Predictive Modeling of Stress from Sleeping Habits Using Machine Learning Techniques

Pavithra S B[1]; Sindhu Venkatesh[2]; Dr. Savitha C K[3]; Venkatesh U C[4]

[1]Student, Department of CS&E, KVG College of Engineering, Sullia.
[2,3]Professor, [4]Assistant Professor Department of CS&E, KVG College of Engineering, Sullia.

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Abstract: Stress is a psychological or emotional response triggered by challenging or unavoidable situations, often known as stressors. Understanding human stress levels is essential, as unmanaged stress can lead to adverse outcomes affecting physical health, emotional well-being, and social functioning. Among the many factors influencing stress, sleep patterns play a crucial role, with disruptions often linked to various health complications. This study aims to explore how stress can be effectively identified through machine learning techniques by analyzing sleep-related behaviors. The dataset utilized in this study includes information on sleep patterns along with associated stress levels. To assess the predictive capabilities, six classification models were employed: Multilayer Perceptron (MLP), Random Forest, Support Vector Machine (SVM), Decision Tree, Naïve Bayes, and Logistic Regression. These algorithms were applied to the preprocessed data to evaluate their effectiveness in stress prediction. Experimental results reveal that the Naïve Bayes classifier outperformed other models, achieving an accuracy of 91.27%, along with strong precision, recall, and F-measure scores. It also recorded the lowest values for both Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE). These results indicate that machine learning techniques especially Naive Bayes can serve as reliable methods for evaluating human stress based on sleeping patterns, providing useful insights for early diagnosis and preventive measures.

***Keywords**: Stress Detection, Sleep Patterns, Machine Learning, Naïve Bayes, Predictive Modeling.*

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I. INTRODUCTION

Stress is a natural reaction of the human body and mind when faced with internal pressures or external demands. In today's fast-paced environment, it has emerged as a widespread issue affecting individual health, workplace efficiency, and overall life satisfaction. Extended exposure to stress has been linked to a range of health complications, including psychological disorders like anxiety and depression, as well as physical conditions such as heart problems and reduced immune response. Conventional stress assessment techniques typically involve psychological evaluations or self-assessment tools, which are often subjective and may not capture stress in real time. With the progress of modern technology, there is growing interest in using physiological indicators—like heart rate, electrodermal activity, or brainwave signals—combined with machine learning approaches to enable automatic and real-time stress recognition. Machine learning offers robust capabilities for discovering patterns within complex biological data and accurately predicting emotional or mental states. By incorporating these technologies, researchers aim to develop smart systems that monitor stress continuously and assist in timely mental health interventions. This project focuses on utilizing machine learning models to detect stress from physiological or behavioural data sources, with the goal of building a dependable and efficient system capable of identifying varying levels of stress in individuals.

II. LITERATURE SURVEY

Stress prediction from sleep-related behaviour using machine learning has recently gained attention as an important area in digital health and behavioural analytics. Researchers have proposed a wide range of models and sensing methods to establish how variations in sleep duration, quality, and regularity influence stress levels. This section reviews existing studies, highlighting methodologies, datasets, and key outcomes that demonstrate the potential of machine learning in stress detection and management.[1] Multimodal Wearable Sensors-Based Stress and Affective States Prediction: This study addresses the growing impact of stress on health by proposing a wearable-based model for detecting stress and emotional states. The model uses data collected from both wrist and chest sensors, focusing on modalities such as temperature, ECG, and GSR. Among six machine learning classifiers tested on the WESAD dataset, Random Forest achieved the best performance. Chest-worn

