MADRAS INSTITUTE OF TECHNOLOGY

ANNA UNIVERSITY, CHENNAI – 600 044

CS6611 - CREATIVE INNOVATIVE PROJECT

StressSense: A Cognitive IoMT Approach for Stress Level Detection

Submitted by:

Swathy K S(2021503052)

Vasanth S (2021503058)

Logith V L (2021503710)

Team No: 5

Supervisor: Dr. V P Jayachitra

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Introduction

In the rapidly evolving landscape of healthcare innovation, the fusion of Internet of Things (IoT) technology with Machine Learning (ML) algorithms stands as a pioneering frontier. Within this domain, IoT devices, ranging from wearable sensors to smart implants and remote monitoring systems, play a pivotal role in continuously acquiring real-time patient data. This influx of data forms the cornerstone for ML algorithms to conduct intricate analyses, facilitating the identification of nuanced patterns, prediction of diseases, customization of treatment protocols, and even the automation of medical interventions.

Stress has become one of the most prevalent issue in this generation without age barrier, due to heavy work loads and hectic schedules. Stress, in a broad way can be classified as acute stress or positive stress and chronic stress or negative stress. Acute stress is stress for short period of time, which helps to elevate performances and increase our capabilities. Chronic stress is considered as distress which persist for prolonged amount of time and can lead to various mental diseases like depression and also physical diseases ranging from cardiovascular diseases, immune system imbalances, and gastrointestinal issues to musculoskeletal disorders. In severe cases, stress can even precipitate heart attacks and fatalities. Hence, detection of stress at is earliest has become very crucial. While stress detection can be challenging for the general population, individuals typically have the advantage of verbal communication, making it somewhat easier to identify their stress levels. However, for people with disabilities, detecting stress poses even greater difficulties due to communication barriers and other limitations. While conventional techniques such as Galvanic Skin Response, Electromyogram, and Electrodermal Activity have been utilized for stress assessment, they may not be appropriate for this demographic due to factors such as impaired skin response or sweat regulation. To address this issue, this project utilizes the Internet of Medical Things (IoMT) technology, integrating electroencephalogram (EEG) and electrocardiogram (ECG) data with machine learning algorithms to accurately detect stress levels.

Problem Statement

- Stress escalates into various serious health problems, ranging from cardiovascular diseases, immune system imbalances, and gastrointestinal issues to musculoskeletal disorders. In severe cases, stress can even precipitate heart attacks and fatalities.
- Stress detection in differently abled individuals poses heightened challenges due to communication barriers, necessitating innovative solutions for early identification and intervention

Objective

Develop a novel solution leveraging Internet of Medical Things (IoMT) technology, integrating EEG and ECG data with machine learning algorithms, to accurately detect stress levels in differently abled individuals. This initiative aims to address the critical need for early identification and intervention of stress, mitigating the risk of serious health complications and improving overall well-being in this demographic.

Literature Survey

Muhammad Amin et al. in [2] develops seven models for real-world driver's stress levels detection using ECG signals based on Xception outperforming the other models. Anusha A. S. et al. in [5] proposes an automatic pre-surgery stress detection scheme based on EDA from the wrist, which involves an initial artifact detection phase followed by multilevel stress classification. [8] involves combining GSR and pulse sensors with a microcontroller for IoT connectivity, reading analog signals, signal processing, evaluation of processed sensor data, wireless transmission to a cloud platform and real-time evaluation of stress levels using algorithms. [7] involves training a deep learning system with different datasets of varying sample sizes for stress level detection. [11] aims to provide a comprehensive review of reliable and effective bio signal indices during stress conditions.

Houtan Jebelli et al. in paper [1] develops a framework that removes EEG signal artifacts and applies different OMTL algorithms to recognize individual’s stress in near real time and in controlled environment. The limitation lies in the fact that the training and testing phases involved only 32 subjects, which represents a notably small sample size. Tee Yi Wen et al. in [9] studies involved employing clustering methods to pre-label stress levels and then using SVM to classify the stress level, aiming to reduce subjective bias and improve the reliability and detection rate of mental stress. Alice Othmani et al. conducts a systematic review of clinical and nonclinical methods for PTSD detection using machine-learning-based approaches, utilizing machine learning techniques for the automatic recognition and assessment of PTSD using video and EEG data, and organizing the review into six sections covering various aspects of the study. [3] presents a novel multiclass classification framework, MuLHiTA, for early identification of mental stress levels, with high classification accuracies and visualization results related to attention weights and electrode placements.

