**International Journal of Research Publication and Reviews**

Journal homepage: www.ijrpr.com ISSN 2582-7421

# Machine learning based human stress detection using sleep monitoring data

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**A B S T R A C T :**

Stress has become a prevalent issue in modern society, significantly impacting mental and physical health. Early detection and intervention can mitigate its adverse effects. This project explores the use of machine learning techniques to detect stress levels by analyzing habitudinal data, such as sleep patterns, physical activity, heart rate, and daily routines, collected from wearable devices and smartphones. By leveraging supervised and unsupervised learning algorithms, including decision trees, support vector machines (SVM), and neural networks, the system aims to classify stress levels into categories such as low, moderate, and high. The dataset is preprocessed to handle missing values, normalize features, and extract relevant patterns. The model's performance is evaluated using metrics like accuracy, precision, recall, and F1-score. The results demonstrate the potential of machine learning in accurately identifying stress levels based on habitudinal data, paving the way for personalized stress management solutions. This project highlights the integration of wearable technology and machine learning to promote mental well-being and proactive health monitoring..

**Keywords**: machine learning, stress monitoring data, random forest , dataset calculation, decision tree, Android App.

## INTRODUCTION

The rise of smart factories has revolutionized the manufacturing industry by integrating advanced technologies like IoT, big data analytics, and AI. These technologies have facilitated the optimization of production processes, enhancing efficiency and productivity. However, stress remains a significant issue, with wearable smart devices emerging as a promising solution for alleviating workplace stress. These devices, such as smartwatches and fitness trackers, can monitor workers' physiological responses to their work environment, providing valuable insights into potential stressors. These devices can also monitor worker movements, posture, and physical activity, detecting potential ergonomic hazards that may lead to musculoskeletal disorders or other injuries.The non-invasive and automated nature of wearable devices allows for continuous data collection without disrupting workflow. By embracing these technologies, smart factories can proactively identify and address sources of worker stress and ergonomic risks, creating safer and more sustainable work environments. These technologies empower workers to monitor and manage their health, well-being, and performance in real time.

This paper investigates the relationship between stress, worker well-being, and productivity within the context of smart factories, focusing on the role of wearable devices and human factors in mitigating workplace stress. The study integrates predictive analytics, wearable devices, and human factors optimization in a novel stress monitoring and management framework, representing a significant leap toward addressing the complex challenge of worker stress in smart manufacturing.

## LITERATURE REVIEW

The review study was completed in a number of stages, which included data gathering using the Web of Science database's closest keywords and network visualization design based on prior data. To analyze the work, they used the four closest keywords, five study papers, three publishers, and four journals. The outcomes demonstrated that SVM successfully classified the signals and had a system sensitivity of 91.18%. This study provided a more thorough and significant description of the path that future research will take.

**Stress Detection using Machine Learning and Deep Learning-2023**

This paper uses a dataset that was obtained using an Internet of Things (IOT) sensor, which led to the collection of information about a real-life situation.

**SaYo Pillow: BlockchainIntegrated PrivacyAssured IoT Framework for Stress Management Considering Sleeping Habits -2021**

A user interface is provided allowing the user to control the data accessibility and visibility. SaYoPillow is novel, with security features as well as consideration of sleeping habits for stress reduction, with an accuracy of up to 96%..

**Stress detection using EEG signal based on Fast Walsh Hadamard transform and Voting Classifier – 2021**

This proposed work has experimented using Jupyter notebook in python programming. The dataset was used here for EEG signal waves that include delta, beta, gamma, alpha, and theta waves. The efficiency of the proposed voting classifier is calculated with experimental & test results. The results are discussed in details in this section.

## PROPOSED SYSTEM

- Collect comprehensive sleep-related data, including parameters like sleep duration, quality, disturbances, and self-reported stress levels.
- Preprocess the data by handling missing values, normalizing features, and encoding categorical variables for consistency and accuracy.
- Select relevant features such as sleep efficiency, latency, and environmental factors for model training.
- Train the Random Forest model using bootstrapped samples and random feature subsets, constructing multiple decision trees for robust predictions.
- Evaluate the model's performance, fine-tune hyperparameters, and deploy it for real-time stress detection and personalized management.

**Support Vector Machine (SVM) :**

SVM is a supervised machine learning algorithm used for classification tasks by finding the optimal hyperplane that separates data into distinct classes. In stress detection, SVM is applied to sleep-related features like sleep duration, respiration rate, and body temperature to classify individuals as stressed or not stressed. The algorithm can handle both linear and non-linear data using kernel functions such as polynomial, radial basis function (RBF), and sigmoid.

