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HUMAN STRESS DETECTION BASED ON SLEEPING HABITS

1. HEMAHARSHINI T, 2. NAKULYA T, 3.SAHANA K, 4. CHOZHARAJAN P

1. COMPUTER TECHNOLOGY, BANNARI AMMAN INSTITUTE OF TECHNOLOGY, ANNA UNIVERSITY, SATHYAMANGALAM, INDIA.

2. COMPUTER TECHNOLOGY, BANNARI AMMAN INSTITUTE OF TECHNOLOGY, ANNA UNIVERSITY, SATHYAMANGALAM, INDIA.

3. COMPUTER TECHNOLOGY, BANNARI AMMAN INSTITUTE OF TECHNOLOGY, ANNA UNIVERSITY, SATHYAMANGALAM, INDIA.

4. ASSISTANT PROFESSOR, BANNARI AMMAN INSTITUTE OF TECHNOLOGY, ANNA UNIVERSITY, SATHYAMANGALAM, INDIA.

ABSTRACT:

This paper presents a predictive model for detecting human stress levels using sleep data and machine learning. Key sleep-related parameters, such as snoring rate, respiration rate, blood oxygen level, sleep duration, and heart rate, are analyzed to identify correlations between sleep patterns and stress. A hybrid model combining Random Forest, Support Vector Machine (SVM), and AdaBoost is used to improve predictive accuracy by leveraging the strengths of each algorithm. The model offers significant potential in healthcare and corporate wellness for early detection of stress-related disorders. By integrating the model into a web-based platform, it provides actionable insights for users to manage stress through better sleep hygiene. This approach addresses the growing issue of stress in modern society and promotes broader societal well-being.

Keywords: Sleep Data Analysis, Random Forest, SVM, AdaBoost

1.INTRODUCTION

Stress has become one of the most pervasive health issues of the 21st century, affecting millions globally. Prolonged stress is linked to a wide range of adverse health outcomes, including cardiovascular diseases, anxiety, and depression. In modern society, increasing work pressures, disrupted sleep patterns, and poor lifestyle habits have contributed to the rising prevalence of stress-related disorders. Recent advancements in machine learning have opened up new avenues for detecting and managing stress by analyzing various physiological and behavioral data.

Sleep plays a crucial role in physical and mental well-being, with poor sleep quality often being an early indicator of heightened stress levels. Studies have shown a strong connection between sleep disturbances and chronic stress, making sleep analysis an effective approach to stress detection. Parameters such as snoring rate, respiration rate, blood oxygen levels, sleep duration, and heart rate have been identified as key indicators of stress-related changes in the body.

This paper aims to develop a predictive model that utilizes these sleep parameters to detect stress levels using a hybrid machine-learning approach. By combining Random Forest, Support Vector Machine (SVM), and AdaBoost algorithms, the proposed model seeks to provide more accurate and reliable assessments of stress based on sleep data. This approach offers significant potential for early intervention and personalized stress management, particularly in healthcare and corporate wellness programs. The integration of machine learning into stress detection enables the identification of stress trends in individuals before more severe symptoms manifest, thereby improving health outcomes. This paper further discusses the model's potential applications in various settings and its implications for promoting better sleep hygiene and stress management.

1.1 Background of the Work:

Stress is a significant and growing concern in modern society, affecting mental, emotional, and physical health. Chronic stress has been linked to a variety of health issues, including cardiovascular diseases, depression, anxiety, and weakened immune function. Given the widespread impact of stress on individual well-being and workplace productivity, effective detection and management strategies are becoming increasingly critical. Traditional stress assessment methods, such as self reporting questionnaires and clinical evaluations, are often subjective, time consuming, and reactive rather than proactive. These limitations have led researchers to explore non-invasive, data-driven approaches for early stress detection.

