Real-Time Mental Stress Detection Using Machine Learning and Wearable Sensors

A *MAJOR PROJECT REPORT* Submitted to

JAWAHARLAL NEHRU TECHNOLOGICAL UNIVERSITY-KAKINADA, KAKINADA

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

BACHELOR OF TECHNOLOGY

In

INFORMATION TECHNOLOGY

Submitted by

G. SONIYA (21KN1A1221)
N. VINAY KUMAR (21KN1A1245)
M. PRAVEEN KUMAR (21KN1A1241)

Under the esteemed Guidance of

Dr. M. Venkateswara Rao

Professor

DEPARTMENT OF INFORMATION TECHNOLOGY

NRI INSTITUTE OF TECHNOLOGY

(AUTONOMOUS)

Approved by AICTE, New Delhi :: Permanent Affiliation to JNTUK, Kakinada
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(2021 – 2025)

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Department of Information Technology

Certificate

This is to certify that the project work entitled **"Real-Time Mental Stress Detection Using Machine Learning and Wearable Sensors"** is a bonafide record work done by

G. SONIYA	(21KN1A1221)
N. VINAY KUMAR	(21KN1A1245)
M. PRAVEEN KUMAR	(21KN1A1241)

In the Department of Information Technology, **NRI Institute of Technology**, which is affiliated to JNTU-Kakinada in partial fulfillment of the requirements for the award of Bachelor of Technology in Information Technology during **2021-2025**. This work has been carried out under my guidance and supervision.

The results embodied in this Project report have not been submitted in any University or Organization for the award of any degree or diploma.

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DIN: 10252403

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Thanks for Your Valuable Guidance and kind support.

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DECLARATION

We hereby declare that project report entitled **"Real-Time Mental Stress Detection Using Machine Learning and Wearable Sensors"** is an authentic record of our own work carried out at **NRI Institute of Technology**, by us for the award of degree **B.Tech**(IT) from **JAWAHARLAL NEHRU TECHNOLOGICAL UNIVERSITY KAKINADA** , **KAKINADA** under the guidance of **Dr.M.Venkateswara Rao,Professor.**

Signature of the Students

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ABSTRACT

Stress is a heightened psycho-physiological state that arises as a response to challenging situations or demanding conditions, known as stressors. Prolonged exposure to multiple stressors, especially when they occur simultaneously, can have detrimental effects on an individual's mental and physical health, potentially leading to chronic health conditions such as anxiety, depression, and cardiovascular diseases. Early detection of stress is crucial to prevent these long-term effects, and continuous monitoring offers an effective solution. Wearable devices, which allow for real-time and continuous data collection, provide an opportunity for personal stress monitoring, helping individuals track their stress levels throughout the day. This paper presents a comprehensive review of various methods for stress detection using wearable sensors in combination with machine learning techniques.

It examines different types of wearable sensors such as Electrocardiogram (ECG), Electroencephalography (EEG), and Photoplethysmography (PPG), as well as the various environments in which stress is monitored, including activities like driving, studying, and working. The review delves into the different stress detection techniques employed in these contexts, highlighting the stressors, methodologies, results, advantages, limitations, and challenges faced in each study. These insights are expected to inform future research and improvements in the field of stress monitoring. Furthermore, the paper proposes a multimodal stress detection system that integrates multiple wearable sensor types with deep learning algorithms, offering a promising approach to more accurate and adaptive real-time stress detection, ultimately aiding in mental health management and preventive healthcare solutions.

Keywords: *Stress Detection, Wearable Sensors, Machine Learning, Electrocardiogram (ECG), Electroencephalography (EEG), Photoplethysmography (PPG), Real-time Monitoring, Mental Health, Psycho-physiological State, Continuous Monitoring, Deep Learning, Multimodal System, Stressors, Personalized Stress Management, Health Monitoring*

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LIST OF ABBREVATIONS

1	UML	UNIFIED MODELLING LANGUAGE
2	ML	MACHINE LEARNING
3	PCA	PRINCIPLE COMPONENT ANALYSIS
4	SVM	SUPPORT VECTOR MACHINE
5	LGBM	LIGHT GRADIENT BOOSTING MACHINE
6	XGBM	EXTREME GRADIENT BOOSTING MACHINE

CHAPTER - 1

1. INTRODUCTION

1.1 INTRODUCTION:

Stress is an inevitable part of life, and while short-term stress can enhance focus and performance, prolonged stress can lead to severe health issues such as anxiety, depression, cardiovascular diseases, and weakened immunity. Early detection and effective management are crucial for maintaining overall well-being.

Traditional stress assessment methods, such as self-reported questionnaires and psychological evaluations, often lack objectivity and real-time monitoring capabilities. However, advancements in wearable sensor technology and machine learning have revolutionized stress detection by enabling continuous and objective monitoring of physiological signals.

These signals include heart rate variability (ECG), brain activity (EEG), skin conductance (PPG), and other biosignals that indicate stress levels. Wearable devices like smartwatches, biomedical sensors, and fitness trackers play a vital role in collecting these signals and transmitting them for real-time analysis.

Machine learning algorithms process this physiological data to detect stress with greater accuracy compared to traditional methods. By identifying patterns and correlations in stress-related biomarkers, AI-driven models can predict and classify stress levels more effectively. Different scenarios, including workplace pressure, academic stress, and driving fatigue, contribute to elevated stress levels, making real-time monitoring an invaluable tool for timely intervention.

Despite these advancements, challenges such as sensor reliability, data privacy, and algorithmic biases remain significant concerns. This study reviews various stress detection techniques, their advantages and limitations, and proposes a multimodal framework that integrates multiple physiological sensors with deep learning models. By enhancing the accuracy and reliability of stress detection systems, this approach can lead to improved mental health management, personalized interventions, and more effective preventive healthcare solutions.

1.2 PROBLEM DEFINITION:

Stress affects mental and physical health, leading to issues like anxiety and heart disease. Early detection is crucial, but traditional methods are subjective and impractical for continuous monitoring. Wearable sensors offer real-time stress detection by capturing physiological signals like heart rate and brain activity. However, processing this data is challenging. Machine learning enables accurate stress detection by analyzing multi-modal data.

The key challenge is developing a reliable system that ensures accuracy, handles data variability, and operates in real-time. Privacy and user comfort are also essential. Addressing these challenges can lead to effective stress management solutions, improving overall well-being.

1.3 SOLUTION FOR PROBLEM DEFINITION:

To enhance real-time stress detection, this research proposes a multimodal machine learning (ML) framework that improves accuracy, efficiency, and adaptability by:

1. **Multimodal Data Integration** – Combining physiological signals such as ECG, EEG, and PPG to capture comprehensive stress indicators.
2. **Advanced Feature Extraction** – Utilizing deep learning techniques to extract relevant features from physiological data for improved stress classification.
3. **Real-Time Processing** – Implementing optimized ML algorithms to ensure low-latency stress detection suitable for real-time applications.
4. **Personalized Stress Models** – Developing adaptive models that consider individual differences in stress responses, influenced by genetics, lifestyle, and environment.
5. **Privacy and Security Enhancements** – Incorporating secure data encryption and federated learning techniques to protect user privacy.
6. **Wearable-Edge Computing Integration** – Leveraging edge AI to reduce dependency on cloud computing, improving speed and efficiency.
7. **Explainable AI (XAI) Implementation** – Ensuring transparency in stress detection decisions by using interpretable ML models.

By addressing these critical aspects, the proposed framework aims to improve stress monitoring accuracy, enhance user comfort, and provide real-time, adaptive solutions for stress management and mental health intervention.

1.4 PROJECT REQUISITES ACCUMULATION AND ANALYSIS:

This is the first and most crucial stage of any project. Since our project is an academic endeavor, we gathered the necessary requisites by referring to IEEE journals and collecting multiple IEEE-related research papers. After careful evaluation, we selected a paper titled "A Review on Mental Stress Detection Using Wearable Sensors and Machine Learing Techniques." For the analysis phase, we conducted a literature survey based on references from this paper and reviewed additional research papers to gain deeper insights.

Application System Design

The system design phase is divided into three key components:

1. GUI Design – This involves designing the graphical user interface to enhance user interaction.
2. UML Design – This includes creating use case diagrams, sequence diagrams, and class diagrams to illustrate system flow, actors, and their interactions. The class diagram provides details about various classes and the methods used within the project.
3. Database Design – The database is structured based on the number of project modules to ensure efficient data management.

Practical Implementation

The implementation phase focuses on converting the design into a working system. During this stage, most of the business logic and coding are executed. This is a crucial phase where the planned system is brought to life through coding and integration.

Manual Testing of the Application

The developer performs manual testing at every stage of the project to identify and resolve errors. Any bugs or issues encountered during development are fixed through continuous testing and refinement. Runtime errors and functionality issues are also addressed in this phase.

Application Deployment

Since this is an academic project, we did not implement automated testing. Instead, we followed a manual testing approach, using a trial-and-error method to verify system performance and functionality.

Project Maintenance

Once the project was completed, we deployed it in our college laboratory environment, ensuring that all necessary software and Windows OS were available. Although real-world deployment was not performed, the system was tested under simulated conditions within our academic setting.

CHAPTER - 2

2.LITERATURE REVIEW

2.1 Paper Title: “A Review of EEG Sensors Used for Data Acquisition “

Authors: A. Tyagi, S. Semwal, and G. Shah.

Published In: Proceedings of the National Conference on Future Aspects of Artificial Intelligence in Industrial Automation (NCFAAIIA), May 2012.

Summary: This paper provides a comprehensive review of EEG sensors used for acquiring brain signal data, particularly in artificial intelligence and industrial automation. It highlights the advancements in EEG technology and compares various sensors based on their efficiency and application areas. The authors discuss the challenges associated with signal acquisition, such as noise and artifact handling. The study emphasizes the importance of selecting appropriate sensors for specific use cases. It serves as a foundational reference for researchers exploring EEG-based applications.

2.2 Paper Title: “Support Vector Machine for Classification of Stress Subjects Using EEG Signals”

Authors: M. M. Sani, H. Norhazman, H. A. Omar, N. Zaini, and S. A. Ghani.

Published In: IEEE Conference on Systems, Process Control (ICSPC), Kuala Lumpur, Malaysia, December 2014.

Summary: This paper examines the effectiveness of Support Vector Machine (SVM) algorithms in classifying stress levels based on EEG signals. The authors analyze EEG data to differentiate between stress and non-stress subjects, demonstrating SVM’s superior accuracy in such tasks. It highlights the importance of EEG signal preprocessing and feature extraction for optimal classification performance. The study also discusses practical challenges like dataset variability and computational requirements. The results underline SVM’s potential as a robust tool for stress detection using EEG signals.

2.3 Paper Title: “An Effective Mental Stress State Detection and Evaluation System Using Minimum Number of Frontal Brain Electrodes”

Authors: O. Attallah.

Published In: Diagnostics, Volume 10, Issue 5, May 2020.

Summary: This research introduces a stress detection system utilizing a minimal number of frontal brain electrodes. The goal is to simplify the stress detection process while maintaining high accuracy. The system relies on advanced feature extraction and machine learning techniques to analyze EEG signals efficiently. The study shows that using fewer electrodes reduces cost and complexity without compromising reliability. This approach is particularly useful for wearable and portable stress detection devices in real-world applications.

2.4 Paper Title:"EEG-Based Emotion, Mental Workload, and Stress Visual Monitoring"

Authors: X. Hou, Y. Liu, O. Sourina, and W. Mueller-Wittig.

Published In: International Conference on Cyberworlds (CW), Visby, Sweden, October 2015.

Summary: Cogni Meter is a system that visualizes emotions, mental workload, and stress levels using EEG signals. The paper demonstrates how real-time EEG analysis can provide insights into cognitive states, making it valuable for applications like workplace monitoring and mental health assessments. The authors explain the system architecture, including data acquisition, processing, and visualization techniques. It highlights the challenges of interpreting EEG data in dynamic environments. The study showcases how Cogni Meter bridges the gap between EEG research and practical applications.

