

Human Stress Detection Based on Sleeping Habits Using Machine Learning Algorithm

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Abstract: *This study explores the use of machine learning algorithms to detect human stress based on sleep patterns. Sleep is closely linked to mental health, and changes in sleep behaviour can indicate stress levels. By collecting data from wearable devices or sleep-tracking apps, key sleep parameters such as duration, quality, and sleep stages can be monitored. The study applies various machine learning techniques, including classification and regression models, to analyze the relationship between sleep patterns and stress levels. The objective is to develop a predictive model capable of identifying stress by examining deviations in sleep habits. Such a system can offer valuable insights for early intervention, enabling users to manage stress more effectively through personalized recommendations for improving sleep quality..*

Keywords: Flask, Web Based Application, Admin Dashboard, User Dashboard, Algorithm

I. INTRODUCTION

Stress has become a prevalent issue in modern society, impacting individuals' physical and mental well-being. Stress is associated with a range of health problems, including, depression, anxiety, and sleep disorders. Among the various indicators of stress, sleeping habits are particularly revealing, as stress often manifests in disrupted sleep patterns. Sleep quality, duration, and consistency are sensitive to the emotional and psychological state of individuals, making them valuable markers for stress detection.

Traditional methods of stress detection, such as self-reported surveys or physiological monitoring (e.g., heart rate or cortisol levels), often rely on intrusive or subjective assessments, which may not always be reliable or timely. Machine learning (ML) offers a promising alternative by enabling the analysis of large-scale, complex datasets to identify patterns that might otherwise go unnoticed. Machine learning algorithms can efficiently process sleep data to identify abnormal patterns linked to stress, thus providing a more objective, real-time approach to stress detection. This study proposes a machine learning-based framework for detecting stress by analyzing sleep habits. By sleep data from wearable devices, this research aims to build a predictive model that can identify stress based on deviations in sleep behaviour. Such a model could not only offer real-time insights into an individual's mental health but also facilitate timely interventions to prevent stress-related health issues.

The primary objectives of this research are to:

1. Investigate the relationship between sleep patterns and stress levels.
2. Develop a machine learning model that can accurately predict stress based on sleep data.
3. Provide practical applications for early detection and personalized recommendations to help individuals manage stress through better sleep practices.

II. LITERATURE SURVEY

Based on the overview of several papers describing recent studies. The detection of human stress using physiological and behavioural patterns has gained increasing attention in recent years. One of the most critical behavioural indicators closely associated with stress is sleep. Sleep metrics such as sleep onset latency, sleep efficiency, total sleep time, and wake after sleep onset have been recognized as reliable indicators of stress [1]. Chronic stress activates the axis,



disrupting normal sleep patterns and reducing the proportion of restorative sleep stages. Machine learning systems trained on these parameters are capable of identifying abnormal sleep behaviour indicative of stress-related conditions [2]. The success of ML-based stress detection systems heavily depends on the quality of features extracted from sleep data. Time-domain features (e.g., duration, latency), frequency-domain metrics (e.g., heart rate variability), and statistical measures are commonly used. Preprocessing techniques such as normalization, noise filtering, and imputation of missing values are essential to ensure model performance [4]. Before feeding this data into a model, various preprocessing steps are conducted such as noise removal, feature normalization, and handling missing values. In some studies, dimensionality reduction techniques are applied to identify the most informative features, thereby improving the performance and interpretability of the models [5].

As wearable technologies collect sensitive health and behavioural data, ethical concerns around data privacy and consent are prominent. Techniques like federated learning and differential privacy are now being explored to ensure user data remains confidential while still enabling model training [8]. With the rise of smart health platforms, integrating stress detection systems with mobile applications, IoT devices, and cloud computing is becoming increasingly feasible. Personalized recommendations, stress management tools, and mental health monitoring applications can empower users and healthcare providers to proactively manage well-being [9]. As machine learning technology continues to evolve, future systems are expected to become more accurate, personalized, and proactive.