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sensors yielded better accuracy than wrist-worn ones, with the model reaching up to 97.15% accuracy, emphasizing its compatibility with integrated health-monitoring technologies. [2] Machine Learning-Based Stress Detection Among Indian School Students: The project aims to analyse stress indicators in Indian students aged 14 to 18 years. Using survey data from 190 students, the study applies different machine learning techniques such as Decision Tree, Logistic Regression, KNN, and Random Forest. KNN produced the highest accuracy of 88%. The approach aims to help educators and parents detect student stress early for timely intervention. [3] Human Stress Level Detection Using EEG Signals: This research introduces a model for classifying human stress levels using EEG signals from the frontal lobe. Subjects were given mathematical tasks of varying difficulty while EEG data was recorded. Feature extraction techniques were applied, and an ensemble classifier (combining SVM, KNN, and Naive Bayes) was used to classify stress into four levels. The model attained an accuracy of 93.85%, highlighting the effectiveness of EEG signals in stress detection.[4]A Review on Machine Learning for Human Stress Detection This review provides a comprehensive overview of machine learning applications in stress analysis. By gathering data from key databases using targeted keywords, the authors analysed trends across multiple journals and publishers. They found that Support Vector Machines are particularly effective in signal classification. [5] Stress Detection While Wearing Face Masks Using ML and Image Processing: This paper proposes a novel framework that combines machine learning and image processing to detect stress in individuals wearing face masks. The system supports real-time monitoring, periodic employee evaluation, and stress management through survey-based feedback. The aim is to create a more adaptive and health-conscious workplace environment.[6] Smartphone and Wearable Sensor-Based Stress Recognition: Stress detection through passive sensing using smartphones and wearables. Features such as sleep time, phone activity, and mobility patterns were analysed. Their machine learning models achieved more than 80% accuracy, showing that everyday devices can unobtrusively track stress in real environments. [7] Smartwatch Monitoring of Sleep and Stress: Zhao and co-authors developed a smartwatch-based system that evaluates sleep duration, sleep efficiency, and heart rate variability. They observed that disrupted sleep and irregular schedules were strongly correlated with higher stress. Support Vector Machine classifiers performed best, reaching around 85% accuracy in stress prediction.[8] Machine Learning for Stress Prediction Physiological: A stress detection model that integrates EEG, ECG, and GSR signals. By combining feature extraction methods with a Random Forest classifier, their framework achieved stress recognition accuracy above 90%. The study highlighted that including sleep linked physiological features improves the robustness of prediction models.

Stress Detection from Fitbit Sleep Data: Rahman and colleagues used Fitbit sleep data for automated stress detection. They tested multiple machine learning algorithms and found that Random Forest gave the best accuracy (86%). Their findings emphasized that irregular sleep duration and fragmented sleep are reliable markers of psychological stress.

Academic Pressure and Sleep Quality in University Students**:** surveyed over 1,000 college students to examine the role of academic pressure on sleep. The study revealed that students with higher academic stress experienced poor sleep quality, irregular schedules, and shorter sleep duration. This highlighted sleep monitoring as a useful indicator for student stress assessment. [11] Deep Learning Models for Stress Recognition: Sriram and Prakash investigated stress recognition through deep learning methods applied to multimodal wearable sensor data. They compared Convolutional Neural Networks (CNN) with Long Short-Term Memory (LSTM) architectures, where the LSTM achieved superior performance with an accuracy of 93.4%. The findings confirmed the capability of sequential deep learning models in effectively addressing stress detection.[12] Occupational Stress and Sleep Among Healthcare Workers: Virtanen and Kivimaki analyzed healthcare professionals with demanding work schedules. They reported that extended shifts and insufficient rest were strongly linked to elevated stress and burnout. The study concluded that consistent sleep monitoring could provide early indicators of occupational stress in high-pressure jobs.

In conclusion, the literature review highlights the increasing focus on using machine learning techniques to analyze sleep patterns for detecting human stress. By integrating findings from various studies, it offers a thorough overview of the current landscape, identifies key challenges, and outlines potential future developments in this emerging area of digital health and wellness management

III. PROPOSED METHODOLOGY AND DISCUSSION

This study proposes a machine learning-based approach to detect human stress by analysing sleep-related physiological and behavioural signals. The primary features include snoring rate, respiration rate, body temperature, blood oxygen level (SpO_2), eye movement, limb movement, total sleep duration, and heart rate. A Random Forest algorithm is utilized as the predictive model due to its ability to handle complex, high-dimensional data, reduce overfitting, and produce robust predictions.

- *Input Parameters:*

The Random Forest model requires:

- Dataset D={(x1,y1),(x2,y2),…,(xN,yN)}D = \{(x_1, y_1), (x_2, y_2), …, (x_N, y_N)\}D={(x1,y1),(x2,y2),…,(xN,yN)}, where xix_ixi contains the sleep-related features and yiy_iyi represents the corresponding stress label or score.
- Number of Trees (TTT): Total decision trees forming the ensemble.