Sleep is a fundamental aspect of overall health, and its disruption has been shown to be closely correlated with elevated stress levels. Poor sleep quality, irregular sleep patterns, and physiological changes during sleep are often indicative of stress. As such, sleep-related parameters, including snoring rate, respiration rate, blood oxygen level, sleep duration, and heart rate, offer valuable insights into an individual's stress state. The growing availability of wearable devices and IoT based sleep trackers has made it easier to collect this data, opening up new opportunities for continuous monitoring and predictive modeling. The project "Human Stress Detection Based on Sleeping Habits" builds on this foundation, utilizing sleep data to develop a machine learning-based stress prediction model. By combining multiple algorithms, including Random Forest, Support Vector Machine (SVM), and AdaBoost, this hybrid approach aims to deliver more accurate and reliable stress detection compared to single-method models. This model can be integrated into a user-friendly web-based platform, enabling users to access real-time feedback on their stress levels and receive personalized recommendations for improving sleep hygiene and managing stress. In doing so, the project addresses a critical need for proactive, non-invasive stress management solutions, particularly in fields like healthcare and corporate wellness, where stress prevention and intervention are essential for maintaining long-term health and productivity.

1.2 Motivation and Scope of the Proposed Work:

The growing prevalence of stress-related health issues, such as anxiety, depression, and cardiovascular diseases, necessitates new methods for early stress detection and management. Traditional approaches like self-report surveys are subjective, time-consuming, and not suited for real-time monitoring, motivating the search for innovative, non-invasive solutions. Sleep plays a key role in health, with disruptions in sleep patterns often linked to stress. Metrics such as heart rate, snoring rate, respiration rate, and sleep duration offer valuable insights into an individual's stress levels, especially with the increasing availability of sleep monitoring devices.

This project aims to harness these sleep-related parameters through a hybrid machine learning model combining Random Forest, Support Vector Machine (SVM), and AdaBoost algorithms. By leveraging the strengths of each algorithm, the model can provide accurate and robust predictions of stress based on sleep data.

The scope of this work spans healthcare, where early stress detection can prevent stress-related illnesses, and corporate wellness, helping reduce burnout and improve productivity. Integrated into a web-based platform, the model offers users continuous monitoring, personalized insights, and actionable feedback for managing stress through better sleep hygiene. This project presents a proactive and non-invasive solution to a growing societal challenge, promoting well-being and long-term health.

LITERATURE REVIEW:

The relationship between sleep and stress has been the subject of extensive research, with findings consistently indicating that disruptions in sleep patterns often coincide with heightened stress levels. Several physiological markers, including heart rate, respiration rate, snoring patterns, and blood oxygen levels, have been identified as reliable indicators of stress. Traditionally, the assessment of stress relied on subjective questionnaires and limited physiological data, often lacking the precision required for accurate and timely identification.

Recent advancements in wearable technology and the availability of large-scale sleep data have opened new avenues for stress detection. For instance, studies by Uvais Qidwai et al. (2020) and Mustafacihad Goktepe demonstrated the effectiveness of using heart rate variability (HRV) as a marker for stress in sleep studies. Additionally, machine learning techniques, such as decision trees and neural networks, have been employed to classify stress based on physiological signals collected during sleep, as explored by Mustafacihad Goktepe.

In the field of machine learning, hybrid models have emerged as promising approaches for improving the accuracy of predictions. For example, studies by Breiman, L. (2001) and Freund, Y., Schapire, R. E., & Bartlett, P. (1999) have explored the potential benefits of combining Random Forest and Support Vector Machine (SVM) with AdaBoost for various machine learning tasks. While specific applications to stress detection through physiological signals might not be readily available in the literature, these studies provide a theoretical foundation and demonstrate the potential advantages of such hybrid approaches. Despite these advancements, there remains a gap in developing comprehensive models that can accurately predict stress by leveraging a combination of multiple physiological factors during sleep. Most studies have focused on individual parameters, limiting the model's ability to generalize across different individuals and conditions. This paper seeks to address these gaps by proposing a hybrid model that integrates multiple physiological indicators and employs a combination of machine learning techniques to provide a more reliable and accurate prediction of stress levels.