III. PROBLEM DEFINITION

Stress is a major contributing factor to numerous physical and mental health issues, including anxiety, depression, cardiovascular diseases, and reduced cognitive performance. In modern society, stress levels are on the rise due to increasing workloads, irregular routines, and lack of sleep. Sleep, being a vital physiological activity, is significantly affected by and also a determinant of stress. Poor sleep quality and irregular sleep patterns are commonly associated with elevated stress levels. Traditional methods for stress detection often involve psychological assessments or the use of complex medical instruments, which may not be practical for daily use.

With the proliferation of wearable devices and mobile health technologies, it is now possible to collect detailed sleep data non-invasively. However, there exists a gap in translating this data into meaningful insights about stress using computational techniques. This project aims to develop a system that can detect human stress levels based on sleeping habits using machine learning algorithms. The proposed system will analyze sleep-related parameters such as sleep duration, sleep efficiency, and sleep quality to identify stress patterns and provide real-time, personalized feedback.

In short, existing systems either need a doctor, are too expensive, or don't use smart technology. They often don't give users detailed reports, 3D graphs, or helpful tips based on their sleep. That's why a new system is needed one that uses machine learning to study sleep habits and detect stress in a simple, smart, and cost-effective way.

This project aims to address these limitations by developing an intelligent, non-invasive system that detects stress levels based on sleeping habits. Using machine learning algorithms to analyze sleep data, the system will provide personalized stress predictions, actionable health recommendations, and visual analytics, ultimately empowering individuals to monitor and manage their stress in a more accessible and efficient manner.

IV. PROPOSED SYSTEM

Recent advancements in technology have significantly enhanced the capability to detect stress based on human sleeping habits. The convergence of wearable sensor technologies, Internet of Things (IoT), and machine learning (ML) has enabled the collection and analysis of high-fidelity physiological and behavioural data in real-time. Devices such as smartwatches and fitness bands can now continuously monitor sleep parameters like heart rate variability (HRV), body movement, sleep stages, and duration with considerable accuracy. These devices provide large-scale, non-intrusive data that can be leveraged for stress detection models. Furthermore, mobile health (mHealth) applications, driven by AI, now offer real-time stress assessment along with personalized health recommendations, relaxation techniques, and mental wellness resources. These applications, powered by advancements in Natural Language Processing (NLP), even allow conversational AI agents to interact with users for emotional support and stress coping strategies. In essence, technological innovations have not only improved the accuracy, efficiency, and scalability of stress detection systems



but have also made them more accessible, user-centric, and privacy-preserving, paving the way for smarter, more proactive mental healthcare solutions.

V. EXISTING SYSTEM

Currently, stress detection mainly relies on traditional methods, such as self-reported questionnaires, psychological assessments, or clinical tools like the Perceived Stress Scale (PSS) and DASS (Depression, Anxiety, Stress Scale). These methods rely heavily on the individual's subjective responses, which can sometimes be inaccurate or incomplete. Additionally, some clinical settings use expensive and complex equipment, such as EEG (electroencephalogram) or ECG (electrocardiogram), which measure brain and heart activity to detect stress. While accurate, these techniques are often impractical for daily use due to their high cost, requirement for medical professionals, and the need for specialized facilities.

In recent years, wearable devices like smartwatches and fitness trackers have gained popularity for monitoring physiological metrics such as sleep patterns, heart rate, and physical activity. However, these devices typically provide basic data without any analysis of stress levels. Although they track sleep quality and duration, they do not use advanced machine learning algorithms to analyze this data and provide personalized stress detection or actionable recommendations.

Furthermore, while some systems may track sleep, they do not recognize the strong link between sleep and stress. They fail to offer real-time analysis or identify patterns of stress that could help individuals manage their well-being better. Overall, the existing systems fall short in combining data intelligence and personalized health insights, which limits their effectiveness in accurately detecting and managing stress over time. In short, existing systems either need a doctor, are too expensive, or don't use smart technology. They often don't give users detailed reports, 3D graphs, or helpful tips based on their sleep. That's why a new system is needed one that uses machine learning to study sleep habits and detect stress in a simple, smart, and cost-effective way.

