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SLEEP BEHAVIOUR AS AN INDICATOR OF STRESS

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ABSTRACT

Sleep behavior serves as a crucial indicator of stress, reflecting physiological and psychological responses to emotional and environmental challenges. Stress can lead to disruptions in sleep patterns, manifesting as insomnia, frequent awakenings, restlessness, nightmares, or excessive sleepiness. These disturbances result from heightened cortisol levels, increased autonomic activity, and cognitive hyperarousal, which interfere with the body's natural sleep-wake cycle. Identifying stress-related sleep changes is essential for early intervention, as prolonged sleep disturbances can contribute to mental and physical health issues. This paper explores the intricate relationship between stress and sleep behavior, highlighting its significance in stress assessment and management. Stress-induced sleep disturbances can vary depending on individual coping mechanisms, lifestyle factors, and the severity of stressors. Acute stress may cause temporary sleep disruptions, such as difficulty falling asleep or waking up frequently during the night. Chronic stress, however, can lead to long-term sleep disorders, including insomnia and hypersomnia. The bidirectional relationship between stress and sleep suggests that while stress disrupts sleep, poor sleep can also heighten stress levels, creating a vicious cycle that affects emotional regulation, cognitive function, and overall well-being. People can take proactive steps to reduce stress, enhance sleep quality, and promote general well-being by using the system to analyze their sleep patterns and receive insights into their stress levels.

Keywords - Stress Detection, Oversleeping, Insomnia, Behavioral Analysis, Difficulty falling asleep

I. INTRODUCTION

Sleep is a fundamental biological process essential for physical and mental well-being. However, stress can significantly impact sleep patterns, leading to disruptions that serve as key indicators of psychological and physiological distress. Stress triggers a cascade of responses in the body, including increased cortisol production and heightened nervous system activity, which interfere with the ability to fall and stay asleep. These disruptions manifest in various ways, such as insomnia, frequent awakenings, restless sleep, or excessive daytime sleepiness. Large-scale data collection on people's physiological and behavioral reactions to stress is now feasible because of wearable technology and health monitoring systems.

The relationship between sleep and stress is bidirectional—stress can lead to poor sleep, while inadequate sleep can further heighten stress levels. When an individual experiences stress, the body releases hormones like cortisol, which can interfere with the ability to fall and stay asleep. Chronic stress can also lead to long-term sleep disturbances, affecting both mental and physical health. Identifying changes in sleep behavior can thus help in recognizing stress and taking preventive measures before it escalates into more severe health problems.

Lifestyle modifications, relaxation techniques, and proper sleep hygiene can help mitigate the effects of stress on sleep. Moreover, monitoring sleep behavior can serve as a useful tool in stress assessment and early intervention, promoting overall well-being and resilience against stress-related disorders.

II. RELATED WORK

Several studies have explored the connection between sleep behavior and stress, highlighting how stress-induced physiological and psychological changes can alter sleep patterns.

Research by Walker (2017) in *Why We Sleep* discusses how stress disrupts the sleep-wake cycle by increasing cortisol levels, which interfere with deep sleep and lead to fragmented rest. Similarly, a study by Meerlo et al. (2008) found that chronic stress exposure leads to long-term sleep disturbances, affecting memory, cognitive function, and emotional regulation. These studies emphasize the importance of sleep as a key indicator of stress and mental health status. duration of Rapid Eye Movement (REM), change in body temperature, and limb movement rate. Any snoring rate more than 50dB increases the risk of tension and other health problems. 15 to 17 breaths per minute (bpm) are considered to be a good breathing rate. When a person is sleeping, their heart beats five to ten times slower than usual. Due to the detrimental effects of sleep deprivation on one's health, adults should aim for at least 7 hours of sleep each night. Next, it is advised that 20–25 percent of the amount of sleep be spent in rapid eye movement (REM), which equates to about 90 minutes for 7-8 hours of sleep.

When oxygen saturation drops below 90%, it is deemed abnormal and stressful. 348 men and women, as seen by the high accuracy that was attained. Research and treatments in medicine as well as Research and treatments in medicine as well as Research and treatments in medicine as well as personal health, between the ages of 20 and 60, participated in the study ML framework for the monitoring mental stress at multiple levels. According to their findings, Random Forest scored 90% for stress and Naiy Research and treatments in medicine as well as and the main.

