science and thereby engage in national grand challenges.

PSO2: Programming and Software Development Skills
The ability to acquire programming efficiency by designing algorithms and applying standard practices in software project development to deliver quality software products meeting the demands of the industry.

PSO3: Professional Skills
The ability to apply the fundamentals of computer science in competitive research and to develop innovative products to meet the societal needs thereby evolving as an eminent researcher and entrepreneur.

Course Outcomes (CO)

Course Outcome 1: Model and solve real world problems by applying knowledge across domains (Cognitive knowledge level: Apply).

Course Outcome 2: Develop products, processes or technologies for sustainable and socially relevant applications (Cognitive knowledge level: Apply).

Course Outcome 3: Function effectively as an individual and as a leader in diverse teams and to comprehend and execute designated tasks (Cognitive knowledge level: Apply).

Course Outcome 4: Plan and execute tasks utilizing available resources within timelines, following ethical and professional norms (Cognitive knowledge level: Apply).

Course Outcome 5: Identify technology/research gaps and propose innovative/creative solutions (Cognitive knowledge level: Analyze).

Course Outcome 6: Organize and communicate technical and scientific findings effectively in written and oral forms (Cognitive knowledge level: Apply).

Appendix C: CO-PO-PSO Mapping

CO-PO AND CO-PSO MAPPING

	PO 1	PO 2	PO 3	PO 4	PO 5	PO 6	PO 7	PO 8	PO 9	PO 10	PO 11	PO 12	PSO 1	PSO 2	PSO 3
CO 1	2	2	2	1	2	2	2	1	1	1	1	2	3		
CO 2	2	2	2		1	3	3	1	1		1	1		2	
CO 3									3	2	2	1			3
CO 4					2			3	2	2	3	2			3
CO 5	2	3	3	1	2							1	3		
CO 6					2			2	2	3	1	1			3

3/2/1: high/medium/low

JUSTIFICATIONS FOR CO-PO MAPPING

MAPPING	LOW/MEDIUM/ HIGH	JUSTIFICATION
100003/ CS722U.1-PO1	M	Knowledge in the area of technology for project development using various tools results in better modeling.
100003/ CS722U.1-PO2	M	Knowledge acquired in the selected area of project development can be used to identify, formulate, review research literature, and analyze complex engineering problems reaching substantiated conclusions.

100003/ CS722U.1-PO3	M	Can use the acquired knowledge in designing solutions to complex problems.
100003/ CS722U.1-PO4	M	Can use the acquired knowledge in designing solutions to complex problems.
100003/ CS722U.1-PO5	H	Students are able to interpret, improve and redefine technical aspects for design of experiments, analysis and interpretation of data, and synthesis of the information to provide valid conclusions.
100003/ CS722U.1-PO6	M	Students are able to interpret, improve and redefine technical aspects by applying contextual knowledge to assess societal, health and consequential responsibilities relevant to professional engineering practices.
100003/ CS722U.1-PO7	M	Project development based on societal and environmental context solution identification is the need for sustainable development.
100003/ CS722U.1-PO8	L	Project development should be based on professional ethics and responsibilities.
100003/ CS722U.1-PO9	L	Project development using a systematic approach based on well defined principles will result in teamwork.
100003/ CS722U.1-PO10	M	Project brings technological changes in society.

100003/ CS722U.1-PO11	H	Acquiring knowledge for project development gathers skills in design, analysis, development and implementation of algorithms.
100003/ CS722U.1-PO12	H	Knowledge for project development contributes engineering skills in computing & information gatherings.
100003/ CS722U.2-PO1	H	Knowledge acquired for project development will also include systematic planning, developing, testing and implementation in computer science solutions in various domains.
100003/ CS722U.2-PO2	H	Project design and development using a systematic approach brings knowledge in mathematics and engineering fundamentals.
100003/ CS722U.2-PO3	H	Identifying, formulating and analyzing the project results in a systematic approach.
100003/ CS722U.2-PO5	H	Systematic approach is the tip for solving complex problems in various domains.
100003/ CS722U.2-PO6	H	Systematic approach in the technical and design aspects provide valid conclusions.
100003/ CS722U.2-PO7	H	Systematic approach in the technical and design aspects demonstrate the knowledge of sustainable development.

