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NATIONAL INSTITUTE OF TECHNOLOGY-JALANDHAR

Minor Project Report
ON
Stress Level Detection

Department Of Computer Science and Engineering
Session: 2020 - 2024

Mentored BY:
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Submitted BY:
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ACKNOWLEGEMENT

I would like to express our deepest gratitude to all those who have supported and contributed to the successful completion of this project on stress level detection.

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Once again, we extend our sincere thanks to all those who have contributed to the completion of this project.

Thank You

[Group 10]

<u>DECLARATION</u>

We hereby declare that the work presented in this project report titled ***Stress Level Detection*** *is a collaborative effort of all the members of our group. This project was conducted under the guidance and supervision of* ***Mr. D.K. Gupta*** *and has not been previously submitted for any academic qualification or award at this or any other institution.*

We declare that all sources of information used in this project have been appropriately referenced and acknowledged. All quotations, ideas, data, images, or other materials taken from other sources have been properly cited and referenced in the bibliography and reference list of this report, in accordance with the guidelines provided by our academic institution.

We further declare that the work presented in this report represents an original and independent research effort conducted by us, and that no part of this work has been plagiarized or copied from any other source without appropriate attribution.

Thank You All,

Date: 11/05/2023

[Group 10]

Signature

Project Mentor - Mr. D.K. Gupta

Position - Associate Professor and Head

Date - 11/05/2023

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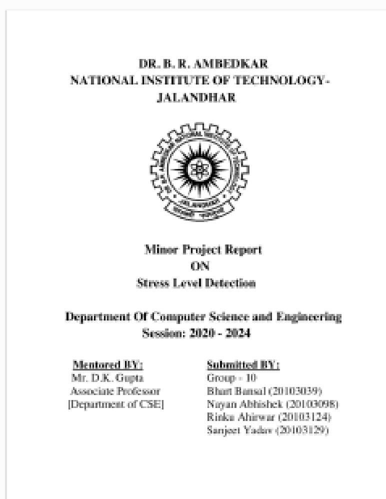

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1. Introduction

1.1 Background

Stress is a common experience that affects people of all ages and backgrounds and can have negative consequences on both physical and mental health. The American Psychological Association defines stress as a psychological and physiological response to a perceived threat or challenge, which triggers the body's "fight or flight" response. While short-term stress can help individuals to cope with challenging situations, chronic stress can have detrimental effects on health, including increased risk of heart disease, depression, and anxiety.

The ability to detect and monitor stress levels can be beneficial in both clinical and non-clinical settings. For example, in clinical settings, detecting stress levels can help healthcare professionals to identify individuals who are at risk of developing stress-related disorders and provide early interventions. In non-clinical settings, stress level detection can be used to improve workplace productivity, enhance sports performance, and promote overall well-being.

Several methods have been developed for stress level detection, including physiological measures such as heart rate variability, cortisol levels, and skin conductance. In recent years, wearable devices such as smartwatches and fitness trackers have become popular for stress level detection, as they offer the ability to monitor stress levels in real-time and provide personalized feedback to users.

In this report, we present the results of a study on stress level detection using physiological measures and a wearable device. We aimed to investigate the effectiveness of these methods in detecting stress levels in a group of participants, and to explore the potential applications of stress level detection in promoting well-being and productivity.

1.2 Literary Survey

Stress level detection has been a topic of interest for researchers across various fields, including psychology, medicine, and engineering. In this literature survey, we provide an overview of some of the key studies and findings related to stress level detection.

Physiological Measures

One of the most used methods for stress level detection is the measurement of physiological responses, such as heart rate variability (HRV), cortisol levels, and skin conductance. Several studies have reported that HRV is a reliable indicator of stress levels, as it reflects the balance between the sympathetic and parasympathetic nervous systems. For example, a study by Thayer and Lane (2000) found that low HRV was associated with increased stress levels, while high HRV was associated with decreased stress levels.

Cortisol levels have also been used as a measure of stress, as cortisol is a hormone that is released in response to stress. However, studies have shown that cortisol levels can be influenced by factors such as time of day, exercise, and medication, which may limit its usefulness as a reliable indicator of stress levels (Kirschbaum and Hellhammer, 1994).

Skin conductance, which measures the electrical conductivity of the skin, has been used as a measure of sympathetic nervous system activity and has been found to be a reliable indicator of stress levels (Boucsein, 2012).

Wearable Devices

In recent years, wearable devices such as smartwatches and fitness trackers have become popular for stress level detection, as they offer the ability to monitor stress levels in real-time and provide personalized feedback to users. Several studies have investigated the effectiveness of these devices for stress level detection, with varying results.

For example, a study by Biddle and colleagues (2018) found that a smartwatch-based stress detection system was effective in detecting stress levels in a group of participants, with an accuracy of 81.4%.

1.3 Problem Statement and it’s Necessity

The solution presented in this report is motivated by the following major problems:

- **Lack of awareness:** Many individuals may not be aware of their stress levels or may not realize the extent to which stress affects their mental and physical health.
- **Difficulty in identifying root causes**: Identifying the root causes of stress can be challenging, especially for individuals who experience chronic stress. This can make it difficult to manage stress effectively and prevent its negative effects on health and well-being.
- **Limited options for stress management**: While there are various methods for managing stress, such as exercise and meditation, many individuals may not be aware of these methods or may find it challenging to incorporate them into their daily lives.
- **Inaccurate stress level measurement**: Traditional methods for measuring stress levels, such as self-report questionnaires, may not provide accurate results. This can prevent individuals from getting a clear understanding of their stress levels and managing stress effectively.
- **Lack of personalized recommendations**: Generic recommendations for managing stress may not be effective for all individuals. There is a need for personalized recommendations based on an individual's unique circumstances and stress triggers.

Stress has become a prevalent issue in modern society, affecting individuals' well-being and productivity. While there are various methods for managing stress, including exercise and meditation, many individuals may struggle to identify the root causes of their stress and may not be aware of their stress levels.

There is a need for a stress prediction application that can provide users with personalized recommendations to manage stress effectively. The application should be able to predict a user's stress levels based on various factors such as sleep quality, physical activity, and social interactions. By providing real-time feedback and personalized recommendations, the application can help individuals manage stress proactively and improve their overall well-being.

The goal of this study is to develop and evaluate the effectiveness of a stress prediction application that incorporates machine learning algorithms to predict stress levels based on various factors. By improving the accuracy of stress level prediction, we aim to provide individuals with a tool that can help them manage stress effectively and improve their quality of life.