2.5 Paper Title:"EEG-Based Stress Level Identification"

Authors: G. Jun and K. G. Smitha.

Published In: IEEE International Conference on Systems, Man, and Cybernetics (SMC), Budapest, Hungary, October 2016.

Summary: This paper explores the identification of stress levels using EEG signals, focusing on feature extraction and classification techniques. The authors use advanced algorithms to analyze EEG data and identify stress patterns with high accuracy. The study addresses challenges like variability in EEG signals and the need for robust feature selection methods. It emphasizes the role of EEG-based stress detection in healthcare and workplace applications. The findings demonstrate the feasibility of using EEG as a reliable tool for stress monitoring and management.

CHAPTER - 3

3 .SYSTEM ANALYSIS

3.1. EXISTING SYSTEM:

Stress, a heightened psycho-physiological state, arises in response to demanding conditions or challenging events. Environmental factors triggering stress, termed stressors, can negatively impact mental and physical health, especially with prolonged exposure.

Chronic stress can lead to severe health complications, necessitating early detection and intervention. Continuous stress monitoring plays a vital role in addressing stress-related issues, and wearable devices have emerged as a promising solution. These devices enable real-time and continuous data collection, facilitating personal stress monitoring and early intervention.

A multimodal stress detection system has been proposed, leveraging wearable sensors and deep learning techniques. This approach aims to enhance the accuracy and reliability of stress detection by combining multiple data sources and advanced computational methods.

While wearable devices offer significant advantages, including convenience and real-time monitoring, challenges like data privacy, device comfort, and accuracy under varying conditions remain. Addressing these limitations is critical for the development of robust and user-friendly stress detection systems.

1. **Definition and Impact:** Stress arises from challenging events, with prolonged exposure leading to chronic health issues.
2. **Need for Monitoring:** Early detection via continuous monitoring is vital for managing stress effectively.
3. **Wearable Devices:** Real-time data collection through wearable sensors enables personal stress monitoring.
4. **Techniques Explored:** Studies employ ECG, EEG, PPG sensors with machine learning for stress detection.
5. **Proposed System:** A machine learning-based approach using wearable sensors promises enhanced accuracy.

Disadvantages:

1. **Data Variability and Accuracy Issues** : Physiological signals can vary significantly among individuals due to genetic, lifestyle, and environmental differences, making it challenging to develop a universally accurate model.

2. **Sensor Reliability and Wearability** : Wearable devices may suffer from inconsistent data collection due to motion artifacts, sensor placement, or user discomfort, leading to reduced accuracy and reliability.
3. **Real-Time Processing Constraints** :Processing large volumes of multimodal physiological data in real-time requires high computational power, which can cause latency issues, especially in edge-based or mobile applications.
4. **Privacy and Security Risks** :Continuous data collection raises concerns about user privacy and data security, as sensitive physiological information must be transmitted and stored securely.
5. **High Implementation Costs** : The integration of multiple sensors, deep learning algorithms, and secure data processing mechanisms can make the system expensive, limiting accessibility for large-scale deployment.

3.2PROPOSED SYSTEM:

Stress significantly impacts mental and physical health, with prolonged exposure leading to chronic issues like anxiety, depression, and cardiovascular diseases. Traditional stress detection methods, such as self-assessments and clinical evaluations, are subjective and unsuitable for continuous monitoring.

Wearable sensors offer real-time data collection, but translating this data into actionable insights remains a challenge. Machine learning (ML) techniques provide a solution by enabling the analysis of complex, multimodal data. The key problem is developing a robust ML-based stress detection system that ensures high accuracy, adapts to diverse environments, operates in real-time, and addresses challenges like data variability, user comfort, and privacy.

Advantages:

1. **Continuous Monitoring** :Wearable sensors provide real-time data on physiological signals like heart rate and skin conductance, allowing for continuous stress tracking and insights into stress triggers.
2. **Personalized Stress Detection**:Machine learning algorithms adapt to individual stress patterns, enhancing detection accuracy by identifying unique stress responses.
3. **Real-Time Stress Feedback** :Immediate feedback enables users to take timely actions, such as deep breathing or relaxation techniques, to manage stress effectively.
4. **Early Detection of Stress** :Identifying stress early helps prevent severe conditions like anxiety, depression, or cardiovascular diseases, promoting better mental and physical health.
5. **Integration with Other Health Monitoring Systems** : The system can be combined

with other health metrics like sleep, physical activity, and nutrition for a more holistic approach to well-being.

3.3 ALGORITHMS:

- **Decision Tree:**

A decision tree is a non-parametric supervised learning algorithm, which is utilized for both classification and regression tasks. It has a hierarchical, tree structure, which consists of a root node, branches, internal nodes and leaf nodes.

- **Gradient Boosting**

Gradient Boosting is a popular boosting algorithm in machine learning used for classification and regression tasks. Boosting is one kind of ensemble Learning method which trains the model sequentially and each new model tries to correct the previous model. It combines several weak learners into strong learners.

- **XGBoost**

XGBoost is a scalable and highly accurate implementation of gradient boosting that pushes the limits of computing power for boosted tree algorithms, being built largely for energizing machine learning model performance and computational speed.

- **CatBoost**

CatBoost or Categorical Boosting is an open-source boosting library developed by Yandex. It is designed for use on problems like regression and classification having a very large number of independent features.

Catboost is a variant of gradient boosting that can handle both categorical and numerical features. It does not require any feature encodings techniques like One-Hot Encoder or Label Encoder to convert categorical features into numerical features.

It also uses an algorithm called symmetric weighted quantile sketch(SWQS) which automatically handles the missing values in the dataset to reduce overfitting and improve the overall performance of the dataset.

- **LightGBM**

LightGBM with Focal Loss: An implementation of the focal loss to be used with LightGBM for binary and multi-class classification problems. The companion Medium post can be found here.

3.4 MODULES:

1. **Data Collection Module**:

   Using this module, we gather real-time physiological data from wearable sensors.

   - **Wearable Devices:** Devices like smartwatches, fitness bands, or specialized patches capture signals related to stress, such as heart rate, skin conductance, temperature, and movement.

- **Data Sources:**
  - Heart Rate Monitor (HRM): Measures heart rate and variability, which can indicate stress.
  - Electrodermal Activity (EDA) Sensors: Tracks skin conductance linked to stress responses.
  - Temperature Sensors: Measures skin or body temperature, affected by stress.
  - Accelerometers: Detect movement patterns that may signal stress.

    The collected data is transmitted in real-time for processing.

2. **Data Preprocessing Module:**

   This module prepares raw sensor data for analysis.

   - Noise Removal: Filters out unwanted noise from sensor signals using methods like low-pass filters.
   - Normalization: Adjusts data values to a consistent range for accurate model performance.
   - Feature Extraction: Identifies key stress indicators from sensor data, like heart rate variability (HRV), skin conductance level (SCL), and movement patterns.

3. **Feature Selection/Dimensionality Reduction Module:**

   This module ensures the use of only relevant features for improved model accuracy.

   - Feature Selection: Techniques like Recursive Feature Elimination (RFE) help eliminate redundant features.
   - Dimensionality Reduction: Methods like Principal Component Analysis (PCA) reduce the number of features, preserving important variance.

4. **Machine Learning Model Module:**

   This module uses machine learning algorithms to classify stress levels based on sensor data.

   - Supervised Learning: Trained using labeled datasets to predict stress levels.
   - Algorithms: Models such as SVM, Random Forest, KNN, and XGBoost are employed for accurate classification.
   - Real-Time Prediction: The model processes real-time data to classify stress levels and provide feedback.

5. **Feedback and User Interaction Module:**

1. **Stress Level Notification:** Users receive real-time notifications, such as vibration alerts or smartphone pop-ups, when stress levels are detected as high. These alerts can be customized based on the severity of stress.
2. **Personalized Recommendations:** The system offers tailored stress management suggestions, such as deep breathing exercises, guided meditation, or physical activity prompts. It can also integrate with health apps to recommend lifestyle modifications.
3. **Intervention Triggers:** Automated interventions, such as mindfulness reminders, guided breathing exercises, or relaxation music suggestions, are activated when necessary. The system can also dim screen brightness, reduce notifications, or suggest short breaks to alleviate stress.
4. **Historical Data Analysis:** Users can track their stress patterns over time through a dashboard, providing insights into recurring stress triggers and helping them adopt healthier coping strategies.
5. **Adaptive Learning:** The system continuously refines its recommendations by learning from user interactions and feedback, ensuring that stress management techniques are increasingly personalized and effective.
6. **Integration with External Support:** If persistent high stress levels are detected, the system can suggest consulting a mental health professional or provide emergency contact options for immediate support.

The real-time mental stress detection system provides a comprehensive approach to managing stress by integrating advanced monitoring and intervention features. Users receive instant notifications, such as smartphone pop-ups or vibration alerts, whenever high stress levels are detected, with customizable alerts based on severity. To help individuals manage their stress, the system offers personalized recommendations, including deep breathing exercises, guided meditation, and physical activity prompts, while also integrating with health apps for lifestyle modifications. Automated intervention triggers ensure timely support by providing mindfulness reminders, guided breathing exercises, relaxation music suggestions, and even adjusting screen brightness or reducing notifications to minimize stressors. Through historical data analysis, users can track their stress patterns over time using an interactive dashboard, gaining valuable insights into recurring triggers and adopting healthier coping strategies. The system continuously enhances its effectiveness through adaptive learning, refining recommendations based on user interactions and feedback, ensuring increasingly personalized and impactful stress management techniques. a mental health professional or provide emergency contact options, offering crucial external support when needed.

CHAPTER - 4

4.SYSTEM REQUIREMEN SPECIFICATION

4.1 FUNCTIONAL REQUIREMENTS:

In software engineering, a functional requirement defines a function of a software system or its component. A function is described as a set of inputs, the behaviour, and outputs (see also software). Functional requirements may be calculations, technical details, data manipulation and processing and other specific functionality that define what a system is supposed to accomplish. Behavioral requirements describing all the cases where the system uses the functional requirements are captured in use cases. Generally, functional requirements are expressed in the form “system shall do <requirement>”. The plan for implementing functional requirements is detailed in the system design. In requirements engineering, functional requirements specify particular results of a system. Functional requirements drive the application architecture of a system. A requirements analyst generates use cases after gathering and validating a set of functional requirements. The hierarchy of functional requirements is: user/stakeholder request -> feature -> use case -> business rule. Functional requirements drive the application architecture of a system. A requirements analyst generates use cases after gathering and validating a set of functional requirements. Functional requirements may be technical details, data manipulation and other specific functionality of the project is to provide the information to the user.

The following are the functional requirements:

- It should meet the functional requirements as mentioned in Objectives.
- It should be able to find all places those are registered in Weather database.

4.2 NON-FUNCTIONAL REQUIREMENTS:

In systems engineering and requirements engineering, a non-functional requirement is a requirement that specifies criteria that can be used to judge the operation of a system, rather than specific behaviors.

The project non-functional requirements include the following:

- Updating work status
- Problem solution
- Error occurrence in system
- Customer requests

Availability: A system’s “availability” or “uptime” is the amount of time that operational and available for use. It’s related to the server providing the service to the users displaying images.

As our system will be used by thousands of users at any time our system must be available always. If there are any cases of updates they must be performed in a short interval of time without interrupting the normal services made available to the users.

Efficiency: Specifies how well the software utilizes scarce resources: CPU cycles, disk space, memory, bandwidth etc. All of the above mentioned resources can be effectively used by performing most of the validations at client

Flexibility: If the organization intends to increase or extend the functionality of the software after it is deployed, that should be planned from the beginning; it influences choices made during the design, development, testing and deployment of the system. New modules can be easily integrated to our system without disturbing the existing modules or modifying the logical database schema of the existing applications.

Portability: Portability specifies the ease with which the software can be installed on all necessary platforms, and the platforms on which it is expected to run. By using appropriate server versions released for different platforms our project can be easily operated on any operating system, hence can be said highly portable.