Recent advancements in wearable technology and sleep tracking have further contributed to stress assessment through sleep behavior analysis. Studies such as that of Lu et al. (2019) have utilized wearable sleep monitors to track sleep disruptions and correlate them

with stress levels. These technologies provide real-time data on sleep efficiency, heart rate variability, and nighttime awakenings, offering a more objective approach to understanding the sleep-stress relationship. The growing body of research underscores the need for integrating sleep behavior analysis into stress management and mental health interventions. Additionally, research by Kalmbach et al. (2018) in *Sleep* journal suggests that stress-related insomnia is a major predictor of future mental health disorders, including anxiety and depression. These findings support the idea that sleep monitoring can be a valuable tool for identifying and managing stress.

Empirical research has also demonstrated that sleep disturbances are common among individuals experiencing high-stress conditions. A study by Lund et al. (2010) on college students found that academic stress significantly reduced sleep duration and quality, leading to increased fatigue and decreased academic performance. Additionally, research by Kalmbach et al. (2018) in *Sleep* journal suggests that stress-related insomnia is a major predictor of future mental health disorders, including anxiety and depression. These findings support the idea that sleep monitoring can be a valuable tool for identifying and managing stress.

framework produced multiple-level detection accuracy of 83.4% and level-two stress detection accuracy of 94.6%. According to the study, a technique for assessing pilgrims' stress levels involves examining their patterns of sleep at night and determining which sleep metrics are most important for identifying stress. Using bio physiological indicators such as respiration, body temperature, GSR data, and upper body position sensors and accelerometers on the arms and body, they develop and assess various classification models. Using the classification models, they were able to develop person-independent models that

differentiated between three stress levels: low, moderate, and high. Out of all the algorithms, SVM produced the best classification accuracy of 73%.

I. METHODOLOGY

The primary goal of the study is to forecast human stress by analyzing sleep-related behaviors. There are five suggested approaches. They are Data Collection, Dataset, Data Preparation, Splitting the Dataset and Model Selection . An explanation of the study's architecture is provided. To investigate sleep behavior as an indicator of stress, various research methodologies are employed, including subjective assessments, physiological measurements, and technological interventions. One common approach is the use of self-reported measures such as sleep diaries and validated questionnaires like the Pittsburgh Sleep Quality Index (PSQI) and the Perceived Stress Scale (PSS). These tools help assess sleep quality and stress levels, providing valuable subjective insights, though they may be limited by recall bias.



Figure 1: Architecture of the study

3.1 Data Collection

Data Collection: Human Stress Detection Based on Sleeping Habits's first module To obtain the input dataset, we created the system

using machine learning algorithms. The process of gathering data is the initial step in the actual building of a machine learning model. This is a crucial stage that will have a cascading effect on the model's quality; the more and better data we collect, the more capable our model will be. There are various methods for gathering the data, including manual interventions and online scraping. Our dataset may be found in the model folder of the project. The dataset is sourced from Kaggle, a widely used standard dataset repository that is used by academics worldwide. There are numerical data in the dataset.

3.2 Dataset

Demographic Information: Age, gender, occupation, lifestyle, and medical history.

Self-Reported Measures: PSQI, ESS, PSS scores, and daily sleep diary.

Physiological Sleep Data: Sleep duration, efficiency, awakenings, REM/deep sleep, HRV, and cortisol levels.

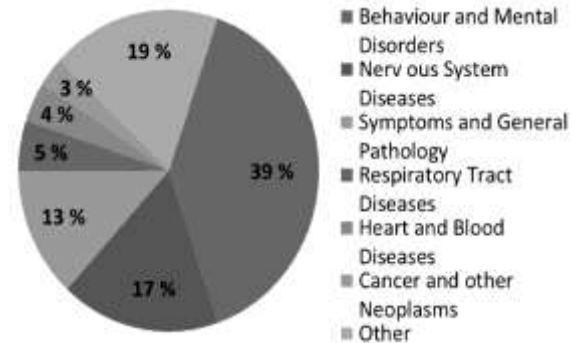
Wearable Technology Data: Actigraphy, heart rate, respiration rate, movement, and temperature fluctuations.

