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Stress Detection Based on Sleeping Habits Using ML

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Abstract: In recent years, the prevalence of stress has become a significant public health concern, influencing both physical and mental well-being. This study examines the possibilities of applying techniques for ML to detect human stress based on sleeping habits. By leveraging data on sleep patterns, such as duration, quality, interruptions, and variability, we aim to develop a forecasting model that can precisely determine stress levels. We collected sleep data from a diverse group of participants using wearable devices and self-reported surveys over several weeks. A number of ML techniques, such as SVM, RF, and NNs, to create predictive models. The models' performance was assessed utilizing measures such as F1-score, recall, accuracy, and precision. Our findings demonstrate that Random Forests and Neural Networks outperform other algorithms in detecting stress from sleep data.

Keywords: SVM- Support Vector Machine, RF-Random Forest, NN-Neural Network, ML-Machine Learning

I. INTRODUCTION

Stress is a ubiquitous and multifaceted issue that profoundly affects human health and well-being. Chronic stress can lead to a myriad illnesses of the body and mind, such as depression, anxiety disorders, and cardiovascular ailments. Thus, minimizing these detrimental health effects requires early stress diagnosis and management outcomes and improving individuals' quality of life. Traditional methods of stress detection, such as self-reported questionnaires and clinical assessments, have limitations. They are often intrusive, subjective, and not suitable for continuous monitoring. In contrast, physiological and behavioral data offer a promising avenue for objective and non-intrusive stress detection. Among various physiological indicators, sleep patterns are closely linked with stress levels. Changes in sleep duration, quality, and continuity are often early signs of stress. Thus, analyzing sleeping habits presents a valuable approach for stress detection.

With the advent of wearable technology and advanced sleep tracking applications, it has become feasible to collect detailed and continuous sleep data from individuals in a non-intrusive manner. This data includes parameters such as sleep efficiency, sleep duration overall, frequency of awakenings, and distribution of sleep stages. Machine learning methods can be used to identify patterns and associations suggestive of stress by utilizing this vast information. Given its capacity to manage big datasets and intricate patterns, machine learning is well-suited for this task. Algorithms such as Decision Trees, Support Vector Machines (SVM), Random Forests, and Neural Networks have shown considerable success in various predictive analytics applications. Applying these algorithms to sleep data can potentially yield accurate models for stress detection, facilitating early intervention and management.

II. PROBLEM STATEMENT

Stress is a significant issue impacting individuals' physical and mental health. Traditional methods for detecting stress, such as self-reported questionnaires and clinical assessments, are often subjective, intrusive, and unsuitable for continuous monitoring. This study aims to explore the use of machine learning algorithms to detect stress based on sleeping habits. Specifically, it seeks to identify relevant sleep-related features indicative of stress, such as sleep duration, quality, interruptions, and pattern variations. We will collect and preprocess sleep data from participants using wearable devices and sleep tracking applications, supplemented with subjective stress reports for labeling. Decision trees, support vector machines, random forests, neural networks, and other machine learning methods will be used to build predictive models for stress detection. The performance of these models will be evaluated using metrics like accuracy, precision, recall, and F1-score to determine the best-performing algorithm. The ultimate goal is to develop a reliable, non-invasive, and continuous monitoring system for stress detection, leveraging everyday sleep tracking technologies to enhance stress management and improve overall health and quality of life.

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III. SCOPE

This study focuses on developing and evaluating a machine learning-based system for detecting human stress through the analysis of sleeping habits. It involves collecting sleep data from participants using wearable devices and sleep tracking applications, including parameters like sleep duration, quality, interruptions, and pattern variations. Subjective stress reports will be collected to label the data. Relevant features indicative of stress, such as total sleep time, sleep efficiency, frequency of awakenings, and sleep stage distribution, will be extracted. Various machine learning algorithms, including Decision Trees, Support Vector Machines, Random Forests, and Neural Networks, will be applied to build predictive models for stress detection. These models will be evaluated using metrics like accuracy, precision, recall, and F1-score to determine the best-performing algorithm. The ultimate goal is to design a reliable, non-invasive, and continuous monitoring system for stress detection, leveraging everyday sleep tracking technologies to enhance stress management and improve overall health and quality of life.

IV. LITERATURE SURVEY

1.Stress and Sleep: Reciprocal Influence and Links to Emotional Regulation
Authors: Daniel S. Baglioni, Anika M. Spiegelhalder, David N. D. Lombardo
This paper explores the bidirectional relationship between sleep and stress, emphasizing how stress disrupts sleep and poor sleep exacerbates stress. The study highlights the potential of sleep analysis for stress detection.

2. Insomnia and Stress: Conceptual Framework and Empirical Evidence
Authors: Charles M. Morin, Rosa M. Rodrigue, Suzanne Ivers
The authors review the impact of stress on sleep, particularly focusing on insomnia. They discuss how stress-induced changes in sleep patterns can serve as indicators for stress detection.