4.3 SYSTEM REQUIREMENTS:

4.3.1 HARDWARE REQUIREMENTS:

- Operating System : Windows Only
- Processor : i5 and above
- Ram : 8gb and above
- Hard Disk : 25 GB in local drive

4.3.2 SOFTWARE REQUIREMENTS:

- Software : Anaconda
- Primary Language : Python
- Frontend Framework : Flask
- Back-end Framework : Jupyter Notebook
- Front-End Technologies : HTML, CSS, JavaScript

CHAPTER - 5

5.FEASABILITY STUDY

5.1FEASIBILITY STUDY:

Feasibility Study is a high-level capsule version of the entire process intended to answer a number of questions like: What is the problem? Is there any feasible solution to the given problem? Is the problem even worth solving? Feasibility study is conducted once the problem clearly understood. Feasibility study is necessary to determine that the proposed system is Feasible by considering the technical, Operational, and Economical factors. By having a detailed feasibility study the management will have a clear-cut view of the proposed system.

The following feasibilities are considered for the project in order to ensure that the project is variable and it does not have any major obstructions. Feasibility study encompasses the following things.

- Technical
- Economical
- Operational

5.2TYPES OF FEASIBILITY STUDY:

A feasibility analysis evaluates the project's potential for success; therefore, perceived objectivity is an essential factor in the credibility of the study for potential investors and lending institutions. There are five types of feasibility study—separate areas that a feasibility study examines, described below.

5.2.1 TECHNICAL FEASIBILITY:

This assessment focuses on the technical resources available to the organization. It helps organizations determine whether the technical resources meet capacity and whether the technical team is capable of converting the ideas into working systems. Technical feasibility also involves the evaluation of the hardware, software, and other technical requirements of the proposed system. As an exaggerated example, an organization wouldn't want to try to put Star Trek's transporters in their building—currently, this project is not technically feasible.

5.2.2 ECONOMIC FEASIBILITY:

This assessment typically involves a cost/ benefits analysis of the project, helping organizations determine the viability, cost, and benefits associated with a project before financial resources are allocated. It also serves as an independent project assessment and enhances project credibility helping decision-makers determine the positive economic benefits to the organization that the proposed project will provide.

5.2.3 LEGAL FEASIBILITY:

This assessment investigates whether any aspect of the proposed project conflicts with legal requirements like zoning laws, data protection acts or social media laws. Let’s say an organization wants to construct a new office building in a specific location. A feasibility study might reveal the organization’s ideal location isn’t zoned for that type of business. That organization has just saved considerable time and effort by learning that their project was not feasible right from the beginning.

5.2.4 OPERATIONAL FEASIBILITY:

This assessment involves undertaking a study to analyze and determine whether—and how well— the organization’s needs can be met by completing the project. Operational feasibility studies also examine how a project plan satisfies the requirements identified in the requirements analysis phase of system development.

This assessment is the most important for project success; after all, a project will fail if not completed on time. In scheduling feasibility, an organization estimates how much time the project will take to complete. When these areas have all been examined, the feasibility analysis helps identify any constraints the proposed project may face, including: • Internal Project Constraints: Technical, Technology, Budget, Resource, etc.

Internal Corporate Constraints: Financial, Marketing, Export, etc.

External Constraints: Logistics, Environment, Laws, and Regulations, etc.

Operational feasibility refers to the practicality of implementing a proposed system or solution within an organization's existing infrastructure, processes, and resources. In the context of analyzing women's safety in Indian cities using machine learning tweets, operational feasibility assesses whether the proposed approach can be effectively deployed and integrated into existing systems and workflows. Several factors contribute to operational feasibility.

operational feasibility plays a critical role in determining the success of a project aimed at analyzing women's safety in Indian cities using machine learning tweets. By carefully evaluating resource availability, compatibility, user acceptance, scalability, legal compliance, and risk factors, organizations can make informed decisions about the feasibility of implementing the proposed solution and take appropriate measures to mitigate potential challenges.

5.2.5 SCHEDULING FEASIBILITY:

Scheduling feasibility assesses the practicality of implementing a proposed system or solution within a specific timeframe, considering deadlines, milestones, and other time-related constraints. In the context of analysing women's safety in Indian cities using machine learning tweets, scheduling feasibility involves evaluating whether the project can be completed within the desired timeframe and whether the proposed timeline aligns with organizational goals.

CHAPTER - 6

6. SOFTWARE DESIGN

We have used the following designs to implement our system and this design is a process to transfer user requirements into some suitable form, which helps the programmer which helps the programmer in software coding and implementation.

6.1 ARCHITECTURE DIAGRAM:

An architecture diagram is a visual representation of all the elements that make up part, or all, of a system. Above all, it helps the engineers, designers, stakeholders — and anyone else involved in the project — understand a system or app's layout.

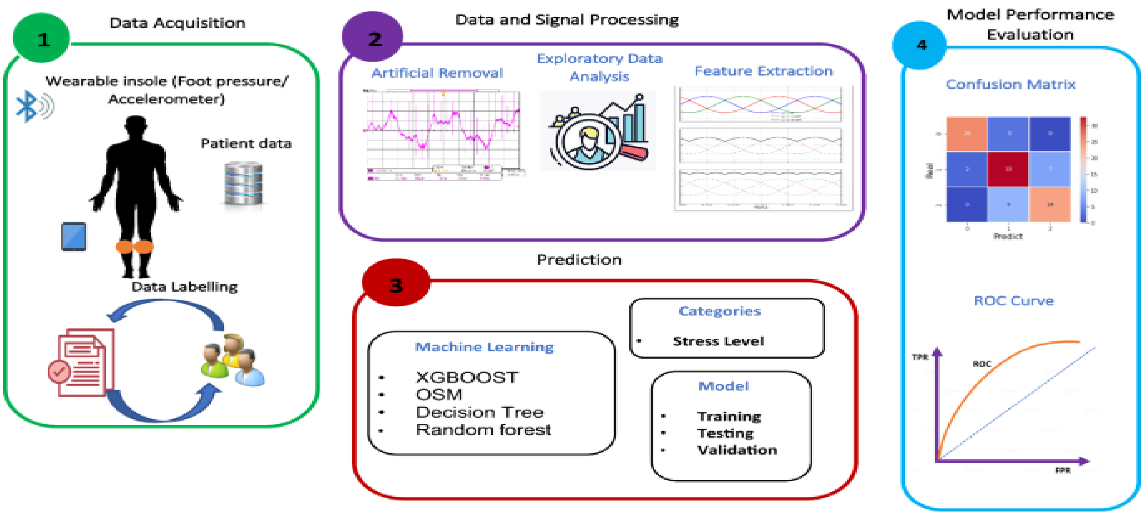

Fig 6.1.Architecture diagram

6.2 UML DIAGRAMS:

It is the general-purpose modelling language used to visualize the system. It is a graphical language that is standard to the software industry for specifying, visualizing, constructing, and documenting the artifacts of the software systems, as well as for business modelling.

6.2.1 USE CASE DIAGRAM:

Use case diagram represents an efficient system for real-time stress detection. The process starts with the user wearing a device equipped with sensors that continuously collect physiological data. This data is then sent to a preprocessing module, which cleans and normalizes it. The processed data is analyzed by a machine learning model to predict stress levels. If stress is detected, a feedback system is triggered to notify the user and provide personalized recommendations. The data is securely stored in the cloud for ongoing analysis and improvement. Overall, this system ensures timely stress detection and proactive stress management.

These diagrams contain actors, use cases, and their relationships.

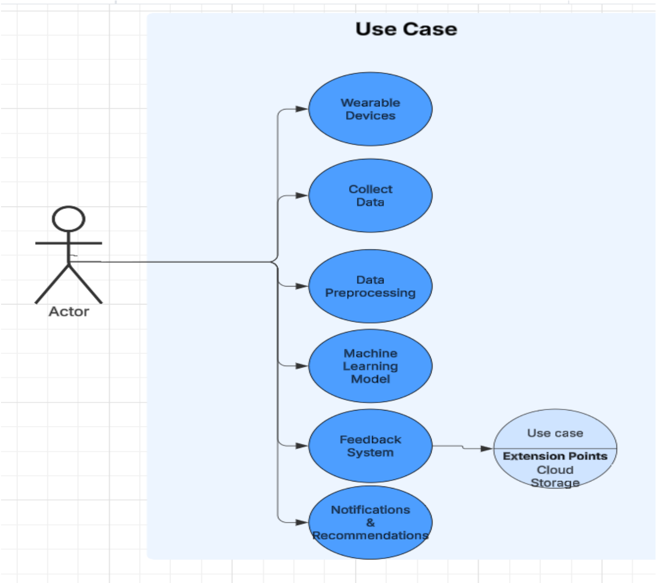

Fig 6.2.1 Use case diagram

6.2.2 CLASS DIAGRAM:

Class diagram is a static diagram. It represents the static view of an application. Class diagram is not only used for visualizing, describing, and documenting different aspects of a system but also for constructing executable code of the software application. Class diagram describes the attributes and operations of a class and also the constraints imposed on the system. The class diagrams are widely used in the modelling of object-oriented systems because they are the only UML diagrams, which can be mapped directly with object-oriented languages. Class diagram shows a collection of classes, interfaces, associations, collaborations, and constraints. It is also known as a structural diagram.

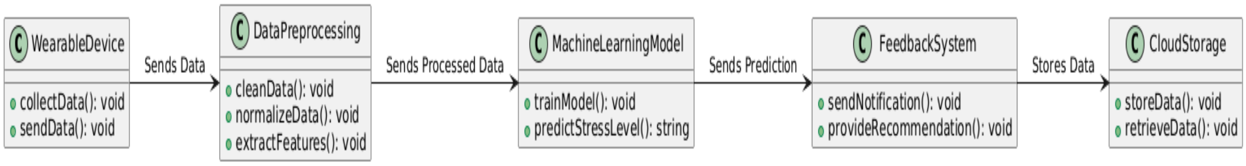

Fig 6.2.2 Class diagram

6.3.3 OBJECT DIAGRAM:

An object diagram shows the structure of a system at a specific moment in time. It represents:

- Concrete objects/instances in the system
- Their attributes and current values
- Relationships between objects
- How objects interact with each other

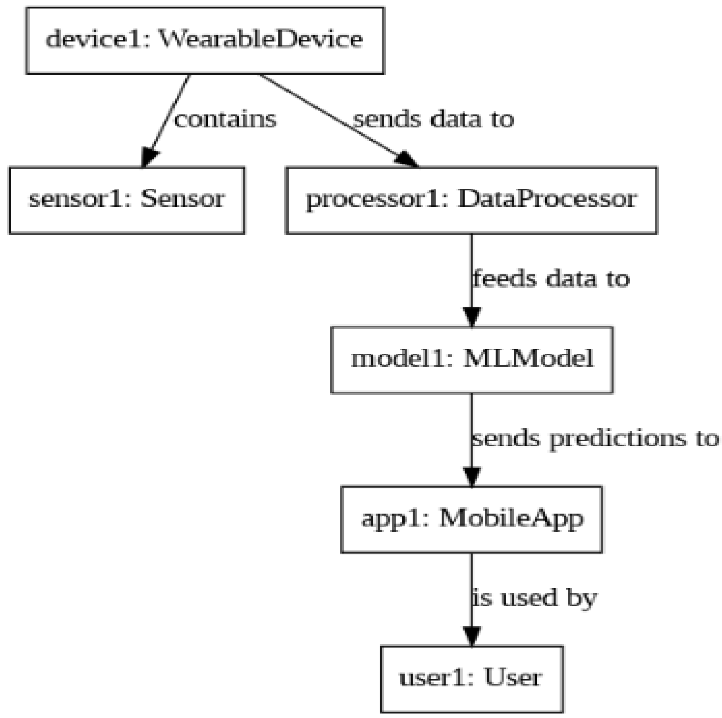

Fig 6.2.3 Object diagram

6.2.4 SEQUENCE DIAGRAM:

A sequence diagram for the analysis of women safety in Indian cities using Machine Learning on tweets would visualize the interactions and messages exchanged between the different objects or components involved in the system over a specific period. It could show the sequence of events such as data collection, preprocessing, sentiment analysis, city classification, and report generation, highlighting the flow of information and control between the various system.