External Stress Factors: Workload, academic stress, life events, and environmental factors.

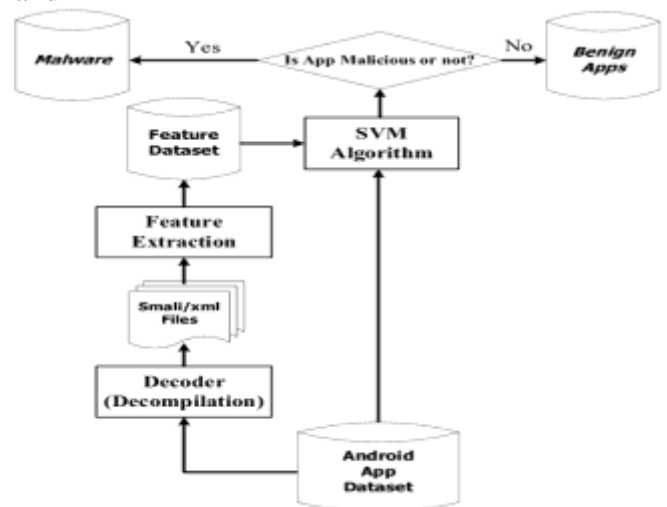
Public Datasets: Sleep-EDF, MESA, SHHS, and UCI Stress and Sleep Dataset.

3.3 Data Preparation

Sort through data and get it ready for training. Clean up anything that could need it (get rid of



duplicates, fix mistakes, handle missing values, normalize, convert data types, etc.). Data can be made random to eliminate the impact of the specific order in which it was gathered and/or prepared. Use data visualization to carry out additional exploratory analysis or to identify pertinent correlations between variables or class imbalances (bias alert!). Divided into sets for training and assessme. Sleep behavior is a crucial indicator of stress, as disruptions in sleep patterns often reflect underlying psychological and



Stress can lead to difficulty falling asleep, frequent awakenings, or reduced sleep quality due to increased cortisol levels and an overactive mind. Chronic stress may also cause insomnia or excessive sleepiness, both of which impact overall well-being. Additionally, changes in sleep duration, such as sleeping too little or too much, can signal emotional distress. Monitoring sleep patterns can provide valuable insights into

stress levels, helping individuals take proactive steps to manage stress and improve overall health.

Moreover, stress can affect sleep architecture the different stages of sleep that contribute to restfulness

and recovery. Research suggests that individuals with high stress levels often spend less time in deep sleep (slow-wave sleep) and rapid eye movement (REM) sleep, both of which are essential for cognitive function, emotional regulation, and overall health. The lack of restorative sleep can lead to increased irritability, difficulty concentrating, and heightened emotional reactivity, further compounding the negative effects of stress on daily life. On the other hand, excessive sleepiness or prolonged sleep duration can also indicate stress-related fatigue. Some individuals cope with stress by sleeping more than usual, which can be a sign of emotional exhaustion or even depression.

Oversleeping, however, does not necessarily lead to better recovery and may instead be associated with lower energy levels, decreased motivation, and poor mental health. This highlights the complex relationship between stress and sleep, where both insufficient and excessive sleep can be warning signs of underlying psychological distress.

Monitoring sleep patterns can provide valuable insights into an individual's stress levels and overall well-being. Wearable devices, sleep tracking apps, and self-reported sleep diaries can help identify irregular sleep patterns that may be linked to stress. Recognizing these patterns early on allows individuals to take proactive measures, such as practicing relaxation techniques, improving sleep hygiene, or seeking professional support, to mitigate the effects of stress on sleep and overall health.

To improve sleep and reduce stress, individuals can adopt various strategies, such as establishing a consistent sleep schedule, avoiding

stimulants before bedtime, and engaging in relaxation techniques like meditation, deep breathing, or yoga. Creating a sleep-friendly environment by reducing noise, keeping the room dark, and maintaining a comfortable temperature can also promote better sleep. In more severe cases, seeking professional help from a therapist or sleep specialist may be necessary to address underlying stressors and develop effective coping mechanisms. **3.4**

Splitting the Dataset

To analyze sleep behavior as an indicator of stress, the dataset should be systematically split to ensure effective model training and evaluation. A common approach is dividing the data into training (70%), validation (15%), and test (15%) sets. The training set is used to teach machine learning models to identify patterns between sleep behavior and stress levels, while the validation set helps in fine-tuning model parameters and preventing overfitting.