[6] involved 15 participants wearing three commercial sensors to record physiological signals during the Maastricht Acute Stress Test. Salivary samples were collected throughout different phases of the test, and statistical analysis was performed using a SVM classification algorithm. [4] involves detecting stress through physiological markers, evaluating the model's performance using accuracy and F1-score, and conducting the study on four standard datasets for validation and generalizability.

In conclusion, the existing literature reveals several challenges in the field of feature selection and utilization for EEG-based systems. Many papers exhibit overlapping issues in their chosen features, leading to redundancy and potential inaccuracies in their results. Additionally, studies employing EEG often suffer from reduced accuracy, while others are limited by small sample sizes during testing phases. Furthermore, certain features, such as sweat rate, GSR, and EDA, may not be applicable for individuals with disabilities due to system compatibility issues.

SL NO	TITLE OF THE PAPER	NAME OF THE PAPER AND PUBLISHED YEAR	MODEL/ TECHNIQUES	LIMITATIONS
1.	A Continuously updated computationally efficient stress recognition framework using EEG by applying OMTL Algorithm	H. Jebelli, M. Mahdi Khalili and S. Lee; IEEE Journal of Biomedical and Health Informatics, pp. 1928-1939, Sept 2019.	▪ Extracts broad range of EEG signals ▪ Applies OMTL (Online multitask learning) algorithm ▪ Acc: 77.61%	▪ Lack of multimodality ▪ Lower accuracy