100003/ CS722U.2-PO8	M	Identification and justification of technical aspects of project development demonstrates the need for sustainable development.
100003/ CS722U.2-PO9	H	Apply professional ethics and responsibilities in engineering practice of development.
100003/ CS722U.2-PO11	H	Systematic approach also includes effective reporting and documentation which gives clear instructions.
100003/ CS722U.2-PO12	M	Project development using a systematic approach based on well defined principles will result in better teamwork.
100003/ CS722U.3-PO9	H	Project development as a team brings the ability to engage in independent and lifelong learning.
100003/ CS722U.3-PO10	H	Identification, formulation and justification in technical aspects will be based on acquiring skills in design and development of algorithms.
100003/ CS722U.3-PO11	H	Identification, formulation and justification in technical aspects provides the betterment of life in various domains.
100003/ CS722U.3-PO12	H	Students are able to interpret, improve and redefine technical aspects with mathematics, science and engineering fundamentals for the solutions of complex problems.

100003/ CS722U.4-PO5	H	Students are able to interpret, improve and redefine technical aspects with identification formulation and analysis of complex problems.
100003/ CS722U.4-PO8	H	Students are able to interpret, improve and redefine technical aspects to meet the specified needs with appropriate consideration for the public health and safety, and the cultural, societal, and environmental considerations.
100003/ CS722U.4-PO9	H	Students are able to interpret, improve and redefine technical aspects for design of experiments, analysis and interpretation of data, and synthesis of the information to provide valid conclusions.
100003/ CS722U.4-PO10	H	Create, select, and apply appropriate techniques, resources, and modern engineering and IT tools for better products.
100003/ CS722U.4-PO11	M	Students are able to interpret, improve and redefine technical aspects by applying contextual knowledge to assess societal, health and consequential responsibilities relevant to professional engineering practices.
100003/ CS722U.4-PO12	H	Students are able to interpret, improve and redefine technical aspects for demonstrating the knowledge of, and need for sustainable development.
100003/ CS722U.5-PO1	H	Students are able to interpret, improve and redefine technical aspects, apply ethical principles and commit to

		professional ethics and responsibilities and norms of the engineering practice.
100003/ CS722U.5-PO2	M	Students are able to interpret, improve and redefine technical aspects, communicate effectively on complex engineering activities with the engineering community and with society at large, such as, being able to comprehend and write effective reports and design documentation, make effective presentations, and give and receive clear instructions.
100003/ CS722U.5-PO3	H	Students are able to interpret, improve and redefine technical aspects to demonstrate knowledge and understanding of the engineering and management principle in multidisciplinary environments.
100003/ CS722U.5-PO4	H	Students are able to interpret, improve and redefine technical aspects, recognize the need for, and have the preparation and ability to engage in independent and life-long learning in the broadest context of technological change.
100003/ CS722U.5-PO5	M	Students are able to interpret, improve and redefine technical aspects in acquiring skills to design, analyze and develop algorithms and implement those using high-level programming languages.
100003/ CS722U.5-PO12	M	Students are able to interpret, improve and redefine technical aspects and contribute their engineering skills in computing and information engineering domains like network design and administration, database design and

		knowledge engineering.
100003/ CS722U.6-PO5	M	Students are able to interpret, improve and redefine technical aspects and develop strong skills in systematic planning, developing, testing, implementing and providing IT solutions for different domains which helps in the betterment of life.
100003/ CS722U.6-PO8	H	Students will be able to associate with a team as an effective team player for the development of technical projects by applying the knowledge of mathematics, science, engineering fundamentals, and an engineering specialization to the solution of complex engineering problems.
100003/ CS722U.6-PO9	H	Students will be able to associate with a team as an effective team player to Identify, formulate, review research literature, and analyze complex engineering problems
100003/ CS722U.6-PO10	M	Students will be able to associate with a team as an effective team player for designing solutions to complex engineering problems and design system components.
100003/ CS722U.6-PO11	M	Students will be able to associate with a team as an effective team player, use research-based knowledge and research methods including design of experiments, analysis and interpretation of data.
100003/ CS722U.6-PO12	H	Students will be able to associate with a team as an effective team player, applying ethical principles and

		commit to professional ethics and responsibilities and norms of the engineering practice.
100003/ CS722U.1-PSO1	H	Students are able to develop Computer Science Specific Skills by modeling and solving problems.
100003/ CS722U.2-PSO2	M	Developing products, processes or technologies for sustainable and socially relevant applications can promote Programming and Software Development Skills.
100003/ CS722U.3-PSO3	H	Working in a team can result in the effective development of Professional Skills.
100003/ CS722U.4-PSO3	H	Planning and scheduling can result in the effective development of Professional Skills.
100003/ CS722U.5-PSO1	H	Students are able to develop Computer Science Specific Skills by creating innovative solutions to problems.
100003/ CS722U.6-PSO3	H	Organizing and communicating technical and scientific findings can help in the effective development of Professional Skills.