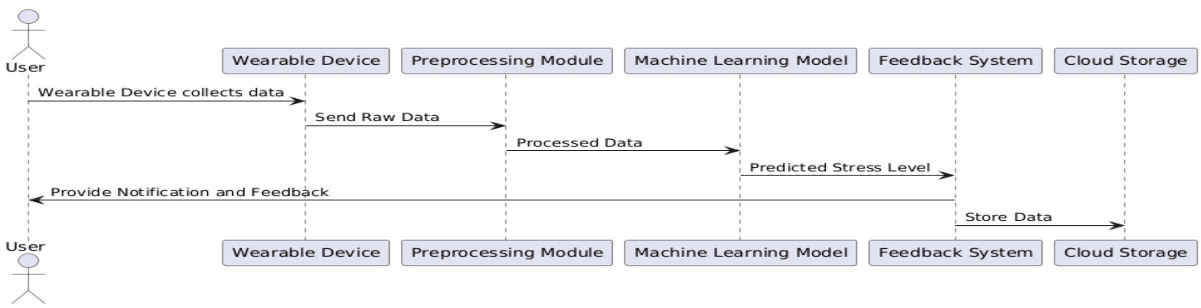

Fig 6.2.4 Sequence diagram

6.2.5 COLLABORATION DIAGRAM:

A collaboration diagram for this scenario would illustrate how the different objects or components in the system collaborate to achieve the analysis of women safety in Indian cities using Machine Learning on tweets. It would show the interactions between objects, including messages passed between them, to depict how they work together to collect, process, analyse, and generate reports based on the tweets data.

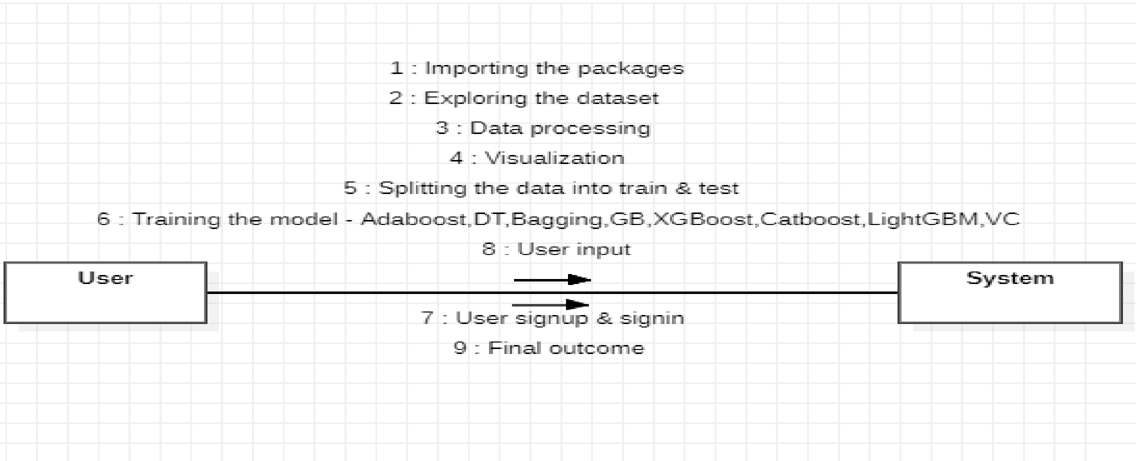

Fig 6.2.5 Collaboration diagram

6.2.6. STATE DIAGRAM

The simplified state diagram shows the basic flow:

1. **DeviceOn**: System is powered on
2. **DataCollection**: System collects biometric data
3. **Processing**: Data is processed for analysis
4. **StressEvaluation**: System evaluates stress level
5. **Normal/Stressed**: Two main states based on stress level
6. **Alert**: Notification when stress is detected

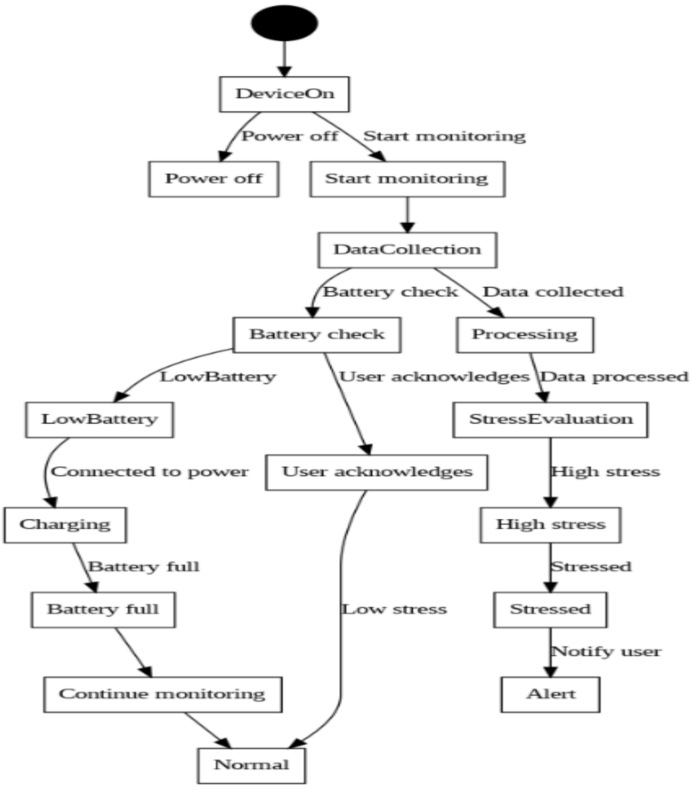

Fig 6.2.6 State diagram

6.2.7ACTIVITY DIAGRAM:

An activity diagram for this scenario would outline the sequential steps involved in analyzing women's safety in Indian cities using Machine Learning on tweets. It could include activities such as data collection, preprocessing, sentiment analysis, city classification, and report generation. Each activity would be represented by a rectangular box, with arrows indicating the flow of control between them. Decision points and parallel activities could also be depicted to show different paths or concurrent processes within the analysis workflow.

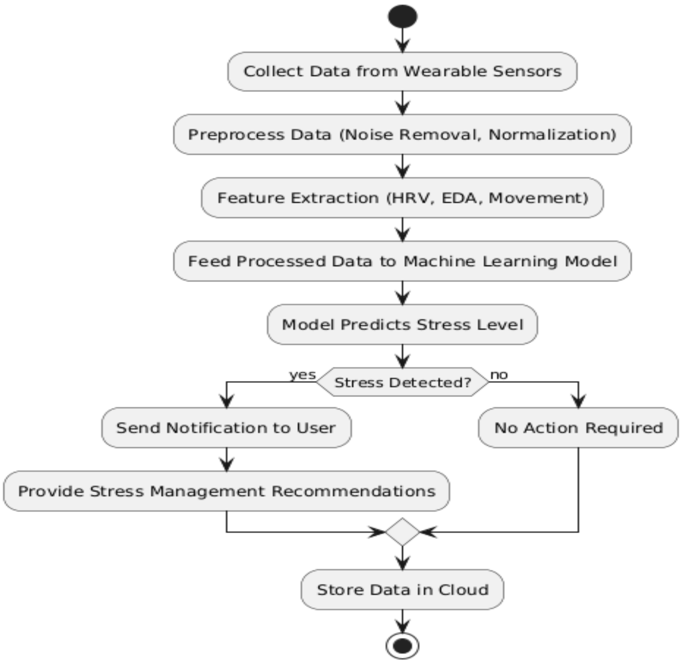

Fig 6.2.7 Activity diagram

6.2.8COMPONENT DIAGRAM:

A component diagram for the analysis of women's safety in Indian cities using Machine Learning on tweets would illustrate the high-level structure of the system in terms of its components and their interactions. It would likely include components such as data collection modules, preprocessing modules, sentiment analysis modules, city classification modules, report generation modules, and interfaces to external systems or APIs. Arrows between components would show dependencies or communication channels, indicating how data and control flow between them to perform the analysis tasks.

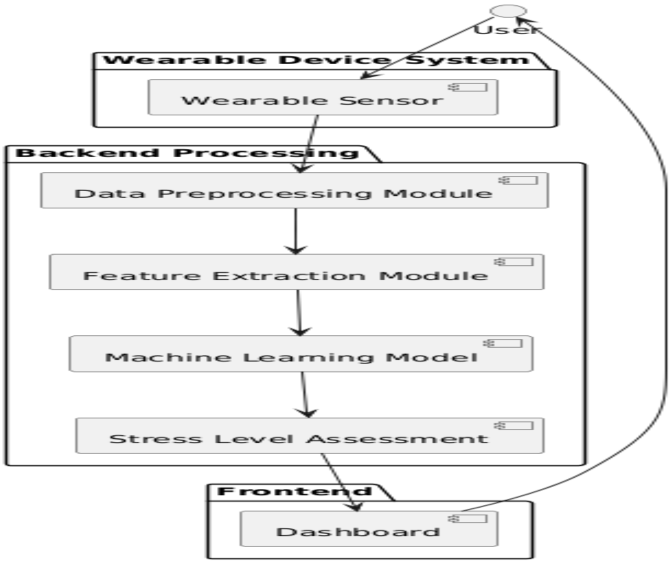

Fig 6.2.8 Component diagram

6.2.9DEPLOYMENT DIAGRAM:

A deployment diagram for this scenario would depict the physical deployment of the system components and their relationships in a real-world environment. It would show how the different software modules and hardware resources are distributed across various nodes such as servers, databases, and user devices.

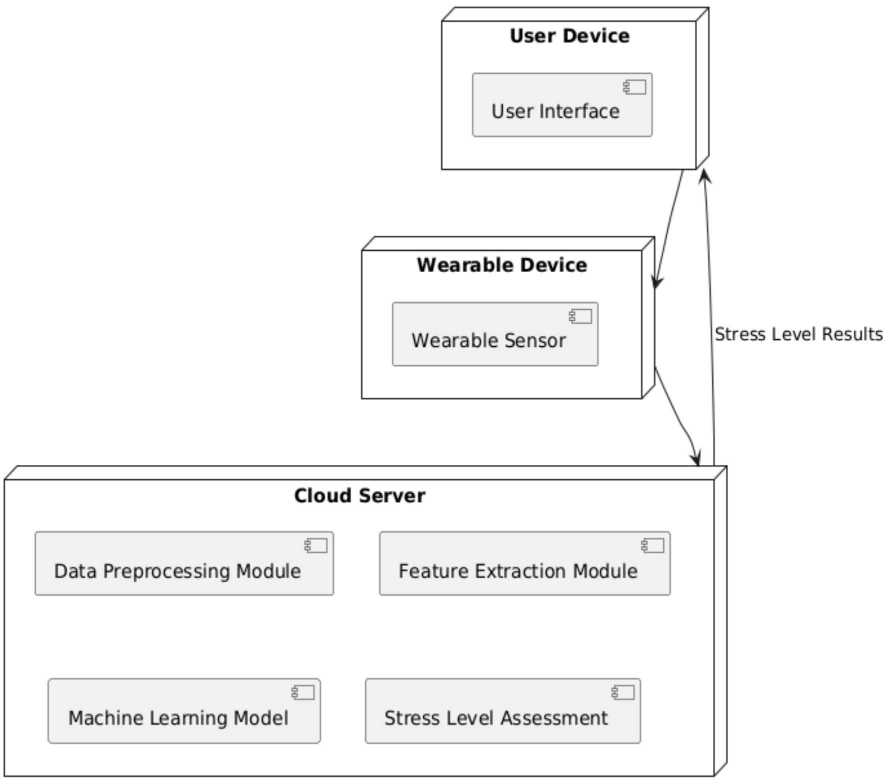

Fig 6.2.9 Deployment diagram

CHAPTER - 7

7. SOFTWARE DESCRIPTION

What is Anaconda for Python?