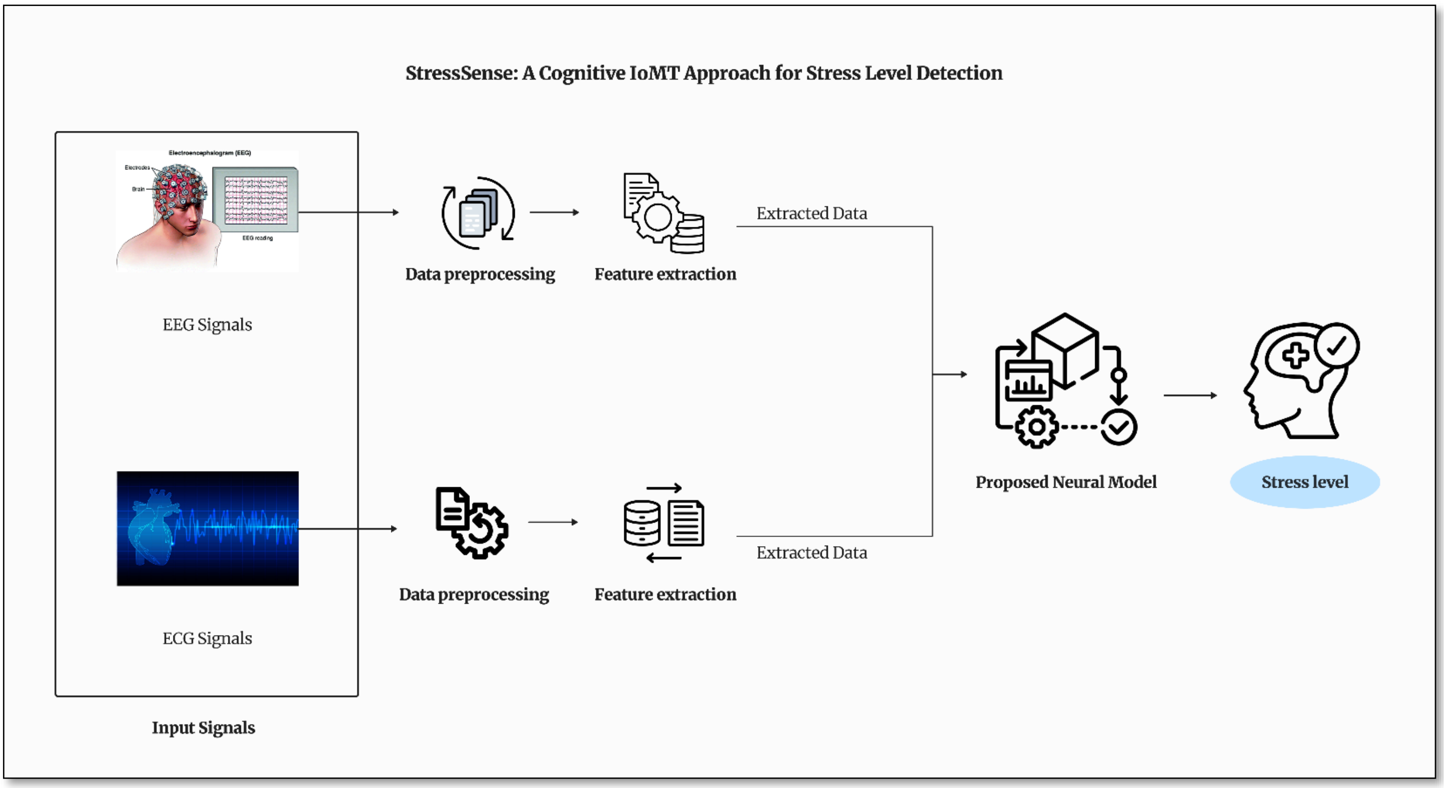
2.	ECG-Based Driver's Stress Detection Using Deep Transfer Learning and Fuzzy Logic Approaches	IEEE Access, vol. 10, pp. 29788-29809, 2022.	▪ Deep transfer learning with seven CNN-based models from ECG signals. ▪ Acc: 90.11%	▪ Lack of multimodality ▪ Overlapping issues
3.	MuLHiTA: A Novel Multiclass Classification Framework With Multibranch LSTM and Hierarchical Temporal Attention for Early Detection of Mental Stress	IEEE Transactions on Neural Networks and Learning Systems, vol. 34, no. 12, pp. 9657-9670, Dec. 2023.	▪ Multiclass classification framework, MuLHiTA	▪ Restricted generalizability due to complexity impacting interpretability.
4.	Multimodal Hierarchical CNN Feature Fusion for Stress Detection	IEEE Access, vol. 11, pp. 6867-6878, 2023.	▪ Detecting stress through physiological markers. ▪ Evaluation of performance using F1 score.	▪ Insufficient training data
5.	Electrodermal Activity Based Pre-surgery Stress Detection Using a Wrist Wearable	IEEE Journal of Biomedical and Health Informatics, vol. 24, no. 1, pp. 92-100, Jan. 2020.	▪ Development of supervised machine learning ▪ Electrodermal Activity (EDA)	▪ Insufficient training data
6.	Evaluation of an Integrated System of Wearable Physiological Sensors for Stress Monitoring in Working Environments by Using Biological Markers	IEEE Transactions on Biomedical Engineering, vol. 65, no. 8, pp. 1748-1758, Aug. 2018.	▪ Model developed using Support Vector Machine (SVM).	▪ Number of samples used for training is low.
7.	Stress-Lysis: A DNN-Integrated Edge Device for Stress Level Detection in the IoMT	IEEE Transactions on Consumer Electronics, vol. 65, no. 4, pp. 474-483, Nov. 2019.	▪ Introduces Stress-Lysis, a deep learning-based system.	▪ Overlapping issues
8.	Galvanic Skin Response based Stress Detection System using Machine Learning and IoT	2023 Second International Conference on Augmented Intelligence and Sustainable Systems (ICAISS), Trichy, India, 2023, pp. 709-714.	▪ Developed an IoT-based stress detection using GSR and pulse sensors.	▪ Overlapping issues
9.	Hybrid Approach of EEG Stress Level Classification Using K-Means Clustering and SVM	IEEE Access, vol. 10, pp. 18370-18379, 2022.	▪ Employing clustering methods to pre-label stress levels ▪ Usage of SVM to classify	▪ Influence of outliers and noisy data on k-means algorithm.
10.	Machine-Learning-Based Approaches for Post-Traumatic Stress	IEEE Sensors Journal, vol. 23, no. 20, pp. 24135-24151,	▪ A review of clinical and nonclinical methods for PTSD detection.	▪ Lack of multimodality

	Disorder Diagnosis Using Video and EEG Sensors: A Review	15 Oct.15, 2023.		
11.	Review on Psychological Stress Detection Using Biosignals	IEEE Transactions on Affective Computing, vol. 13, no. 1, pp. 440-460, 1 Jan.-March 2022.	▪ Provide a comprehensive review of reliable and effective bio signal indices during stress conditions.	▪ Lack of a comprehensive guideline on the relationship between the multitude of bio signal features
12.	Deep Learning Approach for Detecting Work-Related Stress Using Multimodal Signals	IEEE Sensors Journal, vol. 22, no. 12, pp. 11892-11902, 15 June15, 2022.	▪ A deep learning approach using multimodal signals ▪ Acc: 54.4%	▪ Overlapping issues ▪ Less accuracy

Proposed work

This study aims to address the prevalent mental health concern of stress by employing IoT sensors to measure Electroencephalogram (EEG) and Electrocardiogram (ECG) data, in conjunction with machine learning algorithms, with the goal of improving accuracy. By harnessing real-time physiological data and advanced analytics, the aim is to construct a predictive model adept at precisely discerning stress levels, particularly among individuals with disabilities. Data collected from these sensors undergoes extraction, followed by the application of machine learning algorithms and correlation analyses to formulate the model.