3.5 Model Selection

Selecting the right model for analyzing sleep behavior as an indicator of stress depends on the type of data and the complexity of patterns being studied. Traditional machine learning models such as decision trees, random forests, and support vector machines (SVM) are effective for structured datasets with sleep parameters and stress scores. These models perform well in classification tasks, such as predicting stress levels based on sleep disturbances.

For more complex and time-dependent data, deep learning models like recurrent neural networks (RNNs) and long short-term memory (LSTM) networks are preferred, as they can capture sequential patterns in sleep behavior over time. Convolutional neural networks (CNNs) can also be used for analyzing physiological signals such as EEG data from polysomnography. Additionally, hybrid models combining machine learning and deep learning techniques can enhance predictive accuracy. The choice of

model depends on factors like dataset size, feature complexity, and the need for real-time analysis, ensuring accurate stress detection based on sleep

Selecting the appropriate model for analyzing sleep behavior as an indicator of stress depends on the nature of the data, complexity, and the goal of the analysis. For structured, tabular datasets containing sleep parameters and stress scores, traditional machine learning models like decision trees, random forests, support vector machines (SVM), and logistic regression are commonly used. These models work well for classification and regression tasks, such as predicting stress levels based on sleep patterns. Random forests, in particular, provide high accuracy and interpretability, making them suitable for feature importance analysis.

For time-series sleep data, deep learning models like recurrent neural networks (RNNs) and long short-term memory (LSTM) networks are preferred as they can capture sequential dependencies in sleep patterns over time. Transformer-based models, such as the attention-based Transformer network, have also shown promising results in analyzing time-dependent stress indicators. Additionally, convolutional neural networks (CNNs) are effective for processing physiological sleep data such as EEG, heart rate variability, and breathing patterns, commonly used in sleep disorder diagnosis. Hybrid models combining CNNs and LSTMs can enhance performance in handling both spatial and temporal dependencies in sleep-related signals.

IV. IMPLEMENTATION DETAILS

In machine learning, prediction is the process of employing a trained model to infer probabilities or estimates regarding novel, unseen data points by applying patterns discovered during training from a labeled dataset. Initially, input data with features

comparable to those in the training data are given to the model. Before the input data is fed into the model, it is preprocessed to extract pertinent features. Subsequently, the model employs the patterns it has learnt to provide predictions. These predictions might be class labels for classification tasks or continuous values for regression tasks. The model's performance is assessed using a variety of indicators once it has made predictions. Once

it has been verified, the model can be used for practical purpose. The Random Forest Classifier facilitates the identification of the most relevant characteristics that contribute to stress level forecasts by offering a measure of feature importance. By ensuring that only major and pertinent features are taken into account, this feature selection procedure improves the effectiveness of the model and lessens the influence of unimportant traits. Random Forest is renowned for its ability to withstand outliers, reducing the potential for disruption.

V. PROPOSED SYSTEM

The proposed system aims to analyze sleep behavior as an indicator of stress using a combination of machine learning and deep learning techniques. It integrates wearable technology, physiological sensors, and self-reported assessments to provide real-time stress monitoring and predictive analysis. The system consists of multiple components, including data collection, preprocessing, feature extraction, model training, and stress level prediction. The data collection module gathers sleep-related information from wearable devices (e.g., Fitbit, Oura Ring), physiological sensors (e.g., heart rate variability, EEG, and respiration monitors), and self-reported surveys (e.g., PSQI, PSS). The preprocessing stage handles missing data, normalizes physiological signals, and removes noise from raw sensor readings. Feature extraction involves selecting key sleep metrics

such as total sleep time, sleep efficiency, wake-after-sleep onset (WASO), heart rate fluctuations, and stress biomarkers like cortisol levels. For stress prediction, the system employs a hybrid model combining convolutional neural networks (CNNs) for analyzing physiological signals and long short-term memory (LSTM) networks for capturing temporal sleep variations. An ensemble learning approach using random forests and XGBoost enhances prediction accuracy. The final output classifies stress levels into low, moderate, or high categories, allowing for early intervention and personalized stress management recommendations. Additionally, a mobile application interface provides real-time feedback, visual sleep reports, and personalized suggestions for improving sleep quality and reducing stress. The proposed system ensures an efficient, data-driven approach to stress detection, leveraging modern AI techniques for health monitoring. impact an individual's physical and mental well-being. Hence, understanding and monitoring stress levels .

