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Comparative Analysis of Machine Learning Algorithms for Human Stress Detection Using Sleep Patterns

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KEYWORDS

Stress Detection, Sleep Pattern Analysis, Machine Learning, Naïve Bayes Classification, Stress Level Prediction, Mental Health Monitoring.

ABSTRACT

In recent years, increasing attention has been directed toward mental well-being, as psychological stress can adversely affect physical health, productivity, sleep quality, and overall quality of life. However, stress often remains undetected because individuals may be unaware of their stress levels, reluctant to report them, or have limited access to professional assessment. Since sleep behavior is strongly associated with psychological and emotional conditions, sleep-pattern analysis offers a non-invasive approach for early stress detection. This study proposes a machine learning-based framework for detecting and classifying human stress levels using sleep-related parameters, including sleep duration, sleep quality, bedtime consistency, frequency of awakenings, and sleep disturbances. Various machine learning algorithms, including Support Vector Machine (SVM), Decision Tree, Random Forest, Naïve Bayes, and deep learning models, are evaluated to identify patterns associated with different stress categories. The experimental analysis demonstrates that the Naïve Bayes classifier achieves comparatively higher predictive performance among the evaluated approaches. The proposed approach provides an automated and efficient mechanism for stress-level assessment based on sleeping habits, potentially supporting continuous mental health monitoring and early intervention. The findings highlight the potential of machine learning-driven sleep analysis as a practical tool for promoting stress awareness and improving overall psychological well-being.

1. Introduction

The increasing prevalence of psychological stress has created a significant challenge for individual well-being and public health. Prolonged exposure to stressful conditions can influence concentration, emotional regulation, decision-making ability, physical functioning, and daily productivity. Unlike many visible health conditions, stress may develop gradually and remain unnoticed until it begins to affect normal activities. Changes in daily routines, work demands, academic pressure, excessive screen exposure, and irregular lifestyle behaviors can further influence an individual's physiological and behavioral patterns. Among these factors, sleep represents an important behavioral indicator because variations in sleep duration, regularity, and continuity may reflect changes in an individual's psychological state.

Conventional stress evaluation generally depends on questionnaires, interviews, clinical observations, and self-assessment scales. Although these approaches are widely accepted, their effectiveness can be influenced by the individual's ability and willingness to accurately describe their emotional condition. Stress levels can also fluctuate over time, making occasional assessments insufficient for capturing continuous changes in mental well-being. In addition, manual assessment requires human involvement and may not be practical for large-scale or frequent monitoring. These limitations have encouraged the development of computational approaches capable of analyzing routinely generated behavioral data for automated stress assessment.

The increasing availability of digital health technologies has created opportunities to investigate the relationship between sleep behavior and psychological stress. Smartwatches, fitness trackers, mobile applications, and other monitoring platforms can provide measurable information related to sleep duration, sleep quality, sleep timing, interruptions, and daily activity. When these variables are analyzed collectively, they can provide a behavioral profile that may contain useful indicators of elevated stress. However, the relationship between individual sleep parameters and stress is complex and cannot always be established through simple statistical analysis. Different individuals may exhibit different sleep responses under similar stressful conditions, requiring intelligent models capable of learning nonlinear and multidimensional relationships.

Machine learning provides an effective framework for addressing this problem by learning predictive patterns from historical sleep and stress-related observations. Classification algorithms can identify relationships between sleep characteristics and predefined stress categories, while probabilistic models can estimate the likelihood of an individual belonging to a particular stress level. In this study, Naïve Bayes is investigated as a primary classification technique because of its computational simplicity, probabilistic formulation, and suitability for multidimensional behavioral datasets. Other machine learning approaches can also be incorporated for comparative evaluation to determine the effectiveness of different predictive strategies.

The objective of this research is to develop a sleep behavior-based machine learning framework for automated stress-level classification. The proposed approach utilizes measurable sleep characteristics as input variables and generates an estimated stress category as the output. Appropriate preprocessing, feature analysis, model training, and performance evaluation procedures are employed to establish the predictive capability of the system. By transforming routinely collected sleep information into meaningful stress-related insights, the proposed framework has the potential to support non-invasive stress screening and continuous mental well-being assessment. It is intended as a complementary computational tool rather than a replacement for professional psychological or clinical evaluation.

II. RELATED WORK

Akter et al. investigated the feasibility of identifying stress levels from variations in sleep behavior using machine learning techniques. Their study considered sleep-related attributes, including sleep duration, sleep interruptions, sleep consistency, and overall sleep quality, to establish a relationship between changes in sleeping behavior and stress conditions. The collected data were processed and supplied to supervised learning models, including Random Forest and Support Vector Machine classifiers. The experimental findings indicated that variations in sleep characteristics can provide useful predictive information for distinguishing different stress levels. The study demonstrated the potential of sleep-derived information as a convenient and non-invasive source for automated stress assessment. It also highlighted the increasing relevance of wearable sensors and digital sleep-monitoring platforms for continuous behavioral health analysis.