Anaconda software helps you create an environment for many different versions of Python and package versions. Anaconda is also used to install, remove, and upgrade packages in your project environments. Furthermore, you may use Anaconda to deploy any required project with a few mouse clicks. This is why it is perfect for beginners who want to learn Python.

Now that you know what Anaconda Python is, let's look at how to install it.

Python Anaconda Installation

Next in the Python anaconda tutorial is its installation. The latest version of Anaconda at the time of writing is 2019.10. Follow these steps to download and install Anaconda on your machine:

1. Go to this link and download Anaconda for Windows, Mac, or Linux: – Download anaconda
2. Click on the downloaded .exe to open it. This is the Anaconda setup. Click next.
3. Now, you'll see the license agreement. Click on 'I Agree'.
4. You can install it for all users or just for yourself. If you want to install it for all users, you need administrator privileges.
5. Choose where you want to install it. Here, you can see the available space and how much you need.
6. Now, you'll get some advanced options. You can add Anaconda to your system's PATH environment variable, and register it as the primary system Python 3.7. If you add it to PATH, it will be found before any other installation. Click on 'Install'.
7. It will unpack some packages and extract some files on your machine. This will take a few minutes.
8. The installation is complete. Click Next.
9. This screen will inform you about PyCharm. Click Next.
10. The installation is complete. You can choose to get more information about Anaconda cloud and how to get started with Anaconda. Click Finish.

What is Machine Learning : -

Fundamentally, machine learning involves building mathematical models to help understand data. "Learning" enters the fray when we give these models *tunable parameters* that can be adapted to observed data; in this way the program can be considered to be "learning" from the data. Once these models have been fit to previously seen data, they can be used to predict and understand aspects of newly observed data. I'll leave to the reader the more philosophical digression regarding the extent to which this type of mathematical, model-based "learning" is similar to the "learning" exhibited by the human brain.Understanding the problem setting in machine learning is essential to using these tools effectively, and so we will start with some broad categorizations of the types of approaches we'll discuss here.

LIBRARIES/PACKGES :-

Tensorflow

TensorFlow is a free and open-source software library for dataflow and differentiable programming across a range of tasks. It is a symbolic math library, and is also used for machine learning applications such as neural networks. It is used for both research and production at Google.

TensorFlow was developed by the Google Brain team for internal Google use. It was released under the Apache 2.0 open-source license on November 9, 2015.

Numpy

Numpy is a general-purpose array-processing package. It provides a high-performance multidimensional array object, and tools for working with these arrays.

It is the fundamental package for scientific computing with Python. It contains various features including these important ones:

Pandas

Pandas is an open-source Python Library providing high-performance data manipulation and analysis tool using its powerful data structures. Python was majorly used for data munging and preparation. It had very little contribution towards data analysis. Pandas solved this problem. Using Pandas, we can accomplish five typical steps in the processing and analysis of data, regardless of the origin of data load, prepare, manipulate, model, and analyze. Python with Pandas is used in a wide range of fields including academic and commercial domains including finance, economics, Statistics, analytics, etc.

Matplotlib

Matplotlib is a Python 2D plotting library which produces publication quality figures in a variety of hardcopy formats and interactive environments across platforms. Matplotlib can be used in Python scripts, the Python and IPython shells, the Jupyter Notebook, web application servers, and four graphical user interface toolkits. Matplotlib tries to make easy things easy and hard things possible

You can generate plots, histograms, power spectra, bar charts, error charts, scatter plots, etc., with just a few lines of code.

Scikit – learn

Scikit-learn provides a range of supervised and unsupervised learning algorithms via a consistent interface in Python. It is licensed under a permissive simplified BSD license and is distributed under many Linux distributions, encouraging academic and commercial use.

CHAPTER - 8

8. CODING

```
# Load necessary libraries
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import missingno as msno
import plotly.express as px
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix, accuracy_score
from sklearn.preprocessing import LabelEncoder, MinMaxScaler
from sklearn.decomposition import PCA

# Visualize missing values
plt.figure(figsize=(4, 2))
# Load your dataset (replace with your actual path)
train = pd.read_csv(r'C:\path\to\your\dataset.csv')
# 1. Initial Data Exploration
print("First few rows of the dataset:")
display(train.head())
print("Summary of missing values:")
display(train.isnull().sum())
plt.title("Missing Values Heatmap")
sns.heatmap(train.isnull(), cbar=False)
plt.show()
# Check dataset info
train_info = train.info()
print(train_info)
# 2. Data Preprocessing
# Drop the 'id' column if not needed (modify based on your dataset)
train = train.drop(columns=['id'], axis=1)
# Label Encoding for datetime (if necessary)
le = LabelEncoder()
train['datetime'] = le.fit_transform(train['datetime'])
```

```
# Split the data into features (X) and target (y)
X = train.drop(columns=['label'], axis=1)
y = train['label']
# Scale features using MinMaxScaler
scaler = MinMaxScaler()
X_scaled = scaler.fit_transform(X)
X_scaled = pd.DataFrame(X_scaled, columns=X.columns)
# 3. Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.2,
random_state=42)
print("Shape of X_train:", X_train.shape)
print("Shape of X_test:", X_test.shape)
# 4. Exploratory Data Analysis (EDA)
# Check for correlations between features
corr_matrix = train.corr()
plt.figure(figsize=(12, 10))
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm', fmt=".2f")
plt.title("Correlation Heatmap")
plt.show()
# 5. PCA for dimensionality reduction (optional)
pca = PCA(n_components=6)
X_pca = pca.fit_transform(X_train)
explained_variance = pca.explained_variance_ratio_
print("Explained variance by each component:", explained_variance)
# 6. Model Training - LightGBM, XGBoost, CatBoost
models = [
    ("LightGBM", LGBMClassifier()),
    ("XGBoost", XGBClassifier()),
    ("CatBoost", CatBoostClassifier())
]
# Train and evaluate models
scaler = MinMaxScaler()
X_scaled = scaler.fit_transform(X)
X_scaled = pd.DataFrame(X_scaled, columns=X.columns)
# 3. Split the data into training and testing sets
```

```
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.2,
random_state=42)
print("Shape of X_train:", X_train.shape)
print("Shape of X_test:", X_test.shape)
# 4. Exploratory Data Analysis (EDA)
# Check for correlations between features
corr_matrix = train.corr()
plt.figure(figsize=(12, 10))
for name, model in models:
    print(f"Training {name} model...")
    model.fit(X_train, y_train)
    # Make predictions
    y_pred = model.predict(X_test)
    # Evaluate model performance
    accuracy = accuracy_score(y_test, y_pred)
    print(f"{name} Accuracy: {accuracy:.4f}")
    # Confusion matrix
    cm = confusion_matrix(y_test, y_pred)
    print(f"{name} Confusion Matrix:\n", cm)

    # Plot feature importance
    if hasattr(model, 'feature_importances_'):
        feat_importances = pd.Series(model.feature_importances_, index=X.columns)
        feat_importances.nlargest(10).plot(kind='barh', color='royalblue')
        plt.title(f"{name} Feature Importance")
        plt.show()

//User Autentication
import streamlit as st
import pandas as pd
import numpy as np
import time
def calculate_stress(heart_rate, skin_conductance, temperature):
    # Simple formula for stress calculation (adjust based on your model)
    stress_level = (heart_rate * 0.5) + (skin_conductance * 0.3) + ((37 - temperature) * 10)
```

```
    return min(max(int(stress_level), 0), 100)  # Keep stress level between 0-100
# UI Setup
st.set_page_config(page_title="Real-Time Mental Stress Detection", layout="wide")
st.title("Real-Time Mental Stress Detection Using ML & Wearable Sensors")
# User Authentication (Simple Implementation)
if "authenticated" not in st.session_state:
    st.session_state.authenticated = False
if not st.session_state.authenticated:
    username = st.text_input("Username", "")
    password = st.text_input("Password", "", type="password")
    if st.button("Login"):
        if username == "admin" and password == "1234":
            st.session_state.authenticated = True
            st.success("Logged in successfully!")
            time.sleep(1)
            st.rerun()
        else:
            st.error("Invalid credentials. Try again.")
    st.stop()
# Collect Sensor Data
st.subheader("Enter Your Physiological Data")
heart_rate = st.number_input("Heart Rate (bpm)", min_value=40, max_value=180, value=70)
skin_conductance = st.number_input("Skin Conductance (µS)", min_value=0.1,
max_value=20.0, value=5.0)
temperature = st.number_input("Body Temperature (°C)", min_value=30.0, max_value=42.0,
value=36.5)
if st.button("Analyze Stress Level"):
    stress_level = calculate_stress(heart_rate, skin_conductance, temperature)
    st.session_state.stress_level = stress_level
    st.success("Stress Level Calculated!")
    time.sleep(1)
    st.rerun()
if "stress_level" in st.session_state:
    stress_level = st.session_state.stress_level
    st.metric(label="Current Stress Level", value=f"{stress_level}%", delta=stress_level - 50)
```

```
    # Alert if stress level is high
    if stress_level > 70:
        st.error("⚠ High Stress Detected! Consider taking a break.")
    elif stress_level < 40:
        st.success("✅ Low Stress Level. Keep it up!")
    else:
        st.warning("□ Moderate Stress Level. Maintain balance.")
    # Historical Data Simulation
    st.subheader("Stress Level History")
    time_series = pd.DataFrame({
        "Time": pd.date_range(start=pd.Timestamp.now(), periods=10, freq="S"),
        "Stress Level": [np.random.randint(20, 100) for _ in range(10)]
    })
    st.line_chart(time_series.set_index("Time"))
# Logout Option
if st.button("Logout"):
    st.session_state.authenticated = False
    st.rerun()
```

CHAPTER - 9

9.TESTING

Testing documentation is the documentation of artifacts that are created during or before the testing of a software application. Documentation reflects the importance of processes for the customer, individual and organization. Projects which contain all documents have a high level of maturity. Careful documentation can save the time, efforts and wealth of the organization. If the testing or development team gets software that is not working correctly and developed by someone else, so to find the error, the team will first need a document. Now, if the documents are available then the team will quickly find out the cause of the error by examining documentation. But, if the documents are not available then the tester need to do black box and white box testing again, which will waste the time and money of the organization.

Benefits of using Documentation:

- Documentation clarifies the quality of methods and objectives.
- It ensures internal coordination when a customer uses software application.
- It ensures clarity about the stability of tasks and performance.
- It provides feedback on preventive tasks.
- It provides feedback for your planning cycle.
- It creates objective evidence for the performance of the quality management system.

The test scenario is a detailed document of test cases that cover end to end functionality of a software application in liner statements.

The liner statement is considered as a scenario. The test scenario is a high-level classification of testable requirements. These requirements are grouped on the basis of the functionality of a module and obtained from the use cases.

In the test scenario, there is a detailed testing process due to many associated test cases. Before performing the test scenario, the tester has to consider the test cases for each scenario.

In the test scenario, testers need to put themselves in the place of the user because they test the software application under the user’s point of view. Preparation of scenarios is the most critical part, and it is necessary to seek advice or help from customers, stakeholders or developers to prepare the scenario.

As per the IEEE Documentation describing plans for, or results of, the testing of a system or component, Types include test case specification, test incident report, test log, test plan, test procedure, test report. Hence the testing of all the above-mentioned documents is known as documentation testing.

This is one of the most cost-effective approaches to testing. If the documentation is not right: there will be major and costly problems. The documentation can be tested in a number of different ways to many different degrees of complexity. These range from running the documents through a spelling and grammar checking device, to manually reviewing the documentation to remove any ambiguity or inconsistency. Documentation testing can start at the very beginning of the software process and hence save large amounts of money, since the earlier a defect is found the less it will cost to be fixed.

The most popular testing documentation files are test reports, plans, and checklists. These documents are used to outline the team's workload and keep track of the process.