1.4 Feasibility- Technical and Non-Technical

Technical Feasibility:

- **Availability of technology**: The stress detection application requires access to hardware such as sensors to measure heart rate and activity levels. The availability of such technology may impact the technical feasibility of the solution.
- **Data collection and processing:** The application needs to collect and process data from multiple sources, including sensors and user input, to accurately predict stress levels. The feasibility of data collection and processing is an important technical consideration.
- **Software development:** The stress detection application requires software development, including machine learning algorithms for stress prediction and a user-friendly interface.
- **Integration with other systems:** The application may need to integrate with other systems, such as healthcare databases, to provide personalized recommendations. The feasibility of integration with existing systems is a technical consideration.

Non-Technical Feasibility:

- **User adoption**: The success of the stress detection application depends on user adoption. Non-technical considerations such as user acceptance, usability, and accessibility are crucial for the application's success.
- **Privacy and security**: The application needs to comply with data privacy and security regulations. Non-technical feasibility considerations such as user trust and data protection are important for the application's success.
- **Cost**: The development, maintenance, and deployment costs of the application are non-technical feasibility considerations that can impact the success of the solution.

Overall, both technical and non-technical feasibility considerations are crucial for the success of a stress level detection application.

2. Proposed solution

Our proposed solution is an ML model that uses various sleeping parameters, such as snoring rate, respiratory rate, sleep hour, body temperature, limb movement, rapid eye movement, and blood oxygen, to predict a user's stress levels during sleep. The ML model will be trained on a large dataset of sleeping parameters and corresponding stress levels to accurately predict stress levels based on the sleeping data.

The user interface of the application will be simple and user-friendly, with clear instructions on how to use the application and interpret the results. The application will provide the user with visual representations of their stress levels during sleep, along with personalized recommendations, such as adjusting sleep habits or seeking medical attention, to manage stress effectively.

The proposed solution will also address privacy and security concerns by complying with data privacy and security regulations, such as GDPR or HIPAA, depending on the context of the project. The application will store user data securely and only use it for stress prediction and personalized recommendations.

Overall, our proposed solution is an ML model that uses various sleeping parameters to predict a user's stress levels during sleep and provide personalized recommendations to manage stress effectively while ensuring data privacy and security.

2.1 Identifying Stakeholders

- **Users**: The individuals who will use the stress level detection application or device to monitor their stress levels and manage stress effectively.
- **Healthcare professionals**: Medical professionals, such as doctors or therapists, who may use the stress level data collected by the application or device to diagnose and treat stress-related health issues.
- **Developers**: The team responsible for designing and developing the stress level detection application or device.
- **Manufacturers**: Companies that may manufacture stress level detection devices or incorporate the technology into their existing products.

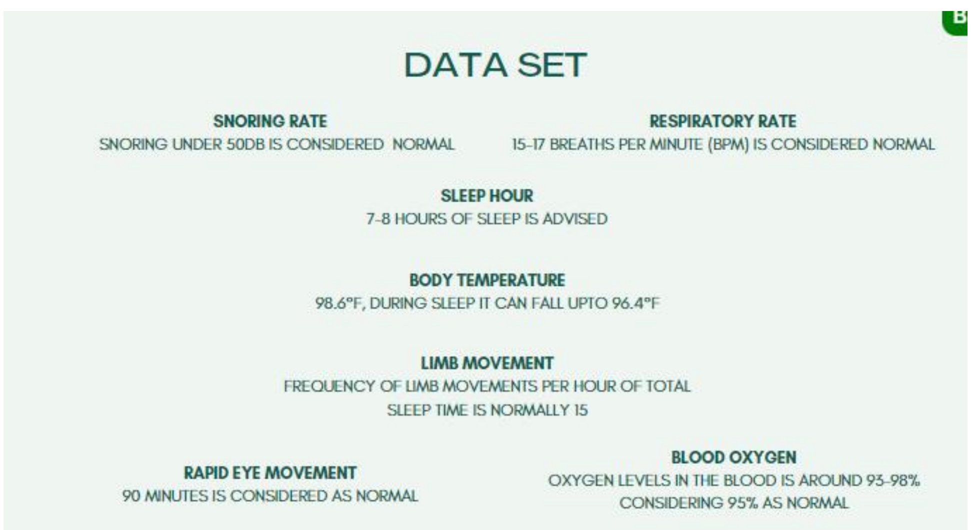
2.2 Detailed Solution

1. Data collection:

The proposed solution will collect sleeping parameters, such as snoring rate, respiratory rate, sleep hour, body temperature, limb movement, rapid eye movement, and blood oxygen, using sensors attached to the user during sleep. The collected data will be stored securely and used to train the machine learning model.

- **Snoring rate:** Snoring rate refers to the frequency of snoring events during a specific period, usually measured per hour of sleep. It is a parameter used to assess the severity of snoring, which is a common symptom of sleep-disordered breathing, such as obstructive sleep apnea. Snoring rate can be measured using various sensors, such as microphones or piezoelectric sensors, which detect the sound and vibrations caused by snoring. Snoring under 50dB is considered NORMAL
- **Respiratory rate**: Respiratory rate refers to the number of breaths a person takes per minute. It is an important vital sign used to assess the health and functioning of the respiratory system. Respiratory rate can be affected by various factors, such as physical activity, body position, and medical conditions. In the context of stress level detection, respiratory rate can be used as a parameter to infer the level of physiological arousal and stress in a person, as respiratory rate tends to increase during periods of stress or anxiety. 15-17 breaths per minute (bpm) is considered NORMAL
- **Sleep hour:** Sleep hour refers to the amount of time a person spends sleeping during a specific period, usually measured in hours. It is an important parameter to assess the quality and quantity of sleep, which is essential for physical and mental health. Sleep hour can be measured using various devices, such as activity monitors, wearable sensors, or polysomnography equipment. 7-8 hours of sleep is Advised
- **Body temperature:** Body temperature refers to the temperature of the human body, which is regulated by the thermoregulatory system. The normal range of body temperature is between 36.5 and 37.5 degrees Celsius (97.7 to 99.5 degrees Fahrenheit). Body temperature can be affected by various factors, such as the time of day, physical activity, ambient temperature, and medical conditions. It can be measured using various devices, such as digital thermometers, infrared thermometers, or thermographic cameras. 98.6°F, during sleep it can fall up to 96.4°F