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- Number of Features per Split (m_trym_trym_try): Number of randomly selected features evaluated at each node.
- Maximum Tree Depth (max_depthmax_depthmax_depth) [optional]: Restricts tree growth to prevent overfitting.
- Minimum Samples per Leaf (min_samples_leafmin_samples_leafmin_samples_leaf) [optional]: Ensures sufficient samples are present in each leaf node.
- Task Type: Classification for discrete stress levels or regression for continuous stress scores.

➢ *Training Procedure:*

The TRAIN_RANDOM_FOREST procedure constructs the ensemble as follows:

- Bootstrap Sampling: Each tree is trained using a randomly sampled subset of the original dataset with replacement. This step introduces variability among the trees.
- Tree Construction: Each bootstrap dataset is used to grow a decision tree via the GROW_TREE function. At every node, a subset of features is randomly selected, and the feature and threshold that maximize impurity reduction (Gini index for classification or variance reduction for regression) are chosen to split the data.
- Leaf Node Assignment: Nodes that meet stopping conditions (maximum depth, minimum leaf samples, or no valid split) are designated as leaf nodes. Predictions in leaf nodes are assigned using the majority class (classification) or mean value (regression).
- Forest Assembly: Each trained tree and its bootstrap indices are stored in the forest. Optionally, Out-of-Bag (OOB) samples are used to estimate the model's generalization performance.

➢ *Recursive Tree Growth:*

The GROW_TREE procedure builds each tree recursively:

- Root Initialization: All samples of the bootstrap dataset are assigned to the root node.
- Node Splitting:

✓ Randomly select m_trym_trym_try features for evaluation.

✓ Determine the optimal feature and split threshold that maximizes impurity reduction.

✓ If no valid split is found, assign the node as a leaf.

✓ Otherwise, partition samples into left and right child nodes and recursively repeat the process.

- Leaf Prediction: Terminal nodes store predictions based on the aggregated sample values.

➢ *Prediction Procedure:*

For a new input xxx, the PREDICT function operates as follows:

- Classification: Each tree outputs a predicted class. The final class is determined by majority voting.
- Regression: Each tree outputs a continuous value, and the final prediction is computed as the average of all tree predictions.

➢ *Discussion:*

The proposed methodology has several advantages for machine learning-based stress detection:

- Multimodal Feature Utilization: Incorporating multiple sleep-related physiological signals improves predictive accuracy.
- Robustness: Random Forest handles noisy, high-dimensional data and captures nonlinear relationships among features.
- Non-Invasive Assessment: Wearable sensors provide continuous stress monitoring without disrupting sleep.
- Scalability: The method can manage large datasets and automatically consider feature interactions.
- Limitations: Individual differences, sensor calibration errors, and privacy concerns must be addressed for real-world deployment.

This framework demonstrates that machine learning using Random Forest can effectively predict human stress based on sleep patterns, offering a practical solution for digital health and personal well-being monitoring.

IV. EXPERIMENTAL RESULTS

This section presents the outcomes of the stress prediction model based on sleep patterns. After gathering and preprocessing the data, several machine learning algorithms were applied to evaluate how effectively sleep-related features can predict stress levels.