VI. FLOW DIAGRAM

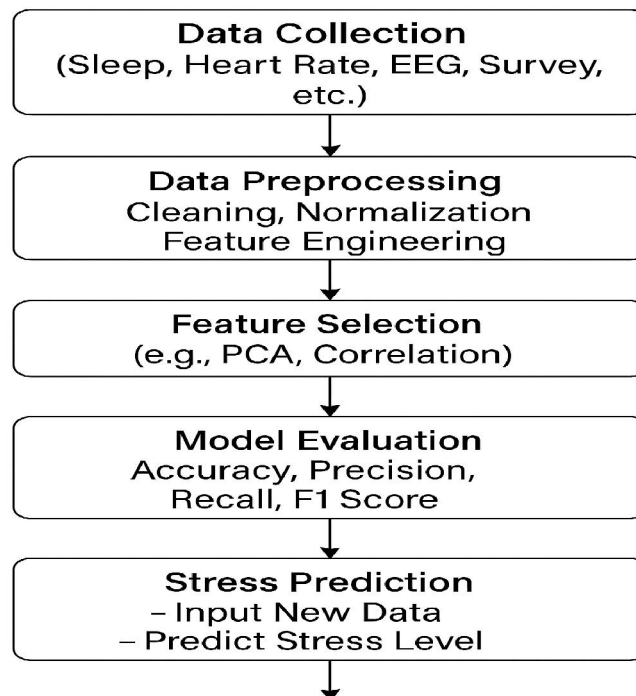


Fig 6.1 Flow Diagram



VII. RESULT

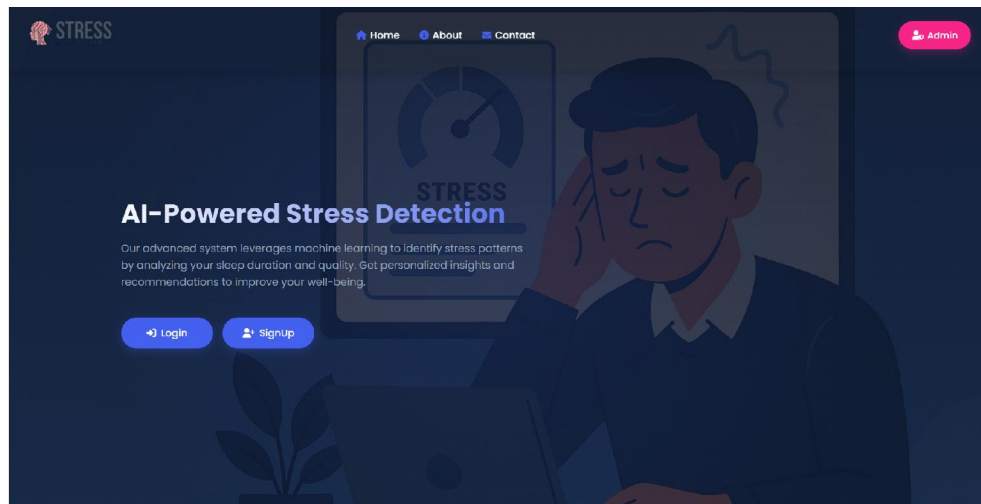


Fig. 7.1. User Dashboard Page

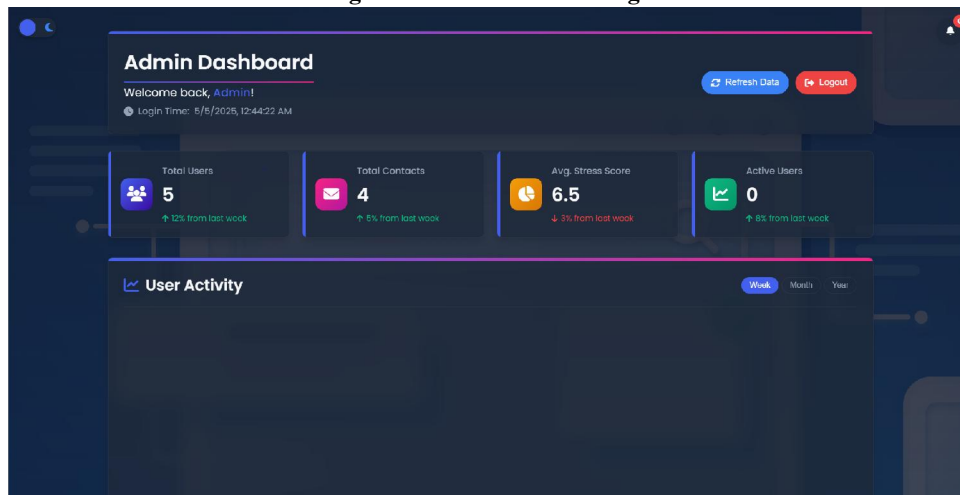


Fig. 7.2. Admin Page

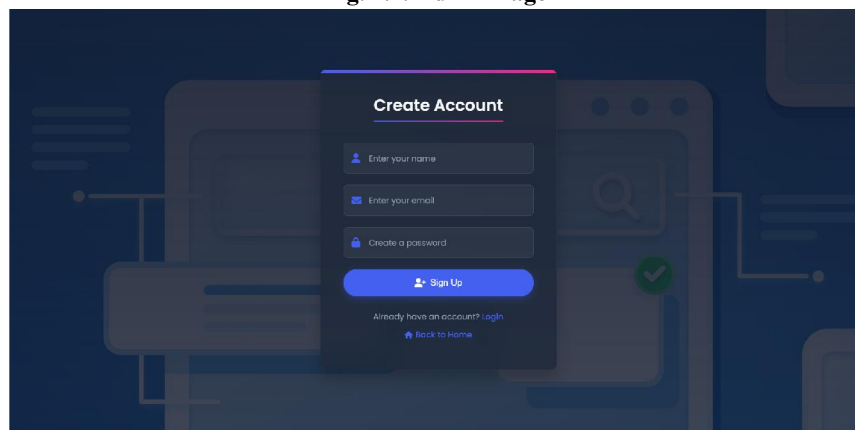


Fig 7.3. Sign Up Page



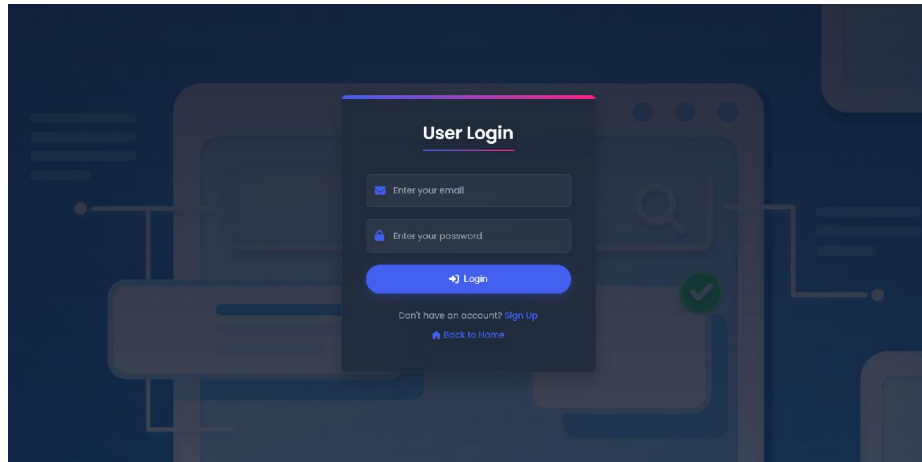


Fig 7.4. User Login Page

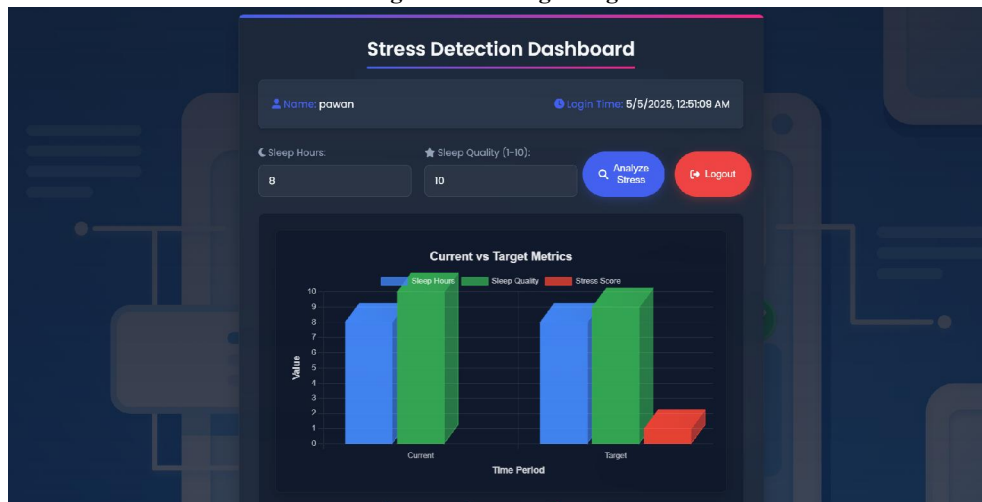


Fig 7.5. Stress Detection Dashboard