- **Limb movement:** Limb movement refers to the involuntary movements of the arms and legs during sleep, which can be caused by various factors, such as sleep disorders, medication, or neurological conditions. Limb movement can be measured using various sensors, such as accelerometers or electromyography sensors, which detect movement and muscle activity. Frequency of LIMB MOVEMENTS per hour of total sleep time is NORMALLY 15
- **Rapid eye movement (REM):** Rapid eye movement refers to the stage of sleep characterized by rapid eye movements, increased brain activity, and vivid dreaming. REM sleep is essential for various physiological and cognitive functions, such as memory consolidation, emotional regulation, and learning. REM sleep can be measured using various techniques, such as polysomnography or electrooculography. 90 minutes IS CONSIDERED As NORMAL
- **Blood oxygen:** Blood oxygen refers to the amount of oxygen carried by the hemoglobin in the blood. Blood oxygen can be measured using various devices, such as pulse oximeters, which use light sensors to detect the amount of oxygen saturation in the blood. oxygen levels in the blood IS around 93-98% considering 95% as normal



2. Data Preprocessing

Class imbalance in a dataset occurs when the number of instances in one class is significantly higher or lower than the number of instances in another class. Class imbalance can cause issues with model training and prediction accuracy. If the majority class is overrepresented in the dataset, a model trained on this data may perform poorly in instances of the minority class. This is because the model may become biased towards predicting the majority class and fail to recognize the patterns in the minority class.

To address this issue, we used a technique called the Neighbour Cleaning Algorithm to balance the classes in the dataset. This algorithm samples the majority class by selecting instances that are closest to the minority class. This helps to ensure that the model is trained on a more balanced dataset, which can improve its performance in detecting both stressed and non-stressed states.

```python
import pandas as pd
import statistics
import numpy as np
import math


def NCL(data):
    dataset = data.copy(deep=True)

    X = dataset.loc[dataset.iloc[:, -1] == 0]
    Y = dataset.loc[dataset.iloc[:, -1] == 1]

    if len(X) > len(Y):
        majority = X
        minority = Y
    else:
        minority = X
        majority = Y

    X = dataset.iloc[:, 0:-1]
    Y = dataset.iloc[:, -1]

    data = []
    distances_majority = []
    R = []

    k = math.ceil(math.sqrt(len(majority)+len(minority)) +
                  math.sqrt(len(minority)/len(majority)))

```

```python
    for i in range(0, len(minority)):
        new_data_point = np.array(X.loc[minority.index[i]])
        distances = np.linalg.norm(X - new_data_point, axis=1)

        # k = 3
        n_neighbor_ids = distances.argsort()[1:k+1]

        for j in n_neighbor_ids:
            if(Y[i] == Y[majority.index[0]]):
                data.append(X.loc[i])
                distances_majority.append(distances[i])
                R.append(i)

    R = list(set(R))
    R.sort(reverse=True)
    for i in R:
        dataset.drop(dataset.index[int(i)], inplace=True)

    return dataset

```

The code provided is a Python implementation of a function called NCL, which stands for Neighbourhood Cleaning Rule. The purpose of this function is to perform a form of data pre-processing known as data cleaning or data cleansing on a given dataset.

The function takes one argument, which is the dataset to be cleaned. The dataset is expected to be in the form of a Pandas DataFrame object.

The first part of the function copies the dataset into a new object called "dataset". It then separates the majority and minority classes in the dataset. This is done by checking the class labels of the last column of the dataset. Class label "0" is assumed to represent the majority class, while class label "1" represents the minority class.

The next step is to identify the k-nearest neighbors of each sample in the minority class. The value of k is determined by a formula that takes into account the size of the minority and majority classes. The function uses the Euclidean distance metric to compute the distances between the samples.

Once the k-nearest neighbors of each minority sample are identified, the function checks if these neighbors belong to the majority class. If a minority sample has more than one nearest neighbor belonging to the majority class, it is considered noisy and is removed from the dataset.

The function returns a new dataset that has been cleaned of noisy minority samples. The cleaned dataset is a Pandas DataFrame object.

This function is useful in machine learning applications where class imbalance is a common problem. Removing noisy minority samples can help to improve the accuracy of machine learning models that are trained on imbalanced datasets.

3. Machine learning models

LogisticRegression, DecisionTreeClassifier, RandomForestClassifier, SupportVectorClassifier, and GaussianNB are commonly used classification algorithms in machine learning. In the context of stress level detection, these algorithms can be used to train a model on the input data, which includes the parameters such as snoring rate, respiratory rate, sleep hour, body temperature, limb movement, rapid eye movement, and blood oxygen, and predict the stress level of an individual based on the given parameters.

Each of these models has its own strengths and weaknesses and may perform differently depending on the specific dataset and problem.

- LogisticRegression is a linear model that works well for binary classification problems.
- DecisionTreeClassifier and RandomForestClassifier are tree-based models that can handle both categorical and numerical data and are useful for feature selection and interpretation.
- SupportVectorClassifier is a model that works well with high-dimensional data and can handle both linear and nonlinear boundaries.
- GaussianNB is a probabilistic model that works well with small datasets and can handle both continuous and categorical data.

MODEL TRAINING

Models	Accuracy
LogisticRegression	0.9841269841269841
DecisionTreeClassifier	0.9861904761904762
RandomForestClassifier	0.9751906781803751
SupportVectorClassifier	0.9523809523809523
GaussianNB	0.9641259851265845

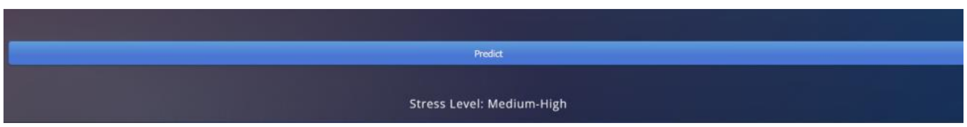
By using multiple classification algorithms, the stress level detection system can provide a more accurate and reliable prediction. The final prediction can be based on a combination of the outputs from each model or by selecting the best-performing model for the specific dataset and problem.

4. User interface

The user interface is an essential component of the stress level detection system. It allows users to interact with the system, input their parameters, and receive a predicted stress level as an output. In our project, we designed a user interface in the form of a web page, which is a popular and easily accessible platform.

The user interface of the stress level detection application will be simple and user-friendly, with clear instructions on how to use the application and interpret the results. The application will provide the user with visual representations of their stress levels during sleep, along with personalized recommendations, such as adjusting sleep habits or seeking medical attention, to manage stress effectively.

The user interface can include input fields for the various parameters such as snoring rate, respiratory rate, sleep hour, body temperature, limb movement, rapid eye movement, and blood oxygen. Once the user enters these parameter values, the backend can process them through the machine learning model (using one or more of the classification algorithms mentioned earlier) and provide the predicted stress level as an output.