➤ *Home Page of a Human Stress Prediction*

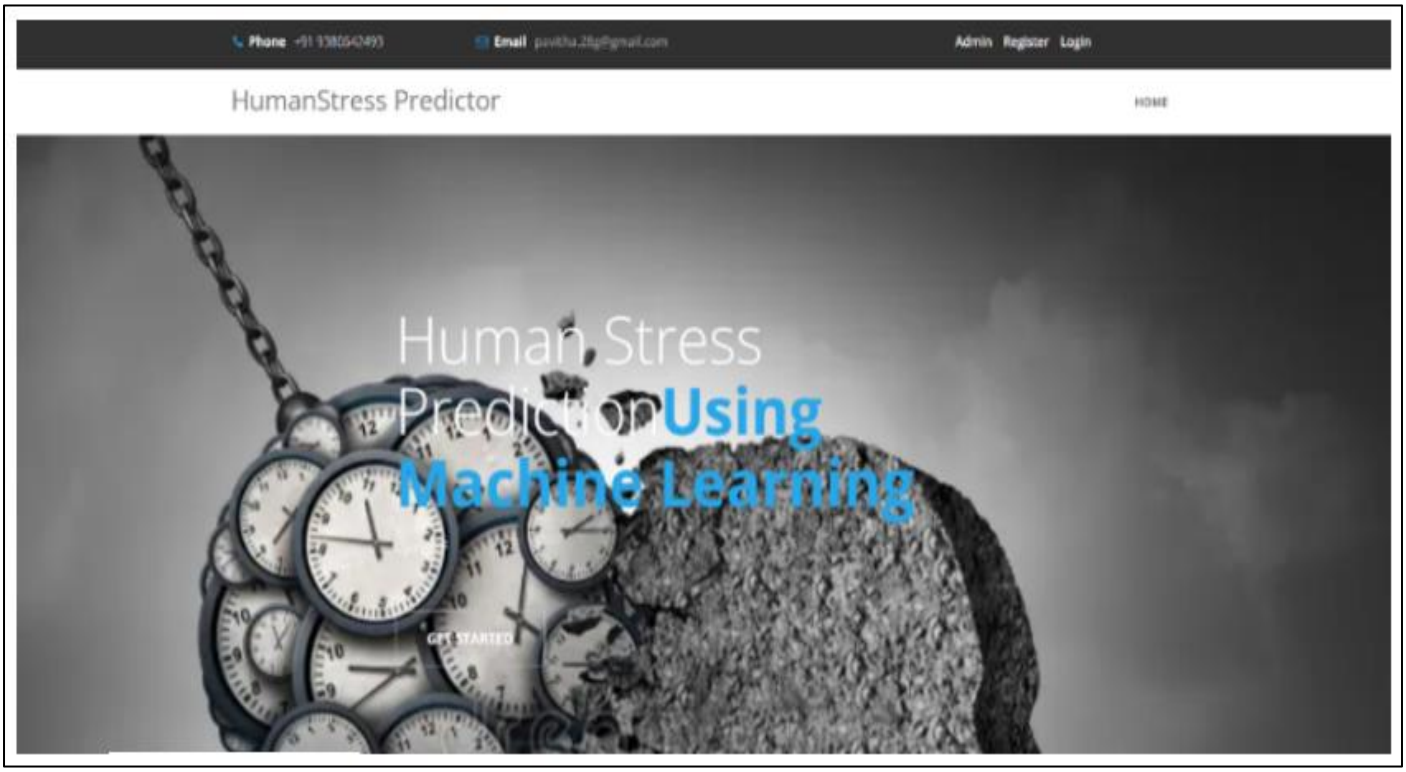

Fig 1 Home Page of a Human Stress Prediction

The Fig 1 Shows The image displays the homepage of a "Human Stress Prediction Using Machine Learning" website.