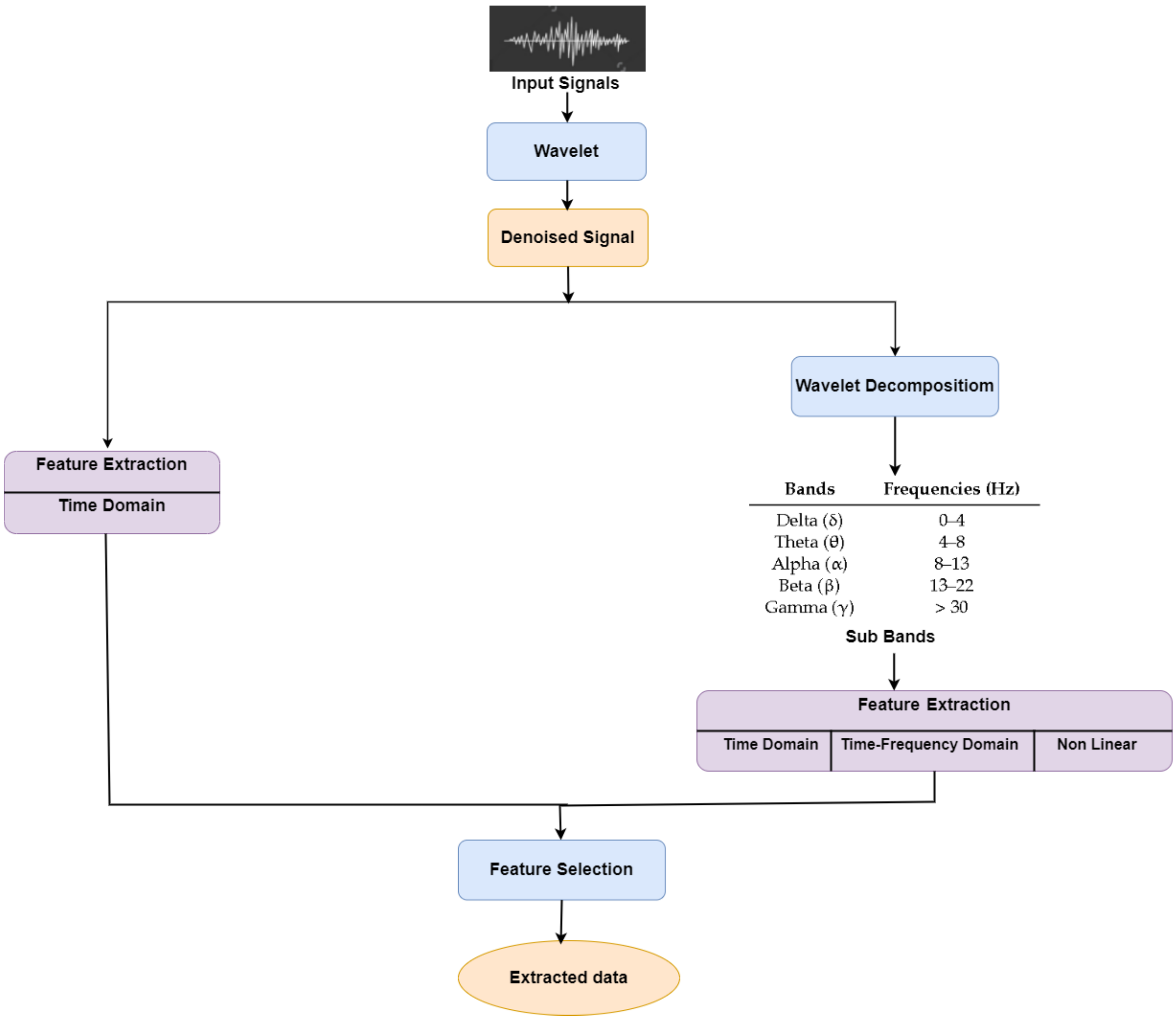
Architecture Diagram



Modules

1. **Data collection and preprocessing:** In this phase, raw EEG (Electroencephalogram) and ECG (Electrocardiogram) data are collected from sensors. The data undergo preprocessing steps such as filtering to remove noise, artifact removal, and normalization to ensure consistency and reliability in subsequent analysis.
2. **Feature Extraction**: Features relevant to stress detection are extracted from the preprocessed EEG and ECG signals.
3. **Early fusion:** Fusion of EEG and ECG signals based on correlated features like Power Spectral Density (PSD), elevated heart rate variability and altered brainwave frequencies.
4. **Model development:** Neural network architectures are designed to process EEG and ECG data for stress level detection. Model is trained using labeled data to effectively predict stress levels, leveraging the complementary information provided by EEG and ECG signals.
5. **Evaluation and Validation:** The model is evaluated using a separate set of labeled data to assess its performance in accurately predicting stress levels. Evaluation metrics such as accuracy, precision, recall, and F1 score are calculated to quantify the model's effectiveness.
6. **Optimization and Deployment**: The stress detection model is optimized for efficiency and scalability. Once optimized, the model is deployed in practical settings, such as wearable devices or healthcare systems.

Feature Extraction



Algorithm

```
Function Feature_Extraction(EEG_epoch):
        PSD = Calculate_PSD(EEG_epoch)
        Relative_Power = Calculate_Relative_Power(PSD)
        Average_Power = Calculate_Average_Power(PSD)
        Spectral_Entropy = Calculate_Spectral_Entropy(PSD)
        HFD = Calculate_HFD(EEG_epoch)
        Wavelet_Coefficients = Calculate_Wavelet_Coefficients(EEG_epoch)
        Wavelet_Features = Extract_Wavelet_Features(Wavelet_Coefficients)
    features.append(Relative_Power)
    features.append(Average_Power)
    features.append(Spectral_Entropy)
    features.append(HFD)
    features.extend(Wavelet_Features)
return 'features' as feature vector
Function Calculate_PSD(EEG_epoch):
        FFT_result = FFT(EEG_epoch)
        PSD = |FFT_result|^2
Function Calculate_Relative_Power(PSD):