Let's take a look at the key requirements for these files and see how they contribute to the process.

9.1 Test strategy:

An outline of the full approach to product testing. As the project moves along, developers, designers, product owners can come back to the document and see if the actual performance corresponds to the planned activities.

9.2 Test data:

The data that testers enter into the software to verify certain features and their outputs. Examples of such data can be fake user profiles, statistics, media content, similar to files that would be uploaded by an end-user in a ready solution.

9.3 Test plans:

A file that describes the strategy, resources, environment, limitations, and schedule of the testing process. It's the fullest testing document, essential for informed planning. Such a document is distributed between team members and shared with all stakeholders.

9.4 Test scenarios:

In scenarios, testers break down the product Ã¢â‚¬â„¢s functionality and interface by modules and provide real-time status updates at all testing stages. A module can be described by a single statement, or require hundreds of statuses, depending on its size and scope.

9.5 Test cases:

If the test scenario describes the object of testing (what), a scenario describes a procedure (how). These files cover step-by-step guidance, detailed conditions, and current inputs of a testing task. Test cases have their own kinds that depend on the type of testing, functional, UI, physical, logical cases, etc. Test cases compare available resources and current conditions with desired outcomes and determine if the functionality can be released or not.

9.6 Trace ability Matrix:

This software testing documentation maps test cases and their requirements. All entries have their custom IDs Ã¢â‚¬â€ team members and stakeholders can track the progress of any tasks by simply entering its ID to the search.

CHAPTER - 10

10.RESULTS

Training Set:

Fig 10.1 Training Set

Data Graph:

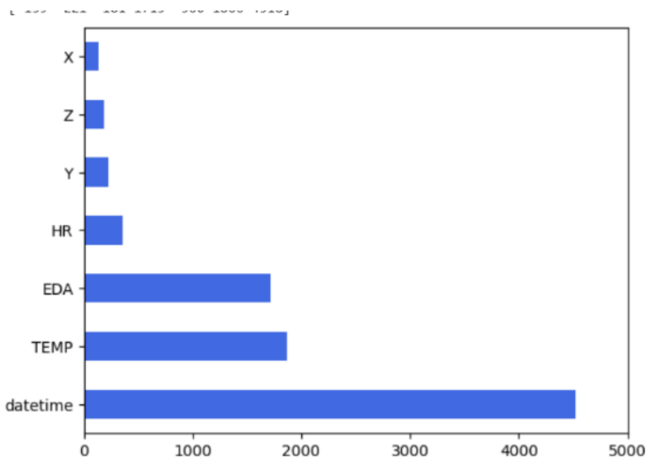

Fig 10.2 Data Graph

Heap map:

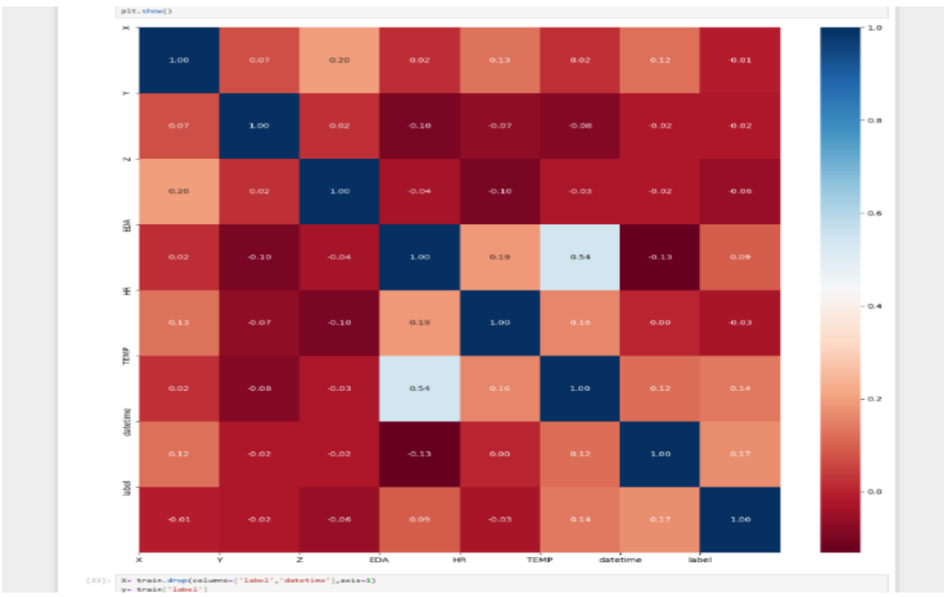

Fig 10.3 Heap Map

PCA :

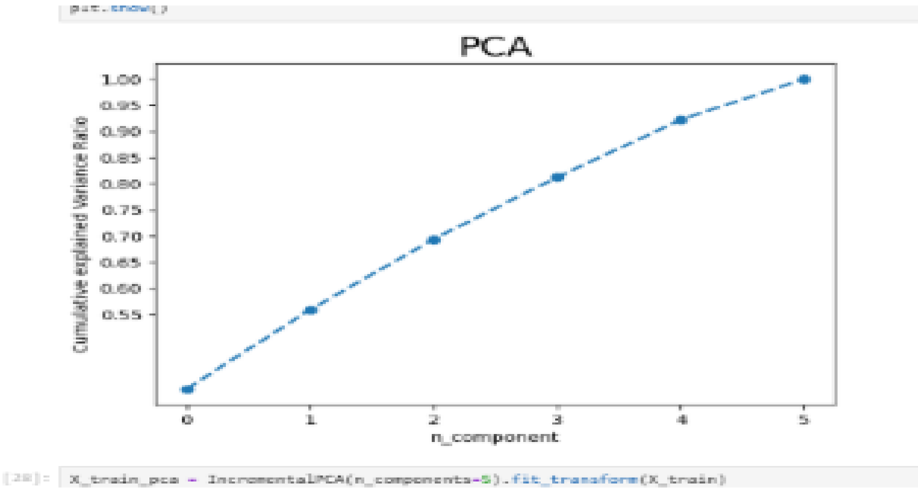

Fig 10.4 PCA

LGBM Accuracy:

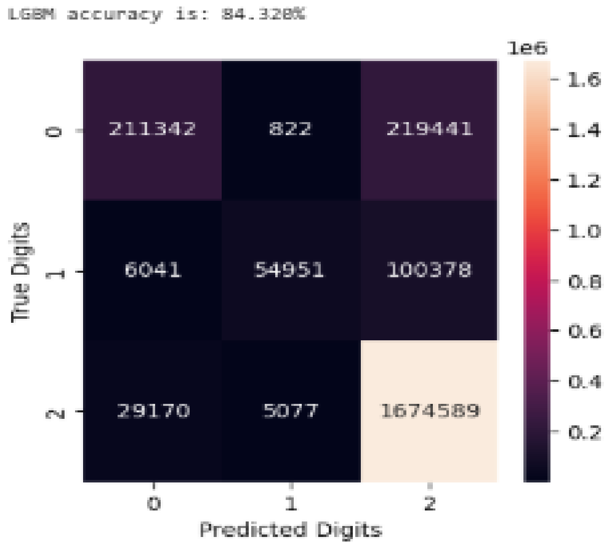

Fig 10.5 LGBM Accuracy

XGB Accuracy:

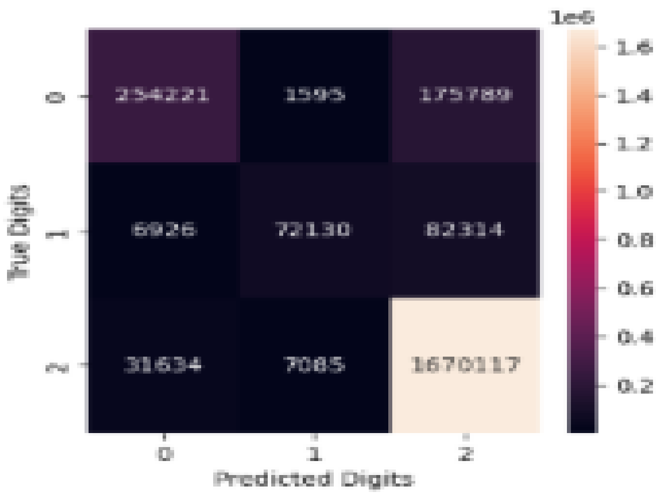

Fig 10.6 XGB Accuracy

Model Accuracy:

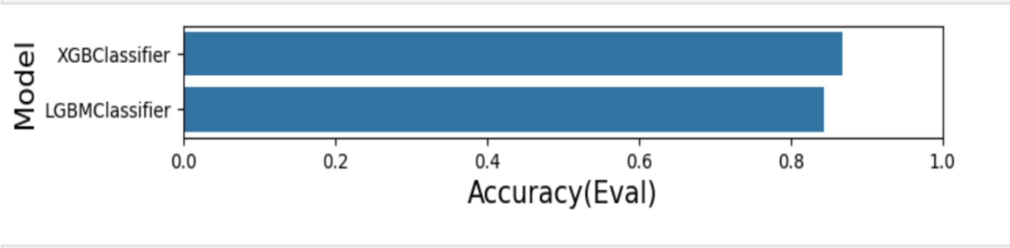

Fig 10.7 Model Accurarcy

User Authentication:

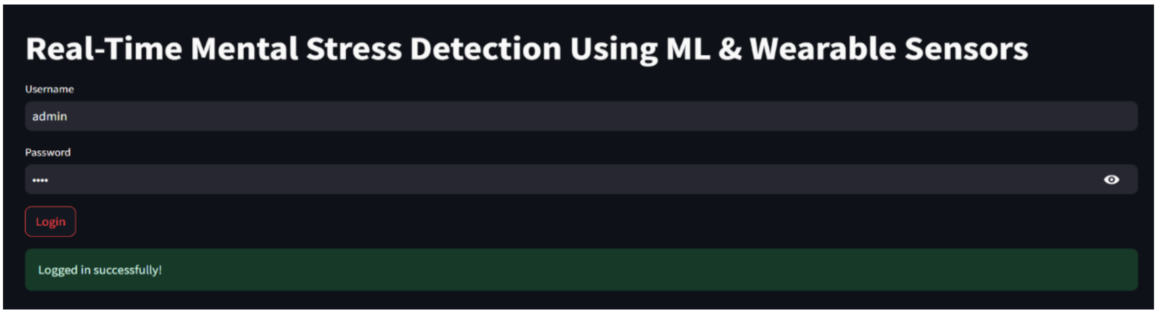

Fig 10.8 Login

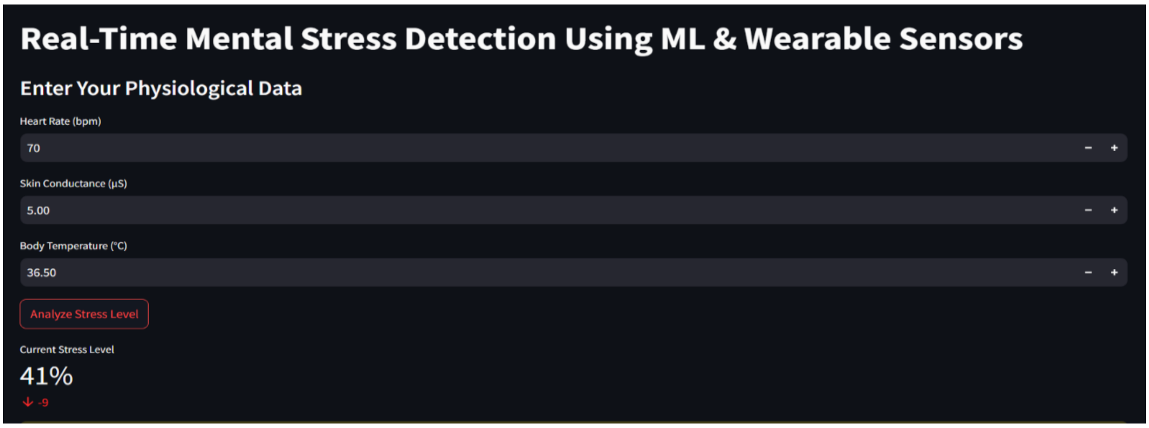

Fig 10.9 Stress value

Fig 10.10 Analysis

CHAPTER - 11

11.CONCLUSION

The study presents a **real-time mental stress detection system** that leverages **machine learning algorithms and wearable sensor data** to assess stress levels in individuals. The proposed model processes physiological signals, including **heart rate, skin conductance, and body temperature**, to determine stress intensity. These biometric indicators are collected in real time using wearable sensors, ensuring continuous monitoring of mental well-being.