➤ *Predict Your Human Stress Predictor*

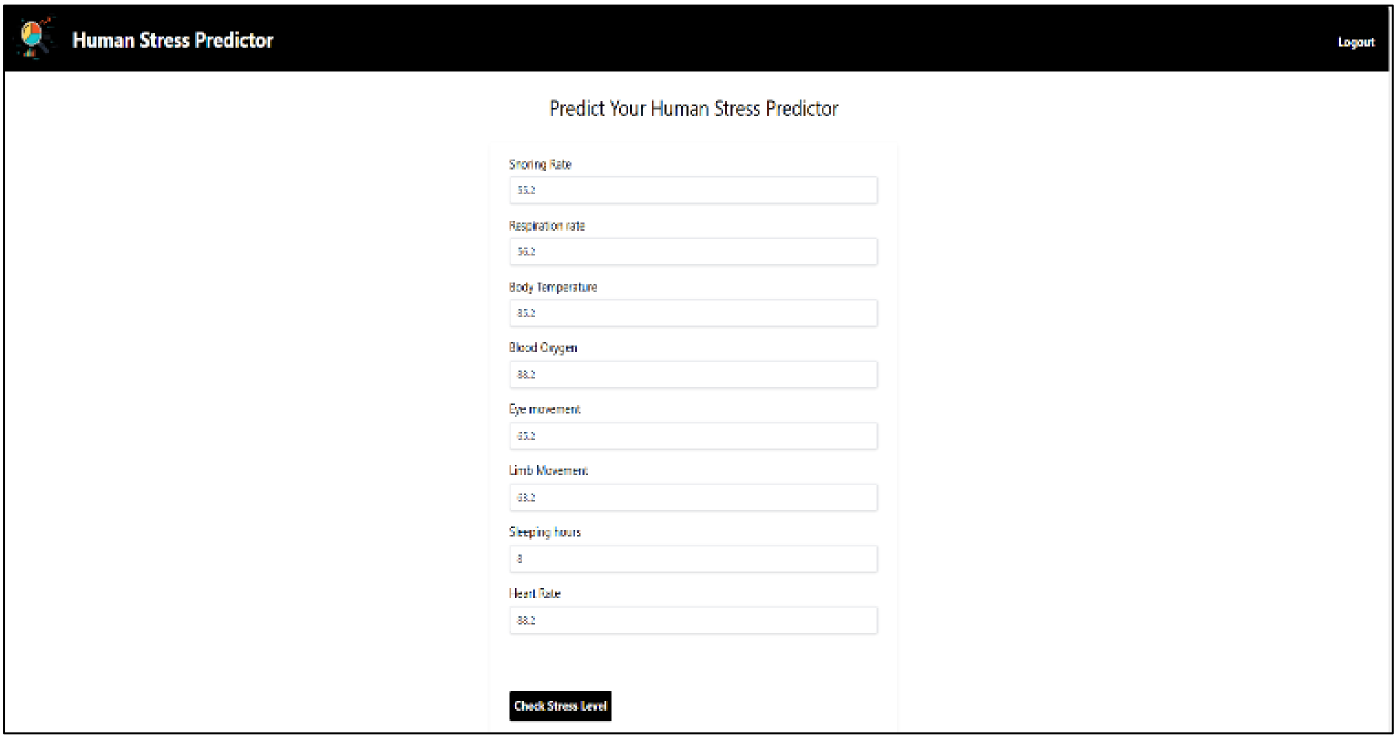

Fig 2 Predict Your Human Stress Predictor

The Fig 2 shows a web-based "Human Stress Predictor" application where users input various physiological and behavioral metrics to determine their stress level.