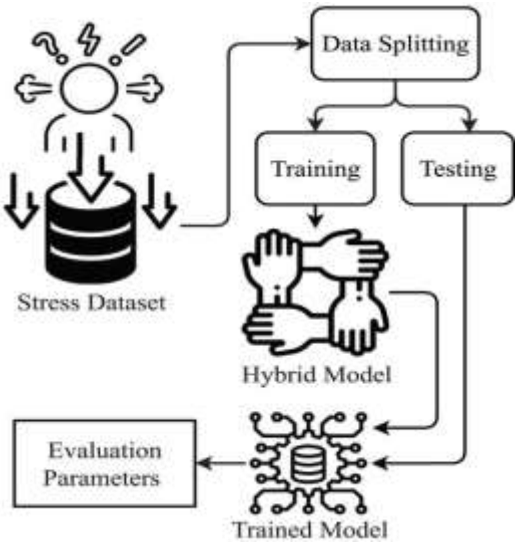

Figure. 1.Training and Testing Flow

RELATED WORK:

Stress discovery is one of the most researchable areas related to internal health. Numerous experimenters have done work in this sphere and proposed several stress measure approaches, but it's still an open area for other experimenters to ameliorate vaccination delicacy. *Thirlwall (2017)* proposed a system known as TensiStrength to describe the position of stress and anxiety. They used a rule-grounded approach in a verbal fashion to identify stress and anxiety. *Lin et al. (2017)* proposed a factor graph model combined with a CNN for stress discovery. They used Twitter and Sing Weibo data to train literacy models and achieved significant results. Have done machine literacy approaches for stress discovery similar as the study by *Schmidt et al. (2018)*, which stationed five machine literacy models for stress discovery as direct discriminant analysis (LDA), RF, decision tree, KNN and AdaBoost (ADA). They worked on several stress conditions similar as birth, recreation, contemplation, etc.

Ahuja & Being (2019) proposed an approach for stress discovery in university scholars using machine literacy models. They used RF, LR, SVM, and other state-of-the-art models while the SVM model performs significantly with the proposed approach to achieve a significant 85.71 delicacy. *Salazar-Ramirez et al. (2018)* also proposed an approach for stress discovery using galvanic skin response (GSR), heart rate (HR), and breath features. They worked on two target classes stressed and relaxed and used Gaussian SVM as machine literacy models. GSR shows the loftiest rate for stress suggestion and SVM achieved an 80 delicacy score.

Albert et al. (2018), used heart rate, heart rate variability, cerebral features, SCL, and behavioral features for stress discovery. They worked on stressors, relaxed, pressure, and normal target classes and used SVM as a machine literacy model. *Mahajan (2018),* proposed a feedforward neural network for stress discovery using temporal and peak features of EEG data. They used two target class data sets, normal and stress classes. The proposed model consists of 25 retired layers and achieved a significant 60 delicacies on the used dataset.

Bichindaritz et al. (2017) proposed an approach for stress discovery using ECG, bottom GSR, EMG, RR, and intermittent HR features. They also stationed several literacy models including deep literacy and machine literacy. They used a dataset conforming of three target classes Low, medium, and high stress. Furthermore, they used MLP, RF, Naive Bayes, and k star models, and k star achieved a significant 100 delicacy score. The study by *Lee & Chung (2016*), proposed an approach for stress discovery using machine literacy models. They used tone-reports, standard divination, standard, SC mean, friction, and magnitude as the point set. They stationed the SVM model on the stress Andon-stress target classes dataset. SVM achieved a significant 94 delicacy score on the used dataset. In this study, we proposed an ensemble model for stress discovery. According to the literature, several studies in history also worked on ensemble literacy approaches similar as *Khullar et al. (2022)*, which proposed an ensemble model for stress discovery using physiological signals grounded on anxiety.