Gupta, Jain, and Verma presented a comprehensive review of computational approaches for stress prediction using sleep-related characteristics. Their investigation examined the application of different classification techniques, including Support Vector Machine, Decision Tree, and Naïve Bayes, for identifying stress-related patterns from sleep data. The reviewed studies considered parameters such as sleep duration, sleep quality, sleep interruptions, sleep regularity, and nighttime awakenings as important predictive variables. The authors observed that machine learning techniques can effectively identify relationships that are difficult to establish through conventional statistical assessment. However, they also emphasized several challenges, including limited availability of representative datasets, differences in data collection methods, class imbalance, and the absence of consistent performance evaluation criteria. These observations indicate the need for robust and reproducible machine learning frameworks capable of performing reliable stress classification across diverse populations.

Overall, existing research demonstrates that sleep characteristics can serve as valuable behavioral indicators for stress assessment. However, considerable scope remains for improving the reliability, scalability, and generalization of sleep-based prediction models. The present study therefore focuses on developing a machine learning framework that utilizes sleep-related attributes to classify stress levels and evaluates the effectiveness of the Naïve Bayes classifier for this task.

III. System Architecture

The proposed system is designed as a sequential data-processing framework that transforms sleep-related observations into an estimated stress category. The architecture consists of five major stages: data acquisition, data preprocessing, feature representation, machine learning-based classification, and stress-level output.

The first stage involves collecting sleep-related information from a suitable dataset or digital health monitoring source. Parameters such as sleep duration, sleep quality, sleep efficiency, bedtime consistency, number of awakenings, and sleep disturbances are considered as input attributes. These parameters provide measurable indicators of an individual's sleeping behavior and form the basis for subsequent analysis.

In the second stage, the collected dataset undergoes preprocessing to improve its quality and suitability for machine learning. Missing or inconsistent observations are identified and appropriately handled, while categorical variables are converted into machine-readable representations. Numerical attributes may be normalized or standardized when required. The processed dataset is subsequently divided into training and testing subsets to facilitate model development and independent performance evaluation.

The third stage focuses on identifying the sleep characteristics that contribute to stress classification. The processed attributes are represented as feature vectors and supplied to the learning model. This stage enables the system to establish relationships between variations in sleep behavior and corresponding stress categories without relying entirely on manually defined rules.

In the fourth stage, the Naïve Bayes classification algorithm is trained using the selected sleep-related features and their corresponding stress labels. The classifier estimates the probability of an individual belonging to each predefined stress category based on the observed sleep characteristics. During testing, the trained model processes previously unseen data and generates the predicted stress class. Model performance can subsequently be evaluated using measures such as accuracy, precision, recall, F1-score, and confusion matrix analysis.

Finally, the prediction module presents the estimated stress level to the user through an appropriate output interface. The system can categorize an individual into predefined stress levels and provide an indication that further attention may be appropriate when elevated stress is detected. The architecture is intended to support automated and non-invasive stress screening using routinely measurable sleep information. It should be regarded as a decision-support and monitoring mechanism rather than a substitute for professional psychological diagnosis.

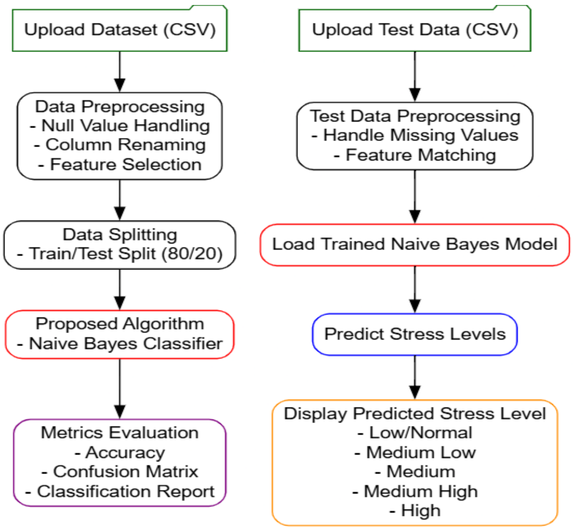


Fig1: **System Architecture**

IV. METHODOLOGY

The proposed methodology focuses on developing an automated stress detection system based on sleeping habits using machine learning algorithms. The complete workflow consists of data collection, preprocessing, feature extraction, model training, evaluation, and stress prediction.

