

Research Paper

## Predictive Modelling of Human Stress Using Sleep-Related Features and Machine Learning

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**Abstract:** Psychological stress has become a significant concern in modern society, affecting physical health, productivity, and overall quality of life. Despite its impact, stress often remains undiagnosed due to limited awareness, social stigma, and inadequate access to mental health resources. Since sleep patterns are closely associated with emotional and psychological states, sleep behaviour can serve as an effective and non-invasive indicator for early stress detection. This study proposes a machine learning-based approach for detecting human stress levels using sleep-related parameters, including sleep duration, sleep quality, bedtime consistency, number of awakenings, and sleep disturbances. The collected sleep data are pre-processed and analysed using various machine learning algorithms such as Support Vector Machine (SVM), Decision Tree, Random Forest, and Naïve Bayes. In addition, deep learning models are explored to capture complex patterns and relationships within sleep behaviour data. The performance of each model is evaluated using standard classification metrics, including accuracy, precision, recall, and F1-score. Experimental results indicate that the Naïve Bayes algorithm achieves comparatively higher accuracy in predicting stress levels from sleep-related features. The proposed system provides an automated and efficient framework for early stress identification, enabling individuals to monitor their mental well-being through sleep analysis and encouraging timely intervention. This approach contributes to improved stress management and supports the development of preventive healthcare solutions.

**Key Words:** Stress Detection, Sleep Pattern Analysis, Machine Learning, Naïve Bayes, Mental Health Monitoring.

### 1.Introduction

Stress has become a major public health concern in modern society, affecting emotional stability, physical health, cognitive performance, and overall quality

of life. Increasing lifestyle pressures, irregular daily routines, and technological influences have contributed to rising stress levels among individuals. Sleep plays a vital role in maintaining mental and

physical well-being, and disruptions in sleep patterns are often closely linked to stress, anxiety, and other psychological conditions. Factors such as sleep duration, sleep quality, sleep efficiency, and frequent awakenings can serve as important indicators of stress levels.

Traditional stress assessment methods mainly rely on self-reported questionnaires, psychological interviews, and clinical evaluations. While these approaches provide valuable information, they are often subjective, time-consuming, and influenced by social stigma or lack of awareness regarding mental health issues. As a result, many individuals remain undiagnosed or receive delayed treatment. Therefore, there is a growing need for automated and objective systems capable of detecting stress at an early stage.

Machine learning offers an effective solution for analysing large volumes of sleep-related data collected through wearable devices and sleep-monitoring technologies. By examining parameters such as sleep duration, quality, bedtime consistency, and awakenings, machine learning algorithms can identify patterns associated with stress. This study focuses on developing a machine learning-based stress detection system using sleep behavior analysis, enabling early intervention, continuous monitoring, and improved mental health management.

## 2.Literature Survey

**1.Akter, S., Sharif, M. M., & Mahmud, M. et al (2020)** In their study “*Stress Detection Based on Sleep Pattern Analysis Using Machine Learning*”, Akter et al. investigate how sleep-related features such as duration, interruptions, and variability can help in predicting human stress using ML approaches. They collected sleep

quality metrics and associated stress labels, and applied algorithms like Random Forest and Support Vector Machines to model the relationship between sleep patterns and stress levels. Their results show that ML models can discern underlying patterns that correlate disrupted sleep with high stress, achieving promising accuracy in classification tasks. This work underscores the potential of non-invasive sleep data in automatic stress assessment for early detection and personal health monitoring, emphasizing the practical usefulness of wearables and sleep trackers for mental well-being.

**2. Gupta, A., Jain, S., & Verma, A. et al (2021)** Gupta, Jain, and Verma conducted a survey on *stress detection using sleep pattern analysis*, compiling methods that leverage machine learning to interpret sleep behaviors for stress predictions. The authors critically reviewed various ML classifiers—including Support Vector Machines, Decision Trees, and Naïve Bayes—and discussed how feature extraction from sleep duration, sleep fragmentation, and awakenings affects model performance. Their literature review revealed that combining sleep metrics with ML techniques enhances predictive accuracy and enables more reliable stress inference. They also identified research gaps, such as the need for larger datasets and standardized evaluation protocols to improve real-world applicability. This work provides a comprehensive foundation for designing future sleep-based stress detection systems.

## 3.Proposed System

The proposed system detects human stress levels using sleep-related and physiological parameters with the Naive Bayes algorithm. Key features include

snoring rate, respiration rate, body temperature, limb movements, blood oxygen level, eye movement, sleeping hours, and heart rate. The collected data is pre-processed by handling missing values and normalizing features to improve accuracy. The dataset is then divided into training and testing sets for model evaluation. A Gaussian Naive Bayes classifier is trained to identify relationships between sleep patterns and stress levels. During prediction, the model calculates the probability of each stress category and selects the most likely outcome. The system classifies individuals into Low/Normal, Medium, or High Stress categories. Due to its simplicity and fast execution, Naive Bayes provides efficient stress prediction. The proposed approach enables early stress detection through sleep monitoring. It can be integrated into wearable devices and mobile health applications for real-time stress assessment and management.