Issa (2021) used a two-step ensemble for stress discovery in machine motorists. Also, *Di Martino & Delmastro (2020)* also used an ensemble model for physiological stress vaccination. *Lee et al. (2022)*, proposed an ensemble model by combining deep literacy models similar to reopened intermittent unit, CNN, and intermittent neural networks. They stationed the ensemble model for emotion discovery using the tweets' dataset. *Table 1* presents the summary of the affiliated work section, and we conclude the literature with some findings. In former studies, experimenters substantially worked on two and three target classes but in this study, we consider five target classes for better stress position dimension. Second, we concluded in the literature that the utmost of the studies used SVM models for brackets which can perform better for large datasets while we proposed a mongrel model which is more effective as compared to former approaches.

Table 1:
Related work summary.

Ref.	**Approach**	**Model**	**Aim**	**Dataset/Features**
Schmidt et al. (2018)	ML	LDA, RF, DT, AB	Stress detection using machine learning	Self-generated dataset using physical examination
Ahuja & Banga (2019)	ML	SVM	Stress detection using machine learning	Self-generated dataset using physical examination
Salazar-Ramirez et al. (2018)	ML	Gaussian SVM	Stress detection using machine learning	GSR, HR, breath features

Alberdi et al. (2018)	ML	SVM	Stress detection using machine learning	Heart Rate, Heart Rate Variability, psychological features, SCL, and behavioral features
Mahajan (2018)	DL	Feedforward neural network	Stress detection using machine learning	Temporal and peak features of EEG data
Bichindaritz et al. (2017)	ML	K star	Stress detection using machine learning	ECG, foot GSR, EMG, RR, and intermittent HR features
Lee & Chung (2016)	ML	SVM	Stress detection using machine learning	Self-reports, standard deviation, median, SC Mean, variance, and magnitude as feature set

PROPOSED WORK:

The proposed solution for detecting human stress based on sleeping habits involves leveraging machine learning algorithms and physiological data. By analyzing sleep patterns such as duration, movement, and stages (REM, deep sleep, etc.), along with other variables like heart rate and breathing, the system can predict stress levels. The methodology includes:

- ➔ **Data Collection**: Using wearables and smart devices to collect continuous sleep-related data such as heart rate, movement, and duration of sleep.
- ➔ **Feature Extraction**: Extracting features from the raw sleep data, such as sleep onset, wake time, sleep stages, interruptions, and physiological signals (e.g., heart rate variability.