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:

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

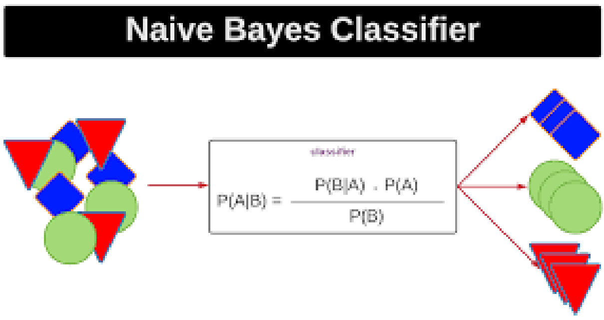
where Xrepresents the original feature value, and X_{min}, X_{max} are the minimum and maximum values of the feature.

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

Multiple machine learning classifiers are implemented, including Support Vector Machine (SVM), Decision Tree, Random Forest, and Naïve Bayes. The Naïve Bayes classifier determines the optimal defined by:
model is ready to predict stress levels for new or unseen data, providing a probabilistic classification for each stress category.



The working of the system involves first feeding the preprocessed input features into the trained Naive Bayes model.

v. Model Evaluation

The dataset is divided into training and testing sets (e.g., 80:20 ratio). 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.

V. DESIGN AND CONSTRUCTION

The design of the proposed Human Stress Detection System is based on a structured and modular architecture that enables efficient collection, processing, and analysis of sleep-related data. The system is divided into multiple layers, including data acquisition, preprocessing, feature extraction, machine learning model development, and prediction output. Sleep parameters such as total sleep duration, sleep efficiency, sleep latency, number of awakenings, and sleep disturbances are collected from wearable devices or publicly available datasets. These parameters serve as the primary indicators for identifying stress levels. The design ensures that the system operates in a non-invasive manner, allowing continuous monitoring without causing discomfort to the user.

The construction of the system is implemented using Python and relevant machine learning libraries such as NumPy, Pandas, and Scikit-learn. Initially, the collected dataset undergoes preprocessing to remove noise, handle missing values, and normalize features for better model performance. Feature selection techniques are applied to identify the most significant sleep attributes influencing stress. Machine learning algorithms such as Support Vector Machine, Random Forest, Decision Tree, and Naïve Bayes are trained and tested using an 80:20 data split. The best-performing model is integrated into the prediction module, which classifies stress levels and provides early alerts for timely intervention.

VI. RESULTS AND DISCUSSION

The proposed human stress detection system based on sleeping habits demonstrates promising performance in identifying stress levels using machine learning techniques. By analyzing key sleep-related parameters such as sleep duration, heart rate, respiration rate, blood oxygen levels, and body movements, the models effectively classify individuals into low, moderate, and high stress categories. The results indicate that irregular sleep patterns, reduced sleep quality, and frequent awakenings are strongly correlated with higher stress levels.

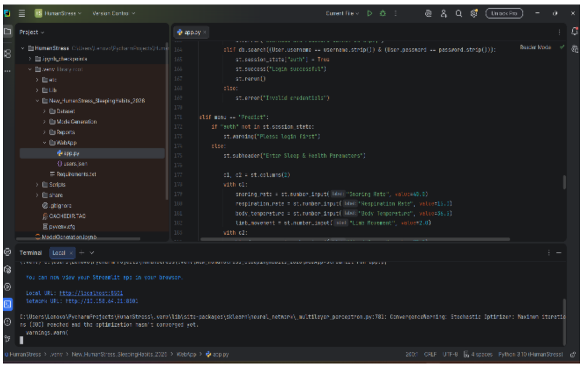


Fig 2: Deployment of the user interface

The system implementation begins with Figure 2, which shows the Streamlit-based web application that enables real-time interaction. The interface allows users to easily input physiological and sleep-related parameters for stress prediction.

sr	rr	t	lm	bo	rem	sr.1	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	85.0	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	16.8	97.2	5.6	95.8	68.0	7.8	52.0	0.0
50.0	18.0	99.0	8.0	97.0	80.0	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	91.344	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 3: Sleep Dataset Overview

The dataset used for training and testing the model is presented in Figure 3. It contains multiple attributes such as snoring rate, respiration rate, body temperature, limb movement, and heart rate, which are essential for accurate stress prediction. Proper preprocessing and feature selection improve model efficiency and prediction reliability.