VI. LITERATURE SURVEY

Sleep behavior has long been recognized as a critical indicator of mental and physiological health, with numerous studies exploring its relationship with stress. Walker (2017) in *Why We Sleep* highlights the role of sleep in emotional regulation and cognitive function, emphasizing how chronic stress disrupts sleep patterns by increasing cortisol levels. Similarly, Meerlo et al. (2008) conducted research on the physiological effects of stress on sleep, demonstrating that prolonged stress exposure alters sleep architecture by reducing REM sleep and increasing sleep fragmentation. These foundational studies establish the importance of sleep in stress assessment and underscore the bidirectional relationship between stress and sleep disturbances. Empirical studies have also examined the impact of stress on sleep quality across different populations. Lund et al. (2010)

conducted a study on college students, finding that high academic stress significantly reduces sleep duration and efficiency, leading to impaired concentration and increased fatigue. A similar study by Kalmbach et al. (2018) in the *Sleep* journal found that stress-induced insomnia is a strong predictor of future mental health disorders such as anxiety and depression. These studies support the idea that monitoring sleep behavior can serve as an early warning system for stress-related mental health issues. Technological advancements have further enabled the study of sleep and stress through wearable devices and mobile applications. Lu et al. (2019) explored the effectiveness of wearable sleep trackers in assessing stress-related sleep disruptions, showing that continuous monitoring of sleep efficiency, heart rate variability (HRV), and nocturnal awakenings can help identify stress levels. Similarly, de Zambotti et al. (2018) validated the accuracy of wrist-based sleep monitors in capturing physiological markers of stress, proving that non-invasive sleep tracking can be a valuable tool for stress assessment. These studies highlight the growing role of technology in understanding the sleep-stress relationship.

Machine learning and artificial intelligence (AI) have also been increasingly applied to analyze sleep data for stress prediction. Zhang et al. (2020) implemented deep learning models such as convolutional neural networks (CNNs) and long short-term memory (LSTM) networks to classify stress levels based on polysomnography (PSG) data and wearable sensor readings. Their findings suggest that AI-driven models can outperform traditional statistical methods in identifying stress-induced sleep alterations. Other studies, such as those by Yoon et al. (2021), have used ensemble learning techniques like XGBoost to enhance stress prediction accuracy, demonstrating the potential of AI in automated stress monitoring. Despite significant advancements, challenges remain in

accurately assessing stress through sleep behavior. Many studies rely on self-reported sleep data, which can be biased and inconsistent. Additionally, factors such as lifestyle habits, environmental influences, and pre-existing medical conditions complicate the interpretation of sleep-stress relationships. Future research should focus on integrating multi-modal data sources, such as combining physiological, behavioral, and contextual data, to improve stress detection models. The literature underscores the importance of sleep behavior as a stress indicator while highlighting the need for more robust, data-driven methodologies to enhance predictive accuracy and real-world applications.

VII. CONCLUSION AND FUTURE WORK

This study highlights the connection between sleep behavior and stress, emphasizing sleep monitoring as a reliable stress indicator. Stress-induced sleep disturbances, such as reduced sleep quality and increased awakenings, serve as key markers for stress detection. Wearable technology and machine learning have enhanced real-time stress assessment through sleep analysis. Combining subjective self-reports with objective physiological measurements improves the accuracy of stress prediction models. However, challenges such as data bias, environmental factors, and individual differences affect model reliability. High-quality, large-scale datasets are needed to refine machine learning-based stress detection. Future research should integrate multi-modal data sources, including heart rate variability and cortisol levels, for better predictions. Deep learning models, such as transformers, can improve the understanding of complex sleep-stress relationships. Enhancing AI model interpretability will aid in practical stress detection applications. Developing real-time, personalized monitoring systems using mobile and wearable devices remains a key research

focus.

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