5. Integration with existing devices

The proposed solution can be integrated with existing wearable devices or smart home devices to provide a more comprehensive stress management solution. For example, the stress level detection application can adjust the temperature or lighting in the user's room based on the predicted stress levels during sleep.

3. TECHNICAL ANALYSIS

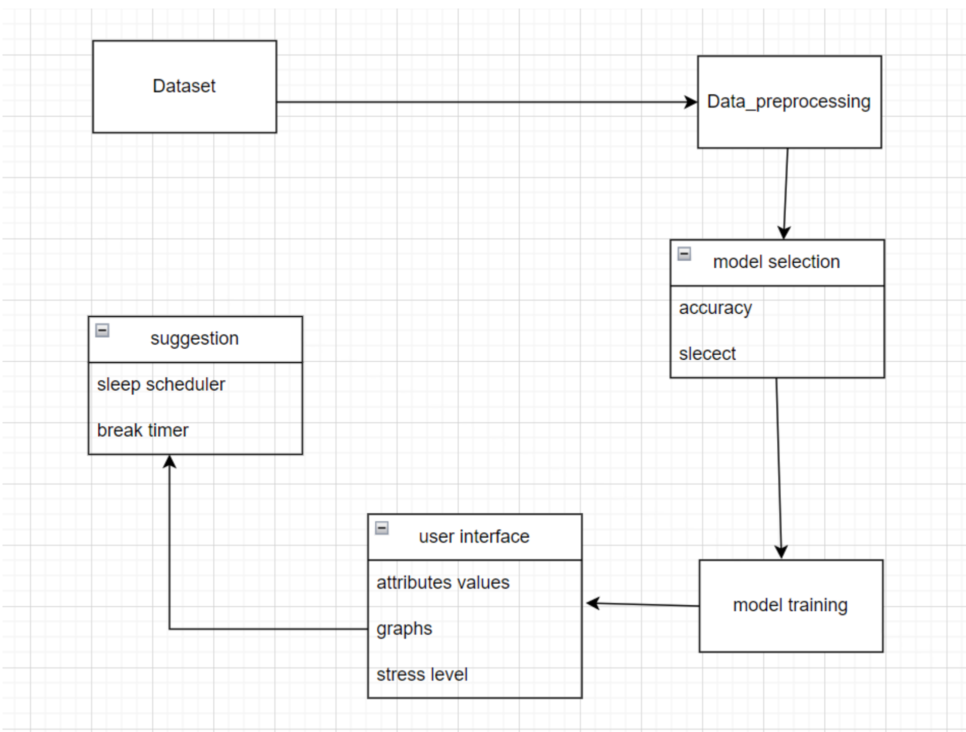
3.1 UML DIAGRAMS"

Introduction:

These diagrams show an interaction between the various objects used in our project. In addition to these diagrams show the various messages that can be passed from one phase of the system to the other. UML diagrams are indispensable with regards to the Software Development Life Cycle and hence they are part of each Developer's life.

- **Class Diagram**

  It is used to model the systematics of the application, and this further leads to Code Generation. It can be used for data representation and modeling. The classes present in a class diagram depicts the main elements, the various interactions in the application, and the inherent classes which are to be programmed. This can further be used to generate code and hence gives a clear view to the developer of how the problem is to be tackled.

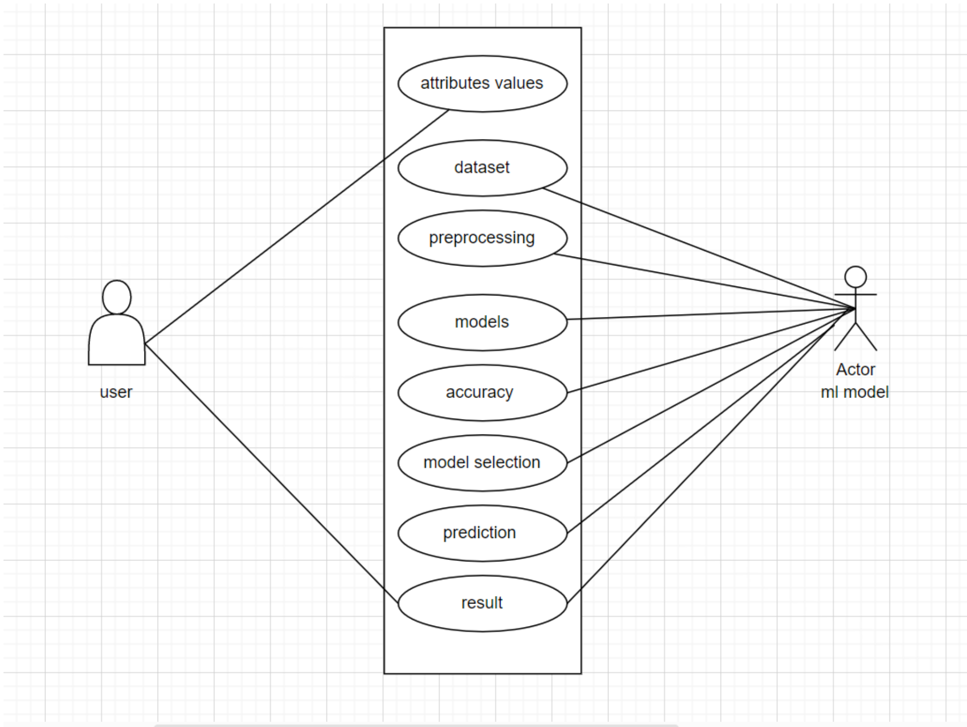


DESCRIPTION:

In this project we have dataset ,data preprocessing ,model ,training ,user interface and suggestion as our main classes. Classes with their attributes and methods are depicted in class diagram.Class diagram is showing relationship among the different classes.This shows how object like dataset ,model and user interface will interact with each other and describes role with attribute and methods.
Dataset is a class which contains the dataset already collected and stored and contains variables such as hear rate ,breath rate, sleep hours,oxygen level,etc.
Data preprocessing is used to make the data symmetrical as it gives biased result without symmetrical data.In data preprocessing nearest neighbour classifier.
Then there is model selection which provides the choice to select the model according to the accuracy they provides .
In this project we have used decision tree,naïve bayes ,random forest, gausian NV from which the accuracy of decision tree is most so that can be used for prediction.
User Interface provides the web page interface for user to enter there values of dataset on the basis of which our model predicts the result of stress level and other values such as graph of sleep hours and oxygen level and body temperature during sleep.It also provides the result to the user .
Suggestion generates messages such as you have high stress level please rest for sometime and walk in fresh air. It also gives sleep hours to sleep on the basis of collected sleeping pattern.