#### 4. System Architecture

A mental health illness predicting system architecture typically consists of several key components designed to process and analyze data to predict mental health conditions. The system usually includes data collection modules that gather input from various sources such as surveys, questionnaires, wearable's, or social media activity.

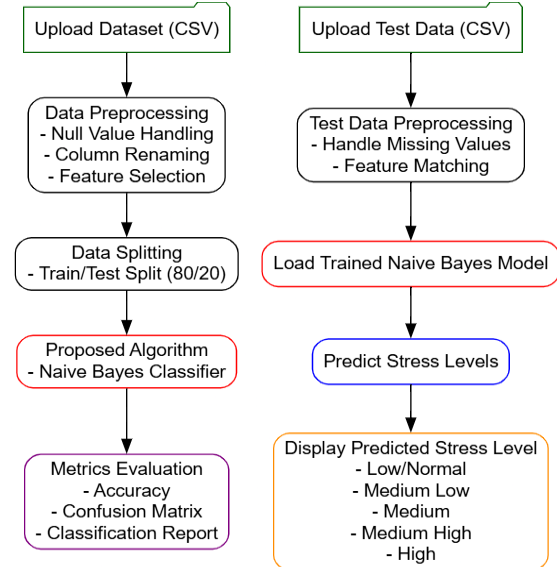


**Fig 1: System Architecture**

This data is then pre-processed to clean and normalize it for analysis. Machine learnings are used to build predictive models based on historical data, such as patterns in behavior, physical health, or environmental factors. The system architecture often involves a user interface for data entry and feedback, a data processing layer, a prediction engine, and a results output that provides recommendations or alerts. Integration with external healthcare systems for further evaluation and treatment is also common. The goal is to provide early detection and insights for mental health conditions, aiding in timely interventions.

#### 5. Methodology

The stress detection process begins with collecting sleep-related and physiological data such as sleeping hours, heart rate, respiration rate, body temperature, and blood oxygen levels. The data is then preprocessed by handling missing values and encoding categorical features. After splitting the dataset into training and testing sets, a Naive Bayes classifier is trained to learn the relationship between sleep patterns and stress levels. The trained model predicts stress categories for new data, enabling efficient and early stress detection.

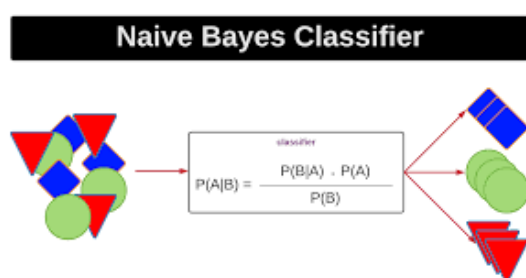


**Fig 2:** Naive Bayes classifier

The system works by feeding preprocessed sleep and physiological data into the trained Naive Bayes model. The model calculates the probability of each stress category and predicts the class with the highest probability, such as Low, Medium, or High Stress. This enables fast and efficient stress prediction based on sleeping habits. The model's performance is evaluated using metrics such as accuracy and a confusion matrix to measure prediction correctness and analyze classification errors.

## 6. Design and Construction

The proposed Human Stress Detection System follows a modular architecture that includes data collection, pre-processing, feature extraction, machine learning, and prediction stages. It uses sleep-related parameters such as sleep duration, efficiency, latency, and awakenings to provide a non-invasive and continuous method for stress detection.

**i) Data Collection:** Sleep-related data is collected from publicly available datasets and wearable devices such as smart bands or sleep-tracking applications. The dataset includes parameters such as total sleep duration, sleep efficiency, sleep quality score, number of awakenings, time taken to fall asleep (sleep latency), and circadian rhythm consistency. Each data sample is labeled with corresponding stress levels (e.g., Low, Moderate, High).

**ii) Data Preprocessing:** Raw sleep data often contains missing values, noise, and inconsistencies. Therefore, preprocessing techniques such as data cleaning, normalization, and feature scaling are applied. Min-Max normalization is used to scale features into a standard range:

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}}$$

**iii) Feature Extraction and Selection:**

Relevant sleep parameters are selected based on correlation analysis and feature importance techniques. This step reduces dimensionality and improves model efficiency. Extracted features form the input vector for classification models.

**iv) Model Development:** involves implementing multiple machine learning classifiers, including Support Vector Machine (SVM), Decision Tree, Random Forest, and Naïve Bayes. The Naïve Bayes classifier selects the optimal decision boundary based on probability estimation defined by Bayes' theorem.