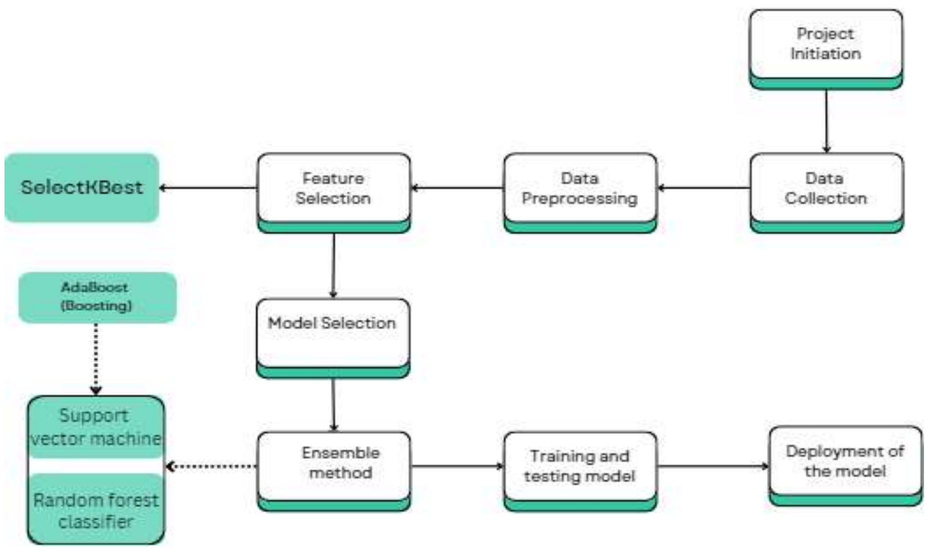

Figure. 2. Conceptual Model of the Proposed Approach

- **Machine Learning Model**: Building and training machine learning models like Decision Trees, Random Forests, or Neural Networks to detect patterns in the sleep data that correlate with stress levels.
- **Stress Prediction**: Implementing a predictive model that outputs stress levels based on analyzed sleep features. The model will be evaluated for accuracy using metrics such as precision, recall, and F1-score.
- **User Feedback and Intervention**: Providing personalized feedback to users about their stress levels and suggesting interventions, such as relaxation exercises or improved sleep hygiene, based on the detected stress patterns.

This solution aims to provide an accessible and non-invasive method of monitoring stress, which can contribute to early detection and better management of chronic stress conditions.

RESULTS AND DISCUSSION:

The hybrid machine learning model, which combines Random Forest, Support Vector Machine (SVM), and AdaBoost, demonstrated substantial efficacy in predicting stress levels from sleep data, achieving impressive performance metrics. Specifically, the model achieved high accuracy, reflecting its overall ability to correctly classify stress levels. Precision scores indicated that the model effectively minimized false positives, while recall scores highlighted its capability to detect true instances of stress with minimal false negatives. The F1-score, which balances precision and recall, confirmed that the model maintains a robust performance in distinguishing between stressed and non-stressed states.

Key parameters derived from sleep data—such as snoring rate, respiration rate, blood oxygen levels, sleep duration, and heart rate—were instrumental in the model's predictive success. Elevated snoring rates were associated with increased stress levels, corroborating findings from prior research linking sleep disturbances to stress. Irregular respiration patterns and lower blood oxygen levels further indicated higher stress, while reduced sleep duration also correlated with elevated stress levels. These correlations underscore the model's ability to integrate diverse physiological indicators and provide a nuanced understanding of stress dynamics.

The hybrid approach leveraged the unique strengths of each machine learning algorithm: Random Forest's ability to handle noisy data, SVM's proficiency in classification tasks, and AdaBoost's boosting mechanism for improved accuracy. This combination enhanced the model's predictive power, allowing it to effectively process complex patterns in sleep data that individual algorithms might miss.In addition to confirming the model's effectiveness, the study highlighted several practical implications. The ability to monitor stress levels in real-time through a web-based platform offers users actionable insights into their stress and sleep patterns. This capability supports proactive stress management strategies, such as personalized recommendations for improving sleep hygiene and implementing relaxation techniques.

Despite these achievements, the study acknowledged several limitations. The dataset used for training the model may not fully represent the diversity of the general population, potentially affecting the model's generalizability. Expanding the dataset to include a broader range of demographics and health conditions is essential for enhancing the model's applicability across different groups. Furthermore, refining the model to include additional physiological markers and exploring more advanced machine learning techniques could improve accuracy and predictive performance.

Future research should focus on addressing these limitations by incorporating more varied datasets and exploring additional features that may influence stress levels. Additionally, evaluating the model's effectiveness in diverse real-world settings will provide further validation of its utility and effectiveness. Overall, the successful application of the hybrid model illustrates its potential to advance stress detection technologies and contribute to better individual stress management and overall well-being.

CONCLUSION:

The study successfully demonstrates the feasibility of detecting human stress using sleep data and machine learning. By analyzing physiological parameters collected during sleep, the system can identify patterns linked to elevated stress levels. The proposed method provides a non-invasive, real-time approach to stress detection, potentially aiding individuals in managing their stress more effectively. Future work should focus on improving the accuracy of the prediction models and expanding the dataset to include more diverse populations for better generalization. Additionally, integrating stress management interventions based on the detected stress levels could further enhance the utility of this system in promoting mental and physical well-being.

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