3.The Perceived Stress Scale: A Reliability and Validity Study
Authors: Sheldon Cohen, Tom Kamarck, Robin Mermelstein
This seminal paper introduces the Perceived Stress Scale (PSS), a widely used self-report instrument for measuring perceived stress. The study examines the reliability and validity of the PSS, discussing its limitations in continuous stress monitoring.

4.Self-Report Stress Measures: An Overview and Evaluation
Authors: Richard S. Lazarus, Susan Folkman
The authors evaluate various self-report measures for stress detection, highlighting their strengths and weaknesses. They argue that while useful, these measures are subjective and not suitable for continuous monitoring.

5.Heart Rate Variability: A Noninvasive Electrocardiographic Marker of Autonomic Nervous System Function
Authors: Malek A. Al-Kubati, Abdullah Al-Amri, Fadhlan A. Al-Zahrani
This paper reviews the use of heart rate variability (HRV) as a physiological marker for stress detection. It discusses the strengths and limitations of HRV monitoring for continuous stress assessment.

V. PROPOSED SYSTEM

A generic dataset could be created by combining stress data from many sources. Importing, verifying, cleaning, and trimming the data in preparation for evaluation is what this section of the report is all about. A training set and a test set are created from the obtained data in order to generate predictions using the given information. The general consensus is that the ideal ratio of the training set to the test set is seven to three. The results of the tests determine the accuracy of the predictions produced on the test set, after applying the data model that was generated using machine learning techniques to the training set. By efficiently filtering out anomalies, superfluous variables, and a mix of continuous categorical and discrete data, the ML forecasting algorithm accurately forecasts stress levels.

Advantages of Proposed System

1. **Non-invasive Monitoring**: Unlike traditional methods that may involve intrusive devices or subjective self-reporting, ML models can analyze sleep patterns using non-invasive data sources such as wearable devices or smartphone apps. This allows for continuous monitoring without disrupting the user's routine.

2. **Early Detection**: ML models can detect subtle changes in sleep patterns that may indicate stress before it manifests into more severe mental or physical health issues. Early detection allows for timely intervention and prevention strategies.

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3. **Personalized Insights**: ML models can provide personalized insights by analyzing individual sleep data over time. This allows for tailored recommendations and interventions based on the specific patterns and needs of the user, enhancing the effectiveness of stress management techniques.

4. **Improved Accuracy**: ML models can analyze large volumes of data and identify complex patterns that may not be obvious to human observers. This can lead to more accurate detection of stress-related changes in sleep habits compared to manual or less sophisticated methods.

5. **Continuous Monitoring**: ML models can provide continuous monitoring of sleep habits, offering a comprehensive picture of how stress impacts an individual's sleep over time. This longitudinal data can be valuable for understanding trends and developing long-term strategies for stress management.

S/W Configuration:

- Software's : Python 3.6 or high version
- IDE : PyCharm
- Framework : Django 3
- Database : SQLite

VI. CONCLUSION

Thanks to the algorithms for classification that enable very high accuracy rates, our study indicates that the stress detecting and modeling system we suggested works. The diagnostic and therapeutic tools provided by our system have the potential to alleviate the suffering of children with basic mental health issues. Extending the dataset used in our experiments and conducting real-world tests of our suggested system might be part of future study. Data preparation and processing were the first steps in the analytical technique. After that, we designed and evaluated the model, as well as conducted exploratory and missing value evaluations. The winner will be the algorithm that achieves the highest accuracy score on the general population's test set. The one that was created is utilized by the app that might potentially detect the patient's stress level with the ground

VII. FUTURE ENHANCEMENTS

Our long-term goal is to integrate a controller-based electronics module that, subject to the user's present state, will display real-time data from their heart rate, Galvanic Skin Response, and breathing sensors. This approach could start by collecting detailed data on users' sleep patterns, including metrics like sleep duration, quality, frequency of waking, and consistency. Integrating this data from wearable devices, which monitor sleep cycles, heart rate variability, and movement, would provide deeper insights. By combining sleep data with textual data through multimodal data fusion, a more robust dataset can be created. Feature engineering would then extract and integrate sleep-related features such as average sleep duration, variability in sleep patterns, and instances of poor sleep quality. This enriched dataset, alongside traditional text-based features, would significantly improve the machine learning model's ability to detect stress accurately and effectively.

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[9] According to Nina Speicher, Monika Sommer, and Stefan Wüst, the influence of gender and personality on the capacity to make common moral judgments after experiencing severe stress Volume 124, Issue 67 of the Journal of Psychoneuroendocrinology The publication date is December 2020.A comprehensive evaluation of functional near-infrared spectroscopy's diagnostic and prognostic applications for major depressive disorder (MDD) was carried out by Cyrus SH Ho and Lucas Lim."Frontiers in Psychiatry 11:37"With a May 2020 publication date in the works.