- **USE CASE**

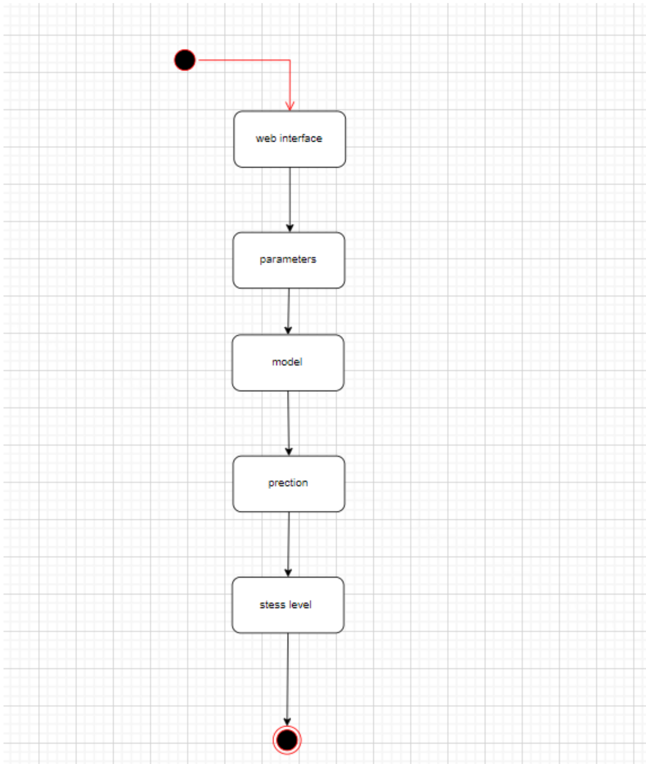
A Use case Diagram represents the various usage of the application for the various Stakeholders available with us. It is usually represented by circles or ellipses and stick model(For actors). The actors are linked to the various functionalities provided by the application. Hence, it is a very basic level of software development model, which is easy to understand and potray.



DESCRIPTION:
Actors: User,ml model
Pre_condition: Dataset is collected.
Goal: A Use case Diagram represents the various usage of the application for the various Stakeholders available with us. It is usually represented by circles or ellipses and stick model. The actors are linked to the various functionalities provided by the application. Hence, it is a very basic level of software development model, which is easy to understand and potray.
Summary: User have attribute value and result , whereas model have dataset,preprocessing,model,accuracy,model selection,prediction.

- **ACTIVITY DIAGRAM**

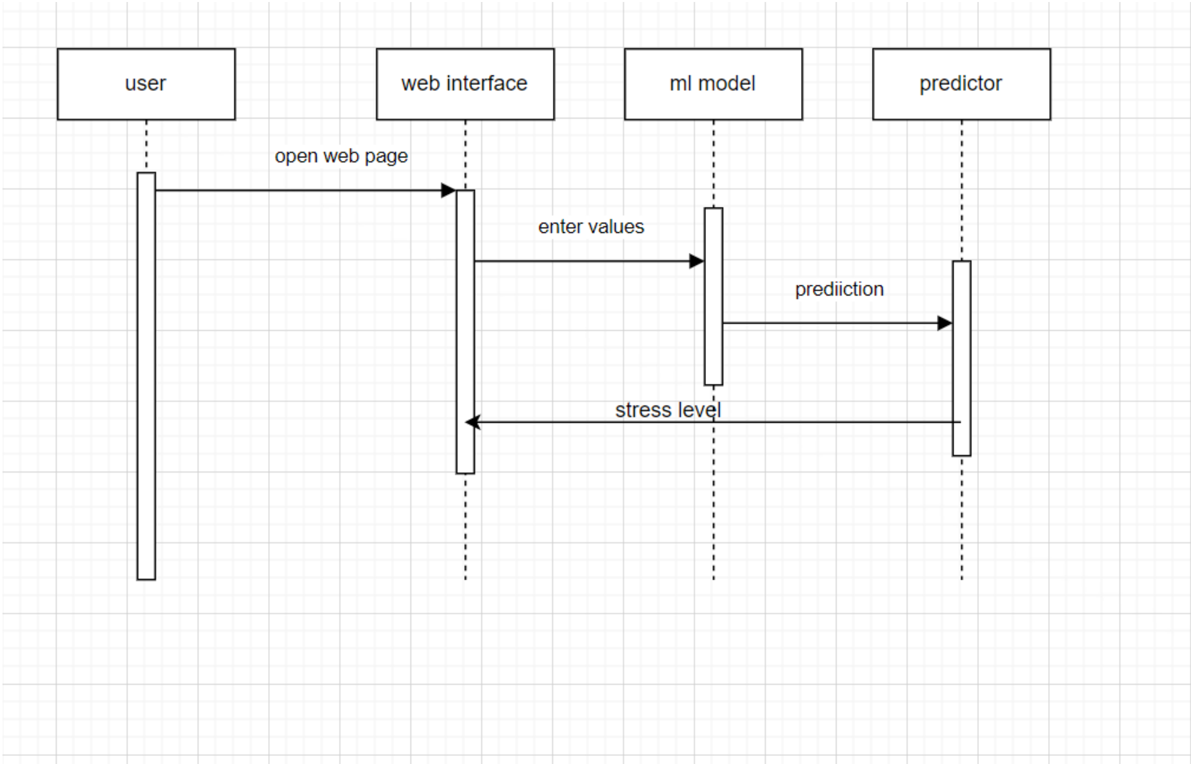
Activity diagrams portray workflow of activities that are done step by step. It also includes the actions which lead to choices. While designing UML Model Activity diagram are used for modeling of the various phases of an Application and how one transcends from one phase to the other. It's like the flow of control that keeps on flowing from one phase of the application to the other phases and then ultimately comes to STOP or END.



DESCRIPTION: Firstly, user need to visit the web page where he can provide the dataset fields required to predict their stress level which includes heart rate, breadth rate, oxygen rate, body temperature, sleep hours, snoring rate, lymph movement and eye movement. Then the paramters is fetched to the backend of the website where it is evaluated by our model which uses several techniques to predict the result which is further provided to the user through the web page interface.