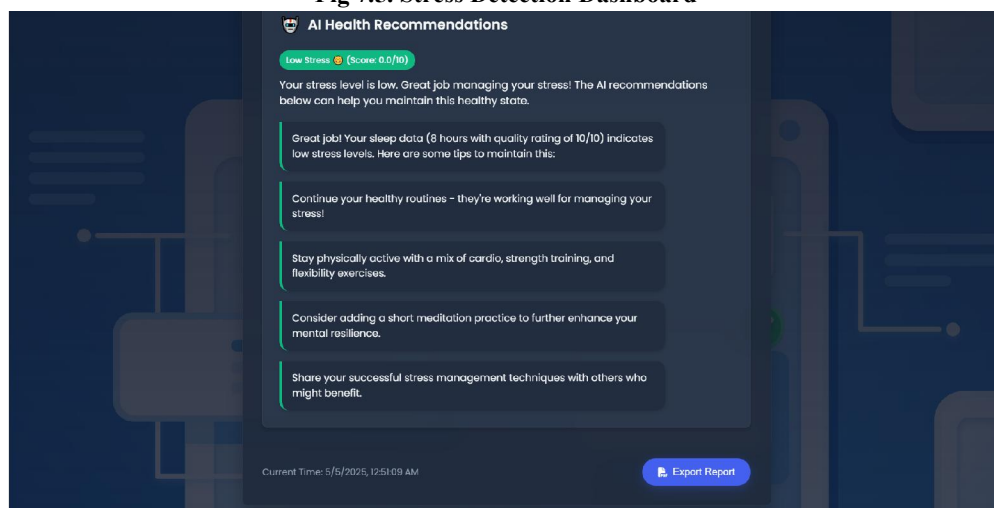


Fig 7.6. AI Health Recommendation



VII. CONCLUSION

In this project, a machine learning-based system for human stress detection was developed using sleep habits as the primary input data. The increasing prevalence of stress-related disorders and their close correlation with poor sleep quality and quantity motivated the development of a non-invasive, intelligent solution for early stress monitoring. By collecting user sleep data such as hours slept and sleep quality and analyzing it with machine learning algorithms, the system is capable of predicting stress levels with a reasonable degree of accuracy. Furthermore, the integration of visual analytics, such as interactive 3D graphs, and the generation of AI-based health recommendations enhance the user experience and usability of the system.

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