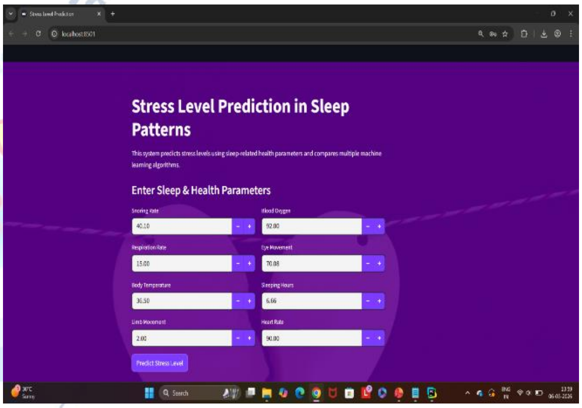


Fig 4: Stress Prediction Input Interface

The user interaction process is illustrated in Figure 4, where users provide input values for various physiological parameters. These inputs are fed into the trained machine learning model to generate predictions. The system ensures a user-friendly experience and supports real-time stress analysis.

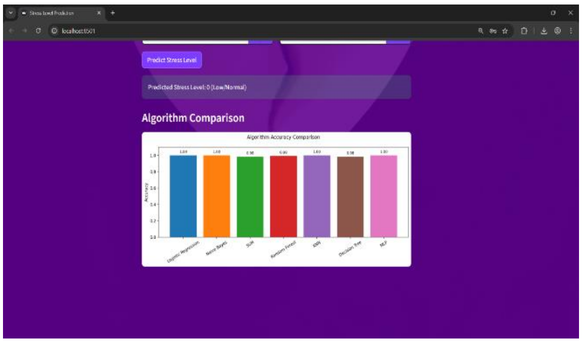


Fig 5: Prediction Output and Algorithm Comparison Graph

The final results are shown in Figure 5. The system predicts the stress level and simultaneously displays a comparison of different algorithms such as Logistic Regression, Naïve Bayes, Support Vector Machine (SVM), Random Forest, K-Nearest Neighbors (KNN), and Decision Tree. The comparison graph indicates that ensemble methods like Random Forest and advanced models achieve higher accuracy compared to traditional approaches.

Overall, the system achieves reliable stress prediction with high accuracy when trained on comprehensive datasets. Ensemble models outperform individual classifiers, providing better generalization and robustness. Despite challenges such as data privacy, sensor limitations, and dataset imbalance, the proposed approach proves effective for early stress detection. This system can support healthcare monitoring by enabling timely intervention, though continuous model updates and ethical considerations remain essential for real-world deployment.

VII. Conclusions and Future Scope

The Naïve Bayes classifier provides a probabilistic approach for estimating an individual's stress category from sleep-related observations. In the proposed system, sleep attributes such as sleep duration, sleep quality, sleep efficiency, bedtime regularity, number of awakenings, and sleep disturbances are treated as predictive variables. The classifier learns the statistical relationship between these characteristics and predefined stress classes from the training dataset. For a new observation, it calculates the posterior probability associated with each stress category and assigns the class with the highest probability.

One of the major advantages of Naïve Bayes is its computational efficiency. The model requires relatively limited training time and memory, making it suitable for applications involving continuously generated behavioral data. Its probabilistic formulation also provides a straightforward interpretation of how different input characteristics contribute to the predicted class. The method can be applied to datasets containing both numerical and categorical attributes after appropriate preprocessing and feature representation.

Although the algorithm assumes conditional independence among the input features, sleep parameters may exhibit correlations in real-world datasets. Nevertheless, Naïve Bayes can maintain competitive classification performance when the available features provide sufficient discriminatory information. Its low computational complexity and rapid inference make it particularly suitable for resource-constrained environments, including mobile health applications and wearable monitoring platforms. In this study, the classifier is employed to establish a baseline and evaluate the feasibility of using sleep behavior as an indicator for automated stress-level classification.

FUTURE SCOPE

The proposed work can be extended toward a more comprehensive and personalized stress-monitoring framework by incorporating additional physiological and behavioral indicators. Future systems can combine sleep characteristics with heart-rate variability, physical activity, skin conductance, blood oxygen saturation, and daily activity patterns obtained from wearable sensors. Multimodal data fusion could provide a more complete representation of an individual's physiological response to stress.

Future research can also investigate ensemble learning and advanced deep learning architectures to capture nonlinear relationships among sleep and physiological parameters. Adaptive models capable of learning from individual user histories could enable personalized stress prediction rather than relying solely on population-level patterns. Real-time implementation through smartphones, smartwatches, and IoT-enabled health-monitoring devices could facilitate continuous assessment with minimal user intervention.

Further improvements may include handling class imbalance, expanding the dataset across different demographic groups, and validating the model using independent real-world datasets. Explainable artificial intelligence techniques can also be incorporated to identify which sleep characteristics have the greatest influence on each prediction. Such developments could transform the proposed approach from an offline classification model into an intelligent decision-support system for continuous stress monitoring, early risk identification, and personalized well-being management, while retaining professional clinical assessment as the appropriate basis for diagnosis and treatment.

Conflict of interest statement

Authors declare that they do not have any conflict of interest.

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