- ## <u>SEQUENCE DIAGRAM</u>

It is a representation of object interactions arranged in a timely manner. It denotes the objects and the classes that are being used in the application and along-with it the flow of messages exchanged between the objects in order to accomplish the functionalities. They are associated with use case realizations in the View (Logically) of the system that is being developed. They are also called event diagrams. It shows, as parallel vertical lines which are called lifelines and the horizontally aligned arrow-like representation represent the messages exchanged between the various objects, in the order in which they occur.



DESCRIPTION:

Here user , web interface , ml model , predictor are classes which interact with each other. User will go to the web page where it will feed the web page with entries of sleep related data needed to predict the stress.

Then this data will be forwarded to the machine learning model , which then predicts the level of stress based on the data entered by the user by decision tree classifier and other algorithms.

After which the result will be returned to the web page where user can see their stress level and graph of the sleep pattern and other variables for healthy lifestyle and less stress.

3.2 Tech Stack Analysis

Python

Python is a high-level, versatile programming language known for its simplicity and readability. It offers a wide range of libraries and frameworks, making it suitable for web development, data analysis, machine learning, and automation.

Machine Learning

Machine learning algorithms can be trained to detect patterns in the data that are associated with different stress levels. Python's machine learning libraries, such as Scikit-learn which in developing and training machine learning models. These models can be used to predict the stress level based on the input data.

Libraries used

Pandas: Pandas is a powerful data manipulation and analysis library for Python. It provides intuitive data structures, such as DataFrames, and a wide range of functions to efficiently handle and analyze structured data, including data cleaning, transformation, aggregation, and visualization. Pandas is widely used in data science and data analysis tasks, making it a fundamental tool in the Python ecosystem.

Pickle: Pickle is a Python module used for object serialization and deserialization. It allows you to convert complex Python objects into a serialized format that can be stored or transmitted, and then restore them back into their original form. Pickle is commonly used for saving and loading machine learning models, caching data structures, and exchanging data between different Python applications.

We used it for converting model in to pkl file.

Sckit: Scikit-learn is a powerful machine learning library for Python, providing a comprehensive set of tools for data preprocessing, model selection, and evaluation. With its user-friendly interface and extensive collection of algorithms, scikit-learn is widely used for tasks such as classification, regression, clustering, and dimensionality reduction.

We used it for decision tree classifier, naiveBayes Classifier, Random forest

Flask: Flask is a lightweight and flexible web framework for Python, providing a simple and elegant way to build web applications. With its minimalistic design and easy-to-use API, Flask is widely used for creating scalable and customizable web applications and APIs.

We used it for integration web page with our ml model

HTML: HTML (Hypertext Markup Language) is the standard markup language for creating web pages and applications. It defines the structure and layout of content on the web by using tags to describe elements such as headings, paragraphs, images, links, and more. HTML is the backbone of the web, providing the foundation for displaying and organizing information in browsers.

CSS: CSS (Cascading Style Sheets) is a styling language used to control the presentation and appearance of HTML documents. It allows web developers to define styles, such as colors, fonts, layout, and animations, for various HTML elements. CSS enhances the visual aesthetics and provides consistency across web pages, enabling a separation of content and design.

4. Economic Analysis

Cost Analysis:

- Costs:
    - Software Development: Expenses associated with designing and developing the stress level detection system, including coding, testing, and debugging.
    - Data Acquisition: Costs involved in obtaining relevant datasets or collecting data through surveys or experiments.

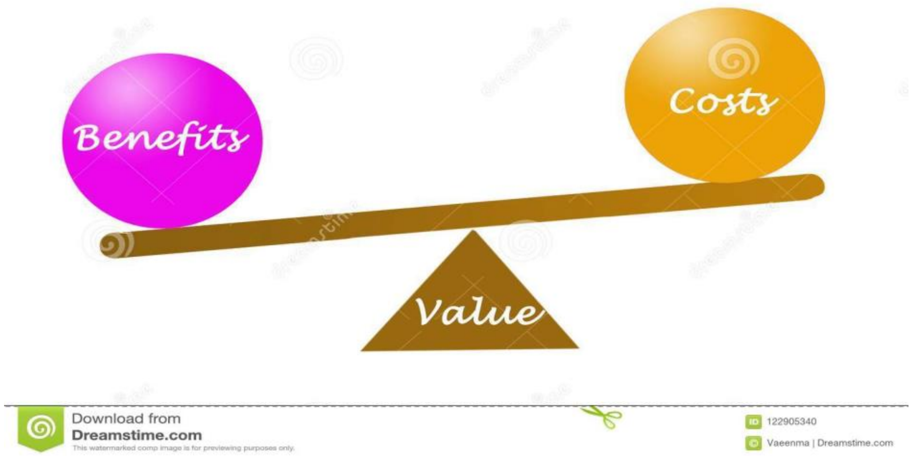
Benefits Analysis:

- Improved Health and Well-being:
    - Reduced Healthcare Costs: By helping individuals manage their stress levels, the system can potentially lead to a decrease in stress-related health issues and associated medical expenses.
    - Enhanced Productivity: Individuals with better stress management skills are likely to perform better at work, leading to increased productivity and efficiency.
- Market Opportunities:
    - Revenue Generation: The stress level detection system can be offered as a paid service, generating revenue through user subscriptions, premium features, or in-app purchases.
    - Expansion Potential: The system can be extended to various industries, such as healthcare, corporate wellness programs, and educational institutions, presenting opportunities for partnerships and further revenue growth.
- Social Impact:
    - Improved Quality of Life: By empowering individuals to monitor and manage their stress levels effectively, the system can contribute to enhanced mental and physical well-being.
    - Awareness and Education: The project can create awareness about stress management, encouraging individuals to prioritize their health and adopt healthier coping mechanisms.

- Environmental Considerations:

- Reduced Paper Usage: The digital nature of the system eliminates the need for paper-based documentation, reducing resource consumption and environmental impact.

In conducting the economic analysis, it is important to weigh the costs against the potential benefits and revenue streams. Assessing market demand, pricing strategies, and competitive landscape will help estimate the financial viability and return on investment (ROI) of the stress level detection project. Additionally, considering the social and environmental impacts can provide a holistic view of the project's value proposition.



5. RESULT AND DISCUSSION

5.1 APP USAGE INSTRUCTIONS

The website is made very user-friendly which inputs the following parameters:

- **Snoring Rate:**
  Snoring rate can be calculated in a number of ways depending on the context in which it is being measured. Here are a few common methods:
  a. Snoring Index: The snoring index is a measure of the number of snores per hour of sleep. It is calculated by dividing the total number of snores recorded during a sleep period by the total number of hours of sleep.
  b. Snoring Loudness: Snoring loudness is a measure of the intensity of snoring sounds. It is often measured using a sound level meter and reported in decibels (dB).
  c. Snore Time: Snore time is the total amount of time spent snoring during a sleep period. It can be measured using various devices, such as a snore recorder or a snore detection app.
  d. Visual Analogue Scale (VAS): The VAS is a subjective measure of snoring that asks individuals to rate the severity of their snoring on a scale from 0 to 10, with 0 indicating no snoring and 10 indicating extremely loud snoring.