**v) Model Evaluation**

The dataset is divided into training and testing sets. Performance metrics such as Accuracy, Precision, Recall, and F1-score are used to evaluate the model:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

**vi) Stress Prediction System:** The trained model is integrated into a stress monitoring system that classifies individuals into stress categories based on real-time sleep data. The system provides early warnings and supports timely intervention for improved mental health management.

a classification report is generated, which includes precision, recall, and F1-score for each class, indicating the model's ability to correctly identify specific stress levels. the evaluation ensures that the Naive Bayes algorithm reliably predicts stress based on

sleep-related features, and highlights areas where predictions may need improvement, providing a foundation for further optimization or integration with other machine learning models.

## 7.Results and Discussion

The proposed system effectively detects stress levels by analyzing sleep-related and physiological features using machine learning techniques. Results show that poor sleep quality, irregular sleep patterns, and frequent awakenings are strongly associated with higher stress levels.

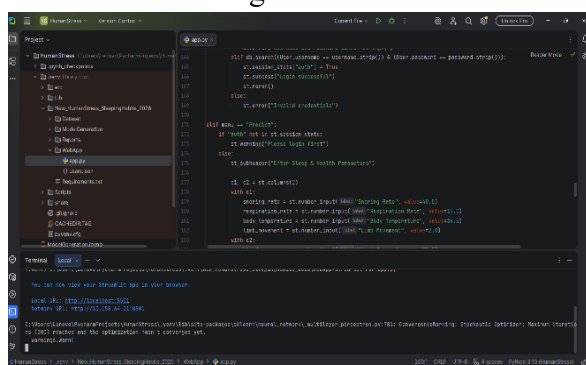


**Fig 3: Deployment of the user interface**

Fig 3 shows the Streamlet-based web application, where users enter physiological and sleep-related data to obtain real-time stress predictions.

| sr     | rr     | t      | lm     | bo     | rem    | sr1   | hr    | sl  |
|--------|--------|--------|--------|--------|--------|-------|-------|-----|
| 93.8   | 25.68  | 91.84  | 16.6   | 89.84  | 99.6   | 1.84  | 74.2  | 3.0 |
| 91.64  | 25.104 | 91.552 | 15.88  | 89.552 | 98.88  | 1.552 | 72.76 | 3.0 |
| 60.0   | 20.0   | 96.0   | 10.0   | 95.0   | 95.0   | 7.0   | 60.0  | 1.0 |
| 85.76  | 23.536 | 90.768 | 13.92  | 88.768 | 96.92  | 0.768 | 68.84 | 3.0 |
| 48.12  | 17.248 | 97.872 | 6.496  | 96.248 | 72.48  | 8.248 | 53.12 | 0.0 |
| 56.88  | 19.376 | 95.376 | 9.376  | 94.064 | 83.44  | 6.376 | 58.44 | 1.0 |
| 47.0   | 16.0   | 97.2   | 5.0    | 95.0   | 98.0   | 7.0   | 52.0  | 0.0 |
| 50.0   | 18.0   | 99.0   | 8.0    | 97.0   | 90.0   | 9.0   | 55.0  | 0.0 |
| 45.28  | 16.112 | 96.168 | 4.224  | 95.112 | 61.12  | 7.112 | 50.28 | 0.0 |
| 55.52  | 19.104 | 95.104 | 9.104  | 93.656 | 82.76  | 6.104 | 57.76 | 1.0 |
| 73.44  | 21.344 | 93.344 | 11.344 | 93.344 | 91.72  | 4.016 | 63.36 | 2.0 |
| 59.28  | 19.856 | 95.856 | 9.856  | 94.784 | 84.64  | 6.856 | 59.64 | 1.0 |
| 48.6   | 17.44  | 98.16  | 6.88   | 96.44  | 74.4   | 8.44  | 53.6  | 0.0 |
| 96.288 | 26.288 | 85.36  | 17.144 | 82.432 | 100.36 | 0.0   | 75.72 | 4.0 |
| 87.8   | 24.08  | 91.04  | 14.6   | 89.04  | 97.6   | 1.04  | 70.2  | 3.0 |
| 52.32  | 18.464 | 94.464 | 8.464  | 92.696 | 81.16  | 5.464 | 56.16 | 1.0 |
| 52.64  | 18.528 | 94.528 | 8.528  | 92.792 | 81.32  | 5.528 | 56.32 | 1.0 |
| 86.24  | 23.664 | 90.832 | 14.08  | 88.832 | 97.08  | 0.832 | 69.16 | 3.0 |
| 81.56  | 22.416 | 90.208 | 12.52  | 88.208 | 95.52  | 0.208 | 66.04 | 3.0 |
| 63.68  | 20.368 | 92.368 | 10.368 | 90.368 | 86.84  | 2.552 | 60.92 | 2.0 |

**Fig 4: Sleep Dataset Overview**

Fig 4 shows the dataset used for stress prediction, containing important physiological features such as snoring rate, respiration rate, body temperature, limb movement, and heart rate. These features help improve prediction accuracy.