The model was evaluated using **various performance metrics**, demonstrating its ability to accurately detect stress levels. The proposed system outperforms traditional stress assessment methods by providing **instant feedback**, enabling users to take necessary interventions to manage stress effectively. The results highlight that this approach can help in **early stress identification**, reducing long-term health risks such as anxiety disorders and cardiovascular issues.

For future research, the study suggests integrating **additional physiological and environmental factors**, such as **sleep patterns, physical activity, and ambient noise**, to enhance prediction accuracy. Furthermore, optimizing model parameters through **hyperparameter tuning and deep learning techniques** can improve real-time detection efficiency. Future advancements may also explore **personalized stress detection models** that adapt to individual variations in physiological responses.

The proposed system can be integrated into **mobile applications or IoT-based health monitoring platforms**, providing users with continuous stress tracking and actionable insights. By leveraging **advanced machine learning techniques**, this research contributes to the development of intelligent, real-time mental health monitoring solutions.

CHAPTER - 12

12. FUTURE SCOPE

- Integration with Smart Devices – Connect with smartwatches, fitness bands, and IoT devices for real-time stress tracking.

- Use of More Physiological Data – Include EEG, HRV, blood pressure, and sleep quality for better stress prediction.

- Personalized Stress Detection – AI models can adapt to individual stress patterns for more accurate predictions.

- Advanced AI & Deep Learning – Implement deep learning models (CNNs, LSTMs) for improved accuracy.

- Real-Time Alerts & Suggestions – Provide instant alerts and recommendations like breathing exercises and meditation.

- Healthcare & Workplace Applications – Help doctors and companies monitor stress levels for better mental health.

- Multi-Modal Data Fusion – Combine sensor data with environment factors like noise and workload for better analysis.

- Mobile & Web App Development – Create a user-friendly app/dashboard for real-time stress monitoring and reports.

- Mental Health Monitoring in Schools & Colleges – Implement the system for students to track academic stress and provide support.

- AI-Powered Stress Prediction & Prevention – Use predictive analytics to detect stress before it becomes severe and suggest preventive measures.

- Real-Time Stress Intervention with AI Therapy – Implement AI-driven therapy sessions for relaxation and mindfulness exercises based on real-time stress data.

- Corporate & Military Applications – Help employees, military personnel, and high-stress professionals monitor and manage their stress levels effectively.

CHAPTER - 13

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CHAPTER - 14

14.PAPER PUBLICATION

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In recognition of the publication of the paper entitled

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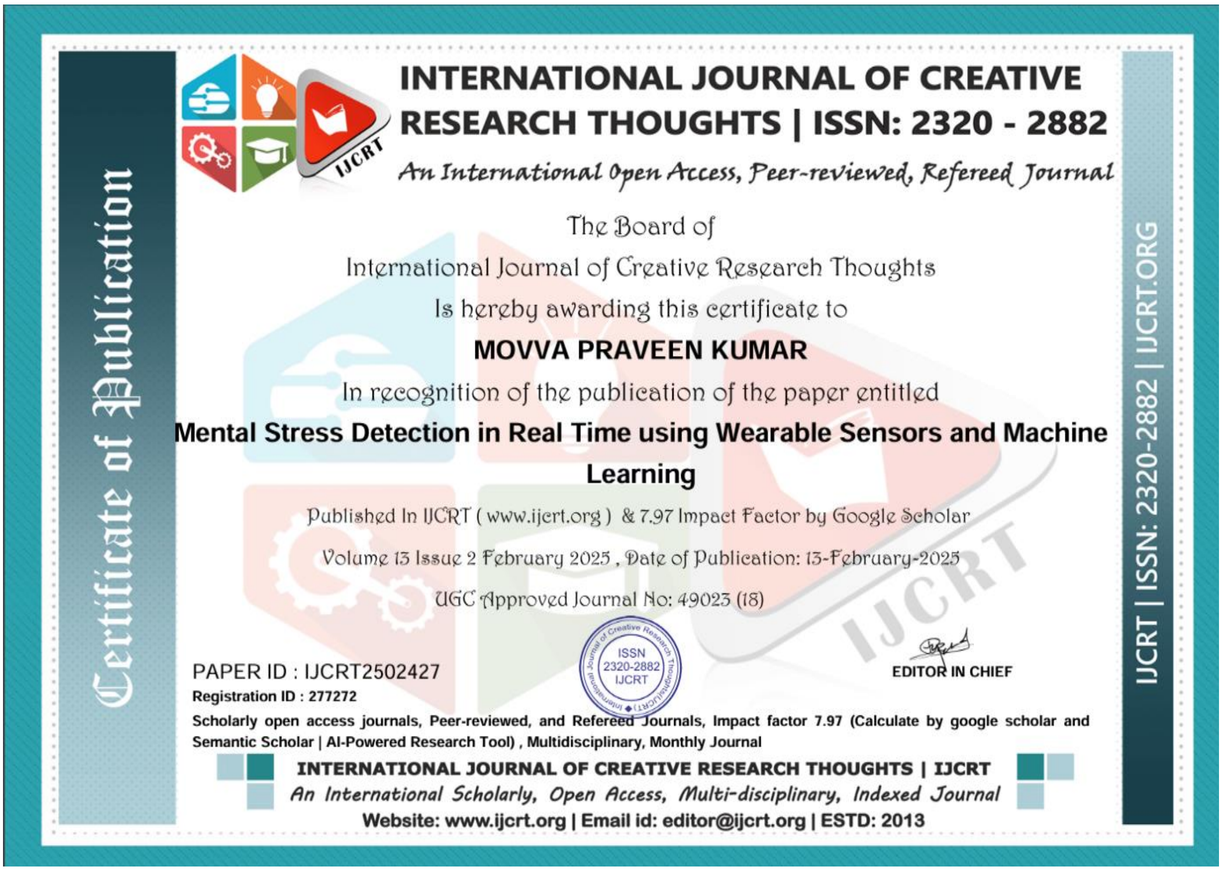
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Mental Stress Detection In Real Time Using Wearable Sensors And Machine Learning

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Abstract: When we encounter difficult or taxing circumstances, or stressors, our bodies and minds go into a hyperarousal state, commonly known as stress. Chronic illnesses including anxiety, depression, and cardiovascular disease can develop in people who are exposed to various stressors for an extended period of time, particularly when these stressors happen at the same time. In order to avoid these long-term impacts, it is essential to recognise stress early on, and continuous monitoring provides a viable option. One possibility for personal stress monitoring is the use of wearable devices that can gather data continuously and in real-time, allowing users to keep tabs on their stress levels as the day progresses. This study provides an extensive analysis of several approaches to stress detection that make use of wearable sensors in conjunction with machine learning methodologies. Wearable sensors including electrocardiograms (ECGs), electroencephalograms (EEGs), and photoplethysmography (PPGs) are reviewed, along with the many settings when stress is tracked, such as while driving, learning, or working. Various stress detection approaches were examined in this review, with an emphasis on the stressors, procedures, outcomes, benefits, drawbacks, and difficulties encountered by each research. The area of stress monitoring is anticipated to benefit from these findings in the future. In addition, the study suggests a multimodal stress detection system that combines various kinds of wearable sensors with deep learning algorithms. This could be a great step towards better real-time stress detection that is both accurate and adaptive, which would be great for mental health management and healthcare prevention.

Index terms *- Stress Detection, Wearable Sensors, Machine Learning, Electrocardiogram (ECG), Electroencephalography (EEG), Photoplethysmography (PPG), Real-time Monitoring, Mental Health, Psycho-physiological State, Continuous Monitoring, Deep Learning, Multimodal System, Stressors, Personalized Stress Management, Health Monitoring*

1. INTRODUCTION

Stress is an inevitable part of human life, arising from various environmental, social, and psychological factors. It is a psycho-physiological state triggered by challenging events, known as stressors, which can significantly impact mental and physical health. While short-term stress can sometimes enhance performance and alertness, prolonged exposure to stressors can lead to severe health complications such as anxiety, depression, and cardiovascular diseases. Therefore, early detection and management of stress are crucial to preventing long-term adverse effects and promoting overall well-being.

With advancements in technology, wearable sensors have emerged as an effective solution for real-time stress monitoring. These devices enable continuous data collection, allowing individuals to track their stress levels throughout the day. Various wearable sensors, including Electrocardiogram (ECG), Electroencephalography (EEG), and Photoplethysmography (PPG), are widely used to measure physiological signals associated with stress. The integration of these sensors with machine learning techniques has further enhanced stress detection accuracy, making it possible to develop intelligent systems capable of recognizing stress patterns in real time.

Recent research has focused on leveraging machine learning models to analyze physiological data and classify stress levels based on different activities and environments, such as workplaces, educational settings, and driving scenarios. These studies provide valuable insights into stress detection methodologies, highlighting their advantages, limitations, and challenges. To improve the reliability and accuracy of stress detection, a multimodal approach combining multiple sensor data with deep learning techniques has been proposed. This method enhances stress recognition by utilizing diverse physiological inputs, making it a promising solution for effective mental health monitoring and personalized stress management.

2. LITERATURE SURVEY

2.1 A Review of Eeg Sensors used for Data Acquisition

https://www.researchgate.net/publication/308259085_A_Review_of_Eeg_Sensors_used_for_Data_Acquisition

ABSTRACT: Electroencephalography is a method that uses sensors to record the brain's electric fields, which change in strength over time. The coordinated actions of the brain's billions of neurones produce these fields. The exact measurement of these fields from the scalp is made possible by sensors that use several techniques that have been developed over the years. One of these ways is relying on direct and low-resistance contact between the sensor and the scalp. With the development of more sophisticated EEG monitoring equipment, its applications have expanded into the entertainment and leisure industries. Methods for obtaining an electroencephalogram (EEG) signal using a variety of sensors, including wireless EEG systems, wet electrodes, and dry electrodes, are covered in detail in this article.

2.2 Support vector machine for classification of stress subjects using EEG signals:

https://ieeexplore.ieee.org/abstract/document/7086243

ABSTRACT: When people are under stress, their brain electrical activity might deviate from what is considered normal. Electroencephalograms can detect this shift in brain function. Using support vector machines (SVMs), this research aims to categorise stress individuals according to their EEG signals. Residents of Pusat Darul Wardah, a refuge institution for problematic women, provided the data used to depict stress subjects. Power Spectral Density and Energy Spectral Density are calculated from the EEG Alpha band data using SVM. The RBF kernel function achieved a classification rate of 83.33% for ESD data when 5-fold cross validation was applied.