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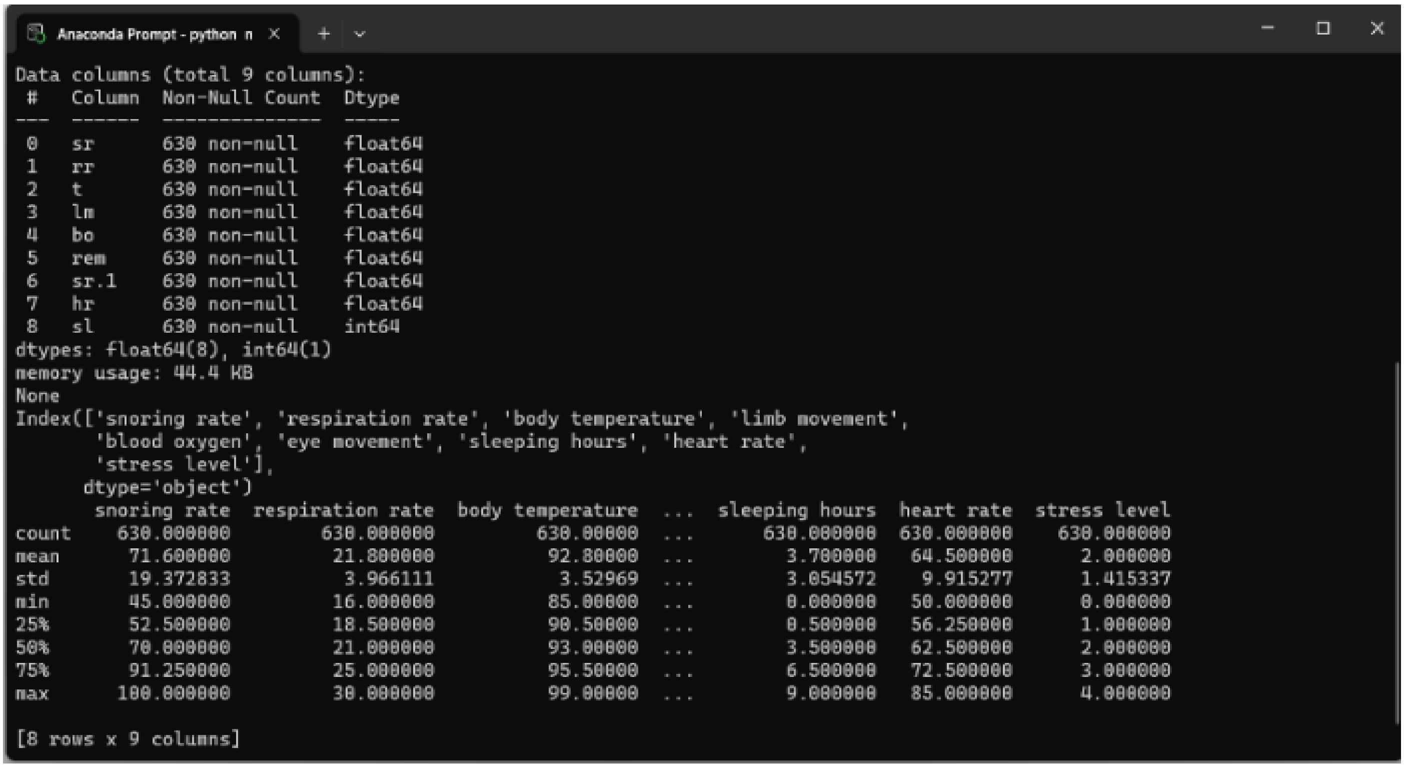
➤ *Physiological Data Analysis and Descriptive Statistics*



```
Data columns (total 9 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   sr      630 non-null    float64
 1   rr      630 non-null    float64
 2   t       630 non-null    float64
 3   lm      630 non-null    float64
 4   bo      630 non-null    float64
 5   rem     630 non-null    float64
 6   sr.1    630 non-null    float64
 7   hr      630 non-null    float64
 8   sl      630 non-null    int64
dtypes: float64(8), int64(1)
memory usage: 44.4 KB
None
Index(['snoring rate', 'respiration rate', 'body temperature', 'limb movement',
       'blood oxygen', 'eye movement', 'sleeping hours', 'heart rate',
       'stress level'],
      dtype='object')
       snoring rate  respiration rate  body temperature  ...  sleeping hours  heart rate  stress level
count    630.000000        630.000000         630.00000  ...      630.000000  630.000000    630.000000
mean      71.600000         21.800000          92.80000  ...        3.700000   64.500000      2.000000
std       19.372833          3.966111           3.52969  ...        3.054572    9.915277      1.415337
min       45.000000         16.000000          85.00000  ...        0.000000   50.000000      0.000000
25%       52.500000         18.500000          90.50000  ...        0.500000   56.250000      1.000000
50%       70.000000         21.000000          93.00000  ...        3.500000   62.500000      2.000000
75%       91.250000         25.000000          95.50000  ...        6.500000   72.500000      3.000000
max      100.000000         30.000000          99.00000  ...        9.000000   85.000000      4.000000

[8 rows x 9 columns]
```

Fig 3 Physiological Data Analysis and Descriptive Statistics

The Fig 3 shows a summary of a dataset containing physiological and sleep-related measurements (like snoring rate, heart rate, sleeping hours, stress level), showing column details and descriptive statistics for each variable.