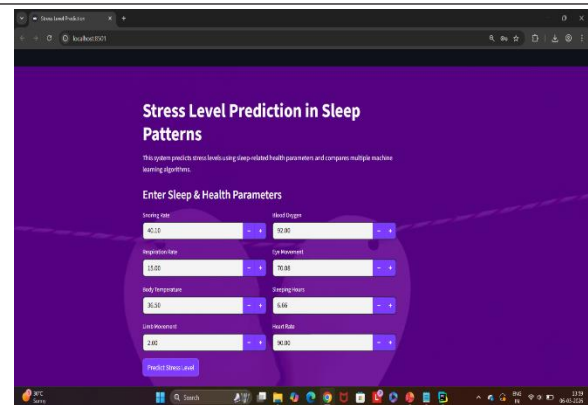


**Fig 5: Stress Prediction Input Interface**

Fig 5 illustrates the user interaction process, where users enter physiological parameters that are analyzed by the trained model to provide real-time stress predictions.

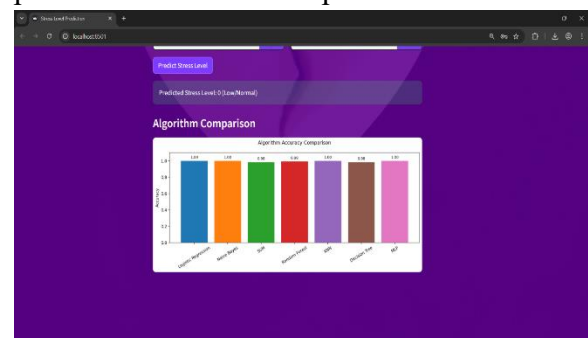


**Fig 6: Prediction Output and Algorithm Comparison Graph**

The system effectively predicts stress levels, with Random Forest providing the best accuracy. Future improvements should focus on data balance, privacy, and model updates.

**ROC Curve Comparison**

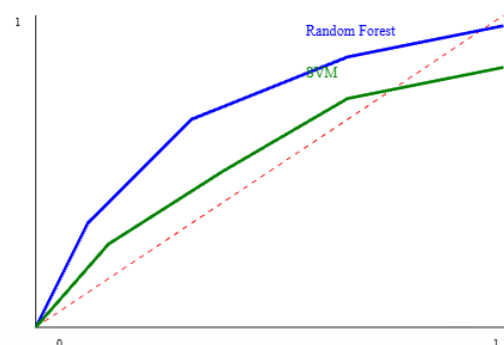


**Fig 7: ROC curve**

Fig 7 ROC curve comparison evaluates multiple models by showing their True Positive Rate versus False Positive Rate. Higher curves with greater AUC indicate

better model performance and classification accuracy.

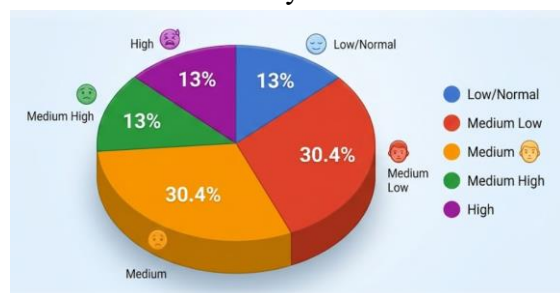


**Fig 8: Prediction Chart**

Fig 8 The majority of individuals (60.8%) fall into the Medium Low and Medium stress categories. In contrast, the Low/Normal, Medium High, and High stress categories are equally represented, each accounting for 13% of the population.

## 8. Conclusion and Future Scope

The proposed stress detection system utilizes the Naïve Bayes algorithm to identify stress levels based on sleep-related and physiological parameters. By analysing features such as sleep duration, heart rate, respiration rate, and sleep quality, the system effectively predicts stress categories. The pre-processing and classification processes ensure reliable and accurate results. Naïve Bayes offers a simple, fast, and computationally efficient approach for stress prediction. Its ability to work with limited datasets makes it suitable for healthcare applications. The system supports early stress detection, enabling timely intervention and improved mental well-being. Compared to traditional assessment methods, it provides an objective and automated solution. The model can be easily integrated into digital health monitoring platforms. Overall, the proposed approach demonstrates the potential of machine learning in mental health assessment. It contributes to the development of accessible and efficient stress management systems.

**Future Scope:** Future enhancements can integrate the system with wearable devices, mobile health applications, and IoT sensors for real-time sleep monitoring. Advanced deep learning techniques may be incorporated to improve prediction accuracy and provide personalized stress management recommendations. Cloud-based platforms can also enable continuous monitoring and timely alerts for healthcare professionals.

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