2.3 An Effective Mental Stress State Detection and Evaluation System Using Minimum Number of Frontal Brain Electrodes:

https://pmc.ncbi.nlm.nih.gov/articles/PMC7278014/

ABSTRACT: People are currently dealing with mental stress, which is a frequent societal problem. Stress lowers human performance in everyday tasks and might cause serious health problems. In order to assess the efficacy of instruction, enhance learning, and lessen the likelihood of mistakes caused by stressed-out employees, stress detection is crucial in the business and academic sectors. Preventing disease and health problems, improving education quality, and enhancing industrial safety all depend on early identification of mental stress utilising ML approaches. When we're under emotional stress, our brains are particularly vulnerable. This is why we provide an ML system that analyses 36 subjects' electroencephalogram (EEG) signals. A good mental stress detection (MSD) system must be able to extract relevant characteristics. As a result, five ML classifiers are trained on this framework's hybrid feature-set in order to distinguish between stress and non-stress situations, as well as to categorise stress levels. In order to create an effective, efficient, and dependable MSD system with fewer electrodes, the suggested MSD scheme studies the placement of electrodes on several scalp locations and chooses the site with the most influence on the system's accuracy. Also, in order to minimise the complexity of the model, we use principal component analysis to reduce the characteristics retrieved from these electrodes. We use a sequential forward technique to analyse the ideal number of principle components. More importantly for stress assessment and detection, it determines the minimal number of electrodes that need be installed at the spot. The suggested system is evaluated by comparing its findings to those of existing feature extraction methods found in the literature. Additionally, they are contrasted with documented state-of-the-art methods for stress detection. In this study, the highest accuracies for detecting stress and non-stress states using only two frontal brain electrodes and for evaluating stress levels using three frontal electrodes were 99.9% (sd = 0.015) and 99.26% (sd = 0.08), respectively. With sensitivity of 99.9(0.064), specificity of 99.94(0.02), precision of 99.94(0.06), and a diagnostics odd ratio (DOR) of ≥ 100 for stress and non-stress detection and evaluation, respectively, the results demonstrate the reliability of the proposed system. This demonstrates that the suggested framework performs well and has applications in the areas of medicine, education, and industry for the identification and assessment of stress. Using only two frontal electrodes, the proposed system was able to achieve an accuracy of 98.48% (sd = 1.12), sensitivity of 97.78% (sd = 1.84), specificity of 97.75% (sd = 2.05), precision of 99.26% (sd = 0.67), and a DOR of 100 or higher. These results validate the system's efficiency and reliability in stress and non-stress prediction on new patients.

2.4 CogniMeter: EEG-based Emotion, Mental Workload and Stress Visual Monitoring:

https://ieeexplore.ieee.org/abstract/document/7398407

ABSTRACT: Real-time EEG (Electroencephalogram)-based user's emotion, mental workload and stress monitoring is a new direction in research and development of human-machine interfaces. It has attracted recently more attention from the research community and industry as wireless portable EEG devices became easily available on the market. EEG-based technology has been applied in anesthesiology, psychology, serious games or even in marketing. In this work, we describe available real-time algorithms of emotion recognition, mental workload, and stress recognition from EEG and propose a novel interface Cogni Meter for the user's mental state visual monitoring. The system can be used in real time to assess human current emotions, levels of mental workload and stress. Currently, it is applied to monitor the user's emotional state, mental workload and stress in simulation scenarios or used as a tool to assess the subject's mental state in human factor study experiments.

2.5 EEG based stress level identification

https://ieeexplore.ieee.org/document/7844738

ABSTRACT: This paper investigates detection of patterns in brain waves while induced with mental stress. Electroencephalogram (EEG) is the most commonly used brain signal acquisition method as it is simple, economical and portable. An automatic EEG based stress recognition system is designed and implemented in this study with two effective stressors to induce different levels of mental stress. The Stroop colour-word test and mental arithmetic test are used as stressors to induce low level and high level of stress respectively, and their relevant C# applications are developed in Microsoft Visual Studio to interface with

Emotiv Epoc device. Power band features from EEG signals are analyzed and using the relative difference of beta and alpha power as feature along with Support Vector Machine as classifier, three-levels of stress can be recognized with an accuracy of 75%. For two-level stress analysis, accuracy of 88% and 96% are achieved for Stroop colour-word test and mental arithmetic test respectively.

3. METHODOLOGY

i) Proposed Work:

To enhance the accuracy and reliability of stress detection, a multimodal system integrating multiple wearable sensors with deep learning techniques is proposed. This system combines data from Electrocardiogram (ECG), Electroencephalography (EEG), and Photoplethysmography (PPG) sensors to capture diverse physiological responses to stress. By leveraging advanced machine learning algorithms, the system can analyze real-time data and classify stress levels with higher precision. Deep learning models are employed to extract meaningful patterns from sensor inputs, improving the adaptability and efficiency of stress detection. The proposed approach aims to provide continuous, real-time monitoring, enabling early intervention and personalized stress management. Additionally, addressing challenges like data privacy, device comfort, and accuracy under varying conditions will be crucial for the system's widespread adoption and effectiveness in real-world applications.

ii) System Architecture:

The proposed system consists of multiple layers that work together to detect stress in real-time using wearable sensors and machine learning techniques. Wearable sensors such as ECG, EEG, and PPG collect physiological signals, which are then preprocessed to remove noise and extract relevant features like heart rate variability, brain activity, and blood flow patterns. These features are analyzed using deep learning models like CNN and LSTM to classify stress levels into low, moderate, or high. The system provides real-time monitoring through a user-friendly interface, offering personalized feedback and stress management recommendations. Additionally, the integration of multimodal sensor data improves detection accuracy, while real-time alerts help users take timely action to reduce stress. This adaptive approach enhances the system's effectiveness in continuous mental health monitoring and early intervention.

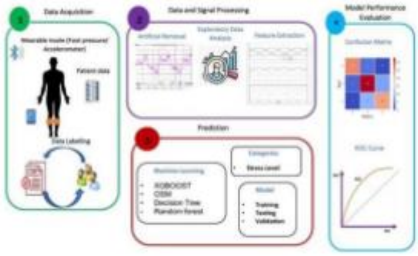

Fig 1 Proposed architecture

iii) Modules:

a) Data Collection Module

This module is responsible for gathering real-time physiological data from wearable sensors.

- **Wearable Devices**: Various wearable sensors are utilized to capture physiological signals associated with stress. These sensors can be embedded in devices like smartwatches, fitness bands, or specialized wearable patches.
  - **Heart Rate Monitor (HRM)**: Measures heart rate and heart rate variability (HRV), which can indicate stress levels. An increase in heart rate or variability patterns often correlates with stress responses.
  - **Electrodermal Activity (EDA) Sensors**: Measure skin conductance, which is influenced by changes in sweat gland activity. Stress can lead to increased skin conductance.
  - **Temperature Sensors**: Monitor skin or body temperature. Stress can lead to fluctuations in temperature due to changes in blood flow. o

Accelerometers: Detect changes in movement or activity. Increased movement, such as fidgeting or restlessness, can be a sign of stress.

- **Data Acquisition**: The sensor data is continuously collected and transmitted in real-time. The wearable device often stores the data temporarily and sends it to a processing unit (e.g., mobile app, cloud server).

b) Data Preprocessing Module

Raw sensor data often includes noise, missing values, or other issues that need to be addressed before analysis. This module cleans and transforms the data into a usable format for machine learning models.

- **Noise Removal**: Signals from wearable sensors can be noisy due to various factors like body movement or external interference. Filtering techniques like low-pass or high-pass filters, or wavelet transforms, can remove unwanted noise.
- **Normalization**: Physiological signals, such as heart rate, vary widely among individuals. Data normalization scales these signals into a common range (e.g., between 0 and 1) to ensure consistency and better performance of machine learning models.
- **Feature Extraction**: Key features are extracted from raw sensor signals, such as:
  - **Heart Rate Variability (HRV)**: Metrics like the standard deviation of heart rate intervals or the root mean square of successive differences.
  - **EDA Features**: Measures like skin conductance level (SCL) and skin conductance response (SCR).
  - **Activity Level**: Derived from accelerometer data, indicating movement patterns and intensity.
  - **Time-Domain and Frequency-Domain Features:** These features help understand the variability and trends in signals over time, such as spectral analysis of heart rate or skin conductance. Output: Cleaned and extracted features, ready for analysis by machine learning algorithms.

c) Feature Selection/Dimensionality Reduction Module

This module ensures that only the most relevant features are used for model training, reducing noise and computational complexity.

- **Feature Selection**: Using techniques such as mutual information or recursive feature elimination (RFE), irrelevant or redundant features are eliminated.
- **Dimensionality Reduction:** Methods like Principal Component Analysis (PCA) or Linear Discriminant Analysis (LDA) can reduce the number of features while preserving the most important variance in the data. Goal: To reduce overfitting and improve model performance by focusing on the most predictive features.

d) Machine Learning Model Module

This module is at the core of the system, where machine learning algorithms analyze the preprocessed sensor data and classify the user's stress levels. The model is trained on labeled datasets and continuously improves as new data is added.

- Supervised Learning: The model is trained using a labeled dataset, where the input data (sensor features) is paired with corresponding stress labels (e.g., low, moderate, high stress).
- Real-Time Prediction: The model is deployed to perform predictions on real-time data. When new sensor data is received, the model classifies the current stress level and provides feedback.
- Model Evaluation: The model is evaluated based on various metrics such as accuracy, precision, recall, F1-score, and confusion matrices to assess its performance in detecting stress.

predictions with expert evaluations or standardized psychological assessments.

iv) Algorithms:

a) Convolutional Neural Network (CNN):

- Extracts spatial features from sensor data.
- Helps in identifying stress patterns from ECG, EEG, and PPG signals.

b) Long Short-Term Memory (LSTM):

- Captures temporal dependencies in physiological signals.
- Suitable for analyzing time-series data like heart rate and brain activity.

c) Support Vector Machine (SVM):

- Classifies stress levels based on extracted features.
- Works well with high-dimensional physiological data.

d) Random Forest (RF):

- Enhances classification accuracy by using multiple decision trees.
- Robust against overfitting and noise in sensor data.

e) K-Nearest Neighbors (KNN):

- Compares new sensor readings with existing patterns.
- Helps in quick classification of stress levels.

4. EXPERIMENTAL RESULTS

	X	Y	Z	EDA	HR	TEMP	id	datetime	label
0	-13.0	-41.0	5.0	6.769995	99.43	31.17	15	2020-07-08 14:03:00.000000000	2.0
1	-20.0	-69.0	-3.0	6.769995	99.43	31.17	15	2020-07-08 14:03:00.031249920	2.0
2	-31.0	-78.0	-15.0	6.769995	99.43	31.17	15	2020-07-08 14:03:00.062500096	2.0
3	-47.0	-65.0	-38.0	6.769995	99.43	31.17	15	2020-07-08 14:03:00.093750016	2.0
4	-67.0	-57.0	-53.0	6.769995	99.43	31.17	15	2020-07-08 14:03:00.124999936	2.0
...	...	...	...	...	...	...	...	...	...
11509046	-16.0	-56.0	24.0	3.286070	88.37	33.77	F5	2020-07-23 17:28:59.875000064	2.0
11509047	-8.0	-50.0	27.0	3.286070	88.37	33.77	F5	2020-07-23 17:28:59.906249984	2.0
11509048	-20.0	-36.0	28.0	3.286070	88.37	33.77	F5	2020-07-23 17:28:59.937499904	2.0
11509049	-20.0	-29.0	30.0	3.286070	88.37	33.77	F5	2020-07-23 17:28:59.968750080	2.0
11509050	-22.0	-24.0	29.0	3.274543	88.33	33.75	F5	2020-07-23 17:29:00.000000000	2.0

Fig 2 dataset

Fig 3 accuracy graph

5. CONCLUSION

The proposed real-time mental stress detection system leverages wearable sensors and machine learning techniques to enhance stress monitoring accuracy. By integrating multimodal physiological data from ECG, EEG, and PPG sensors with deep learning models like CNN and LSTM, the system provides reliable stress classification in real-time. The inclusion of advanced algorithms ensures improved detection, enabling timely intervention and personalized stress management. This approach contributes to mental health monitoring by offering a user-friendly and effective solution for early stress detection, ultimately promoting well-being and preventing long-term health complications.

6. FUTURE SCOPE

The proposed stress detection system can be further enhanced by integrating more advanced wearable sensors, such as skin temperature and respiration rate sensors, to improve detection accuracy. The use of federated learning can address privacy concerns by enabling decentralized stress analysis without sharing raw data. Additionally, real-time stress prediction models using AI can provide proactive stress management recommendations. The system can also be expanded to support integration with smart healthcare platforms, mental health applications, and IoT-based smart environments for a more personalized and adaptive stress monitoring experience.

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