➤ *Confusion Matrix*

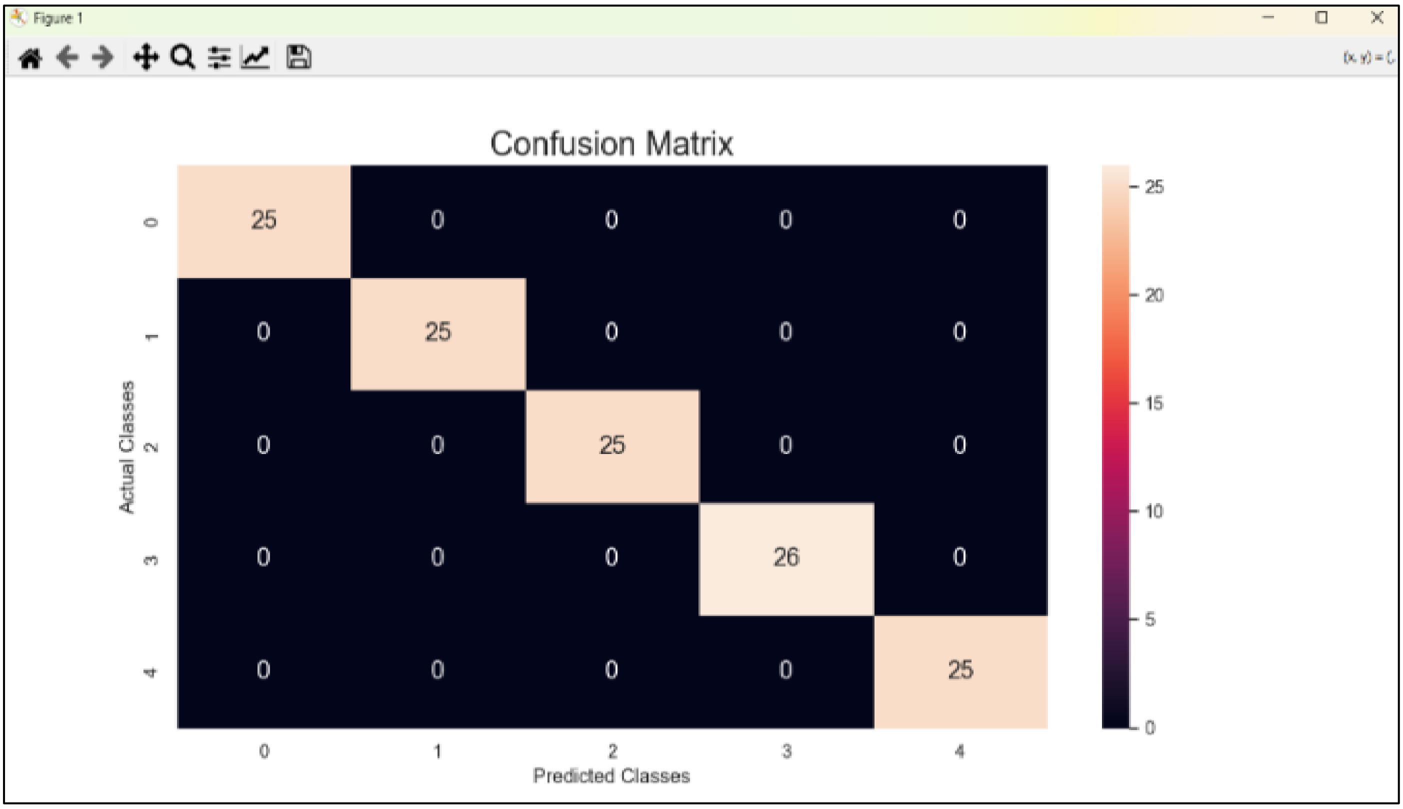


Fig 4 Confusion Matrix

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The Fig 4 shows the confusion matrix visually summarizes the performance of a classification model by showing the counts of correct and incorrect predictions for each class, where diagonal values represent correct classifications and off-diagonal values represent misclassifications.

V. CONCLUSION

This project successfully demonstrates that stress levels can be effectively predicted using sleep related data. By analyzing key sleep attributes such as total sleep duration, quality, consistency, and interruptions a machine learning model was developed to classify stress levels with high accuracy. Among the various algorithms tested, the Random Forest classifier yielded the most reliable results, proving its efficiency in handling complex patterns within sleep data.

The study highlights the strong correlation between irregular or inadequate sleep and elevated stress levels. The predictive system developed here offers a non-invasive, cost-effective, and practical approach to mental health monitoring. By helping users identify poor sleep habits that may lead to stress, it supports early detection and encourages proactive self-care.

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