        delta_band = [0.5, 4]
        theta_band = [4, 8]
        alpha_band = [8, 12]
        beta_band = [12, 30]
        gamma_band = [30, 100]
    total_power = sum(PSD)
    Relative_Power = [delta_power/total_power, theta_power/total_power, alpha_power/total_power,
beta_power/total_power, gamma_power/total_power]
Function Calculate_Average_Power(PSD):
        delta_band = [0.5, 4]
        theta_band = [4, 8]
        alpha_band = [8, 12]
        beta_band = [12, 30]
        gamma_band = [30, 100]
     Average_Power = [Integrate_PSD(PSD, delta_band)/(delta_band[1]-delta_band[0]),
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                    Integrate_PSD(PSD, theta_band)/(theta_band[1]-theta_band[0]),
                    Integrate_PSD(PSD, alpha_band)/(alpha_band[1]-alpha_band[0]),
                    Integrate_PSD(PSD, beta_band)/(beta_band[1]-beta_band[0]),
                    Integrate_PSD(PSD, gamma_band)/(gamma_band[1]-gamma_band[0])]
Function Calculate_Spectral_Entropy(PSD):
            normalized_PSD = PSD / sum(PSD)
             Spectral_Entropy = -sum(normalized_PSD * log2(normalized_PSD))
Function Calculate_HFD(EEG_epoch):
            k_max = floor((len(EEG_epoch)-1) / 2)
           HFD_values = []
    for k in range(1, k_max+1):
        L_k = Calculate_L_k(EEG_epoch, k)
        HFD_k = log(L_k) / log(1/k)
        HFD_values.append(HFD_k)
 HFD = mean(HFD_values)
Function Calculate_L_k(EEG_epoch, k):
           N = len(EEG_epoch)
    for m in range(1, k+1):
        Lm = 0
        for i in range(1, floor((N-m)/k)):
            Lm += abs(EEG_epoch[i+m*k] - EEG_epoch[i+(m-1)*k])
        Lm /= ((N-1)/((N-1)/k)*m*k)
        Lmk.append(Lm)
Function Calculate_Wavelet_Coefficients(EEG_epoch):
           DWT_coefficients = DWT(EEG_epoch)
Function Extract_Wavelet_Features(DWT_coefficients):
              wavelet_features = []
              for coeffs in DWT_coefficients:
                      mean_coeff = mean(coeffs)
                      std_coeff = std(coeffs)
                      energy_coeff = sum(coeffs**2)
                      entropy_coeff = -sum((coeffs*2) * log2(coeffs*2))
                      skewness_coeff = skew(coeffs)
                       kurtosis_coeff = kurtosis(coeffs)
```

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