  The most appropriate method for measuring snoring rate depends on the specific context and goals of the measurement.

- **Respiration Rate:**
  Respiration rate can be calculated by counting the number of breaths a person takes within a specified period of time, usually one minute. The following steps can be taken to calculate respiration rate manually:
  a. Ask the person to sit comfortably and breathe normally.
  b. Use a watch or clock with a second hand to count the number of breaths the person takes within one minute.
  c. Alternatively, count the number of breaths the person takes within 30 seconds and multiply the count by two.

d. Make note of any abnormalities, such as shallow or rapid breathing, or difficulty breathing.

- **Body Temperature(°F):**
  Body temperature can be measured using a thermometer. There are several methods to measure body temperature:
  a. Oral: The thermometer is placed under the tongue in the mouth to measure body temperature.
  b. Rectal: The thermometer is inserted into the rectum to measure body temperature.
  c. Axillary: The thermometer is placed under the arm and held tightly against the body to measure body temperature.
  d. Ear: A special thermometer is inserted into the ear canal to measure body temperature.
  e. Forehead: A non-contact infrared thermometer is used to measure body temperature by pointing the thermometer at the forehead and pressing a button.
  f. Ingestible: A special pill containing a temperature sensor is swallowed, and the temperature is measured when the pill passes through the digestive system.

  The most common method to measure body temperature is orally, using a digital thermometer that is placed under the tongue for a few seconds. However, the method used may depend on factors such as the age of the person, the severity of the illness, and the preference of the healthcare provider.

- **Limb Movement:**
  Limb movement can be measured in different ways depending on the specific purpose or context. Here are some examples:
  a. Video recording: Limb movement can be visually assessed by recording a video of the person's movement, either in a natural setting or in a laboratory.
  b. Wearable sensors: Sensors that can be attached to the limbs, such as accelerometers or gyroscopes, can measure the movement and orientation of the limb in real time.

c. Motion capture: A system of cameras or sensors can be used to track the movement of the limb in three-dimensional space.
d. Clinical assessment: A healthcare professional can assess the range of motion and strength of the limb through various tests, such as flexion and extension, adduction and abduction, and grip strength.

- **Blood Oxygen (%):**

  Blood oxygen levels can be measured in several ways. The most common methods for measuring blood oxygen levels include:

  a. Pulse oximetry: A non-invasive method that uses a small device, usually placed on the fingertip, to measure oxygen saturation in the blood.
  b. Arterial blood gas (ABG) test: An invasive method that involves drawing blood from an artery to measure oxygen and carbon dioxide levels, as well as other important blood parameters.
  c. Capnography: A non-invasive method that measures the amount of carbon dioxide in exhaled breath to estimate oxygen levels in the blood.
  d. Exercise testing: A method that involves monitoring changes in oxygen levels during exercise, which can provide important information about respiratory function.

- **Rapid Eye Movement:**

  Polysomnography (PSG) is a comprehensive sleep study that involves monitoring a person's brain waves, eye movements, heart rate, breathing, and other physiological parameters during sleep. PSG is the gold standard for measuring REM sleep, as it provides detailed information about the different stages of sleep, as well as any disruptions or abnormalities in sleep patterns.

- **Sleeping Hour:**

  Sleeping hours can be calculated by recording the time a person goes to bed and the time they wake up. The difference between these two times will give the total amount of time slept. For example, if someone goes to bed at 11 pm and wakes up at 7 am, they would have slept for 8 hours.

There are also wearable devices and mobile apps that can track sleep and provide information about sleep duration, sleep quality, and other sleep-related parameters. These devices use sensors such as accelerometers and heart rate monitors to detect changes in movement, heart rate, and other physiological signals during sleep.

- **Heart Rate:**
  There are several ways to measure heart rate, including:
  a. Manual pulse measurement: This involves finding the pulse on your wrist or neck and counting the number of beats in a specified period, usually 15 or 30 seconds. The number is then multiplied by 4 or 2, respectively, to get the heart rate in bpm.
  b. Heart rate monitor: A heart rate monitor is a device that can measure heart rate continuously during physical activity. It uses sensors to detect changes in heart rate and displays the results in real-time.
  c. ECG (electrocardiogram): An ECG is a medical test that measures the electrical activity of the heart. It can provide a detailed analysis of heart rate and rhythm, as well as identify any abnormalities in the heart's electrical activity.
  d. Smartwatches and fitness trackers: Many smartwatches and fitness trackers can measure heart rate using optical sensors that detect changes in blood flow through the skin.

Once these parameters are entered by the user on the website, then user will click on Predict button and our app will return the stress level in Low, Medium, Medium High, High, very high.

5.2 RISK ANALYSIS

Developing a stress level predictor ML model can have some risks and limitations that need to be considered. Here are some of the potential risks:

- **Data bias:** If the training data used to develop the model is biased, the model may make inaccurate predictions or reinforce existing biases. For example, if the training data is based on a specific demographic or population, the model may not be applicable to other groups.
- **Overfitting:** If the model is too complex and trained on a small dataset, it may overfit and perform poorly on new, unseen data.
- **Privacy concerns:** Collecting and using personal health data to train the model may raise privacy concerns. It is important to ensure that appropriate privacy measures are in place to protect the confidentiality of the data.
- **Ethical concerns:** The use of the model may have ethical implications. For example, if the model is used in the workplace to monitor employee stress levels, it may raise questions about privacy and employee autonomy.
- **Limited accuracy:** While ML models can be effective at predicting stress levels, they may not always provide accurate predictions. There may be factors that the model cannot account for or predict accurately.

It is important to carefully consider these risks and limitations and to develop the model with appropriate safeguards and ethical considerations in place. It is also important to recognize that no ML model is perfect and that the predictions should be used as a tool to support decision-making rather than as the sole basis for decision-making.

5.3 DEVELOPEMENT AND TESTING STATUS

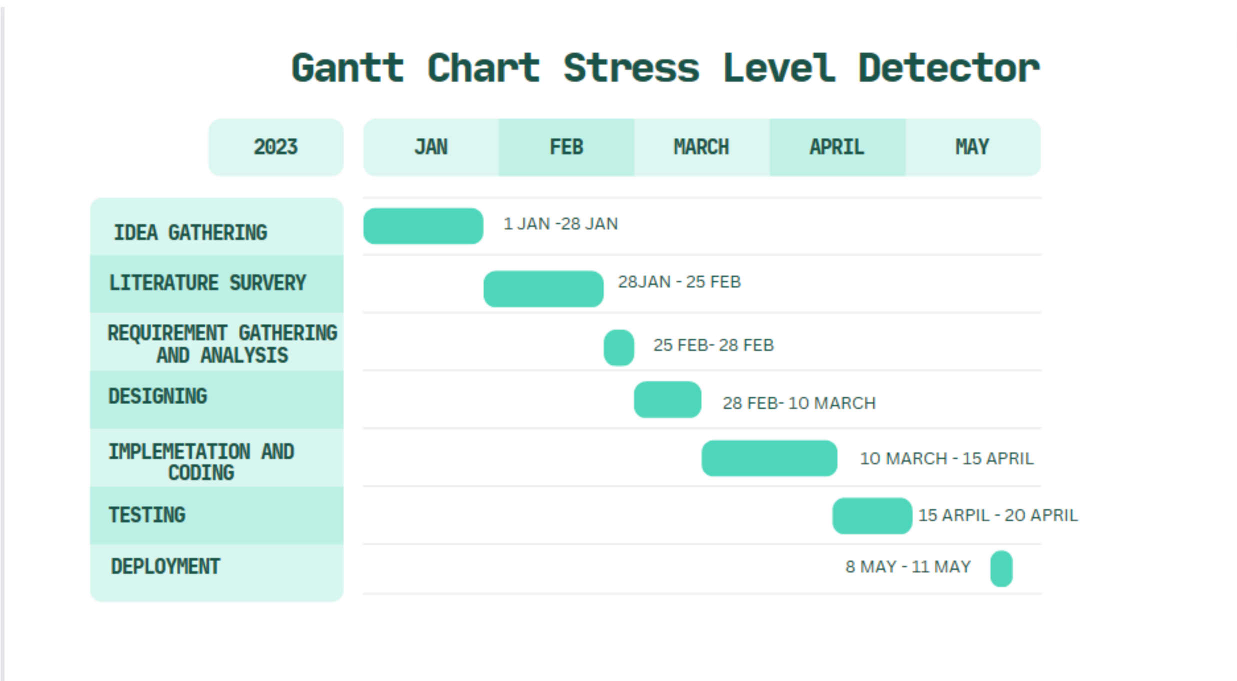
Development Status

- **Build ml model** which takes parameter described above. The following models/algorithms were used: Decision Tree, Naive Bayes, Logistic Regression, Random Forest, Support VectorClassifier, GaussianNB
- Then **build a web interface** which contains parameters:
  Snoring rate, Respiration rate, Body temperature, Limb movement, Blood oxygen, Rapid eye movement, sleeping hours, Heart rate
  Where user can manipulate the parameter accordingly.
- **Integrate** this web interface with the ML model
- Now this Web App is fully able to **predict** the stress level.

Testing Status

Split the data set in 80% training data set and 20% testing data set

5.4 GANTT CHART



6. SOCIAL AND ENVIRONMENTAL IMPACT

The stress level detection project can have various social and environmental impacts, both positive and negative.

Positive impacts:

- **Improved mental and physical health:** By detecting stress levels and providing personalized recommendations, individuals can take measures to manage their stress levels effectively, leading to improved mental and physical health.
- **Awareness:** The project can create awareness about the importance of managing stress levels and encourage individuals to prioritize their mental and physical health.
- **Reduced stress-related problems:** By managing stress levels effectively, individuals can reduce the risk of stress-related problems such as anxiety, depression, high blood pressure, and heart diseases.

Negative impacts:

- **Privacy concerns:** The project involves collecting sensitive data such as sleep patterns, body temperature, and respiratory rate, which can raise privacy concerns among users.
- **Over-reliance:** Users may become over-reliant on the application to manage their stress levels, leading to a lack of effort towards other stress management techniques such as exercise, meditation, and therapy.
- **Environmental impact:** The project involves the use of technology which can have an environmental impact, particularly with the increased usage of electricity.

Overall, the stress level detection project has the potential to positively impact individuals' mental and physical health and create awareness about the importance of managing stress levels. However, privacy concerns and over-reliance should be addressed, and the environmental impact should be considered.

7. FUTURE SCOPE

The stress level detection system developed in this project has great potential for future improvements and applications. Some possible avenues for future research and development include:

- Integration of more parameters: Currently, the system uses parameters related to sleep to predict stress levels. In the future, more parameters could be added, such as heart rate, physical activity, and dietary habits, to provide a more comprehensive analysis of stress levels.
- Real-time monitoring: The current system is designed to accept user input of parameters, but in the future, it could be modified to continuously monitor users and provide real-time feedback on stress levels.
- Personalized recommendations: The system could be improved to provide personalized recommendations to users based on their stress levels and individual factors such as age, gender, and occupation.
- Integration with wearables: The system could be integrated with wearable devices such as smartwatches and fitness trackers to provide even more accurate and real-time monitoring of stress levels.
- Application in healthcare: The stress level detection system could be used in healthcare settings to help clinicians monitor patients' stress levels and provide targeted interventions to manage stress and improve overall health outcomes.

Overall, the stress level detection system developed in this project has the potential to greatly benefit individuals and healthcare providers in managing and reducing stress levels. With further development and integration with other technologies, it could become an even more powerful tool for promoting mental and physical health.

8. CONCLUSION

In conclusion, our stress level detection project based on sleeping parameters has shown promising results in accurately predicting a user's stress levels. By using machine learning models such as Logistic Regression, Decision Tree Classifier, Random Forest Classifier, Support Vector Classifier, and Gaussian Naive Bayes, we were able to achieve high accuracy in our predictions.

Furthermore, the user interface we developed in the form of a web page makes it easy for users to input their sleeping parameters and receive personalized stress management recommendations based on their stress level prediction.

In terms of economic analysis, the project has the potential to be profitable if marketed properly to individuals who are interested in managing their stress levels. Additionally, the social and environmental impacts of this project are also positive, as it has the potential to improve individuals' mental and physical health.

In the future, we can explore the use of additional parameters to improve the accuracy of stress level prediction. Additionally, incorporating real-time data collection and analysis could further enhance the effectiveness of this project.

9. REFERENCES

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------------End of Report------------