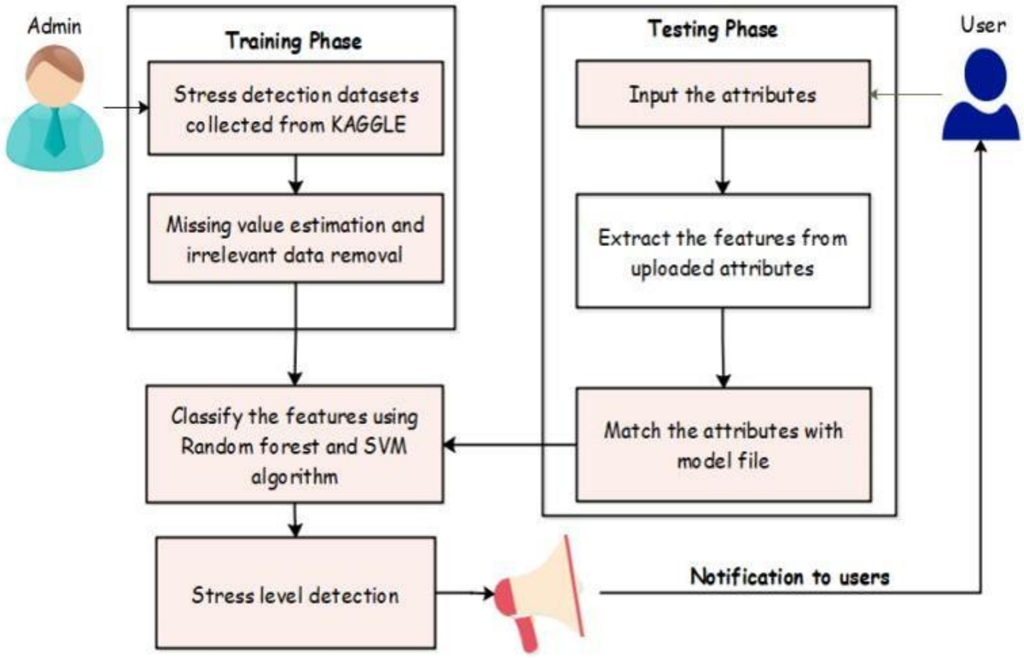
**Random Forest :**

Random Forest is an ensemble learning algorithm that builds multiple decision trees and combines their predictions to improve accuracy and reduce overfitting. In the proposed system, Random Forest is trained on sleep-related data, capturing complex relationships between features like sleep disturbances, snoring range, and body temperature.

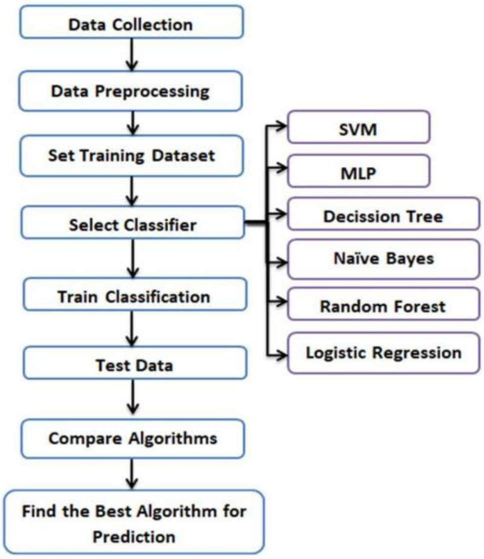
## METHODOLOGY

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..

**Fig 1 – Architecture Diagram**




Additionally, the current research does not make any predictions; it just examines the connection between stress and sleeping patterns. We couldn't find any research using ML systems to analyze sleep patterns before, after and during sleep to determine human stress. The most of obtainable research use only a few independent factors to predict human stress in and through sleep. However, with only a few independent factors, detecting human stress is challenging. By extending the number of attributes in our study, we were able to increase the accuracy.





*B. Data preprocessing*

**Fig. 2. Attributes in the sample**

## WORKING

In this work, Decision Tree (J48), Nave Bayes, MLP, Random Forest, SVM, and Logistic Regression were used for comparison and evaluation. The accuracy outcomes of these algorithms employing cross validation are shown in Fig. 4.

The WEKA software employs cross-validation (by 10) to manage test results and determine the precision of each strategy. The Naïve Bayes classifier has the better accuracy when checking with other algorithms. The Naïve Bayes model, which has an accuracy of 91.27%, is the best one for forecasting human stress.

The recall, precision, and f-measure computations were then used to compare the evaluation findings, as shown in (1), (2), and (3). These are utilized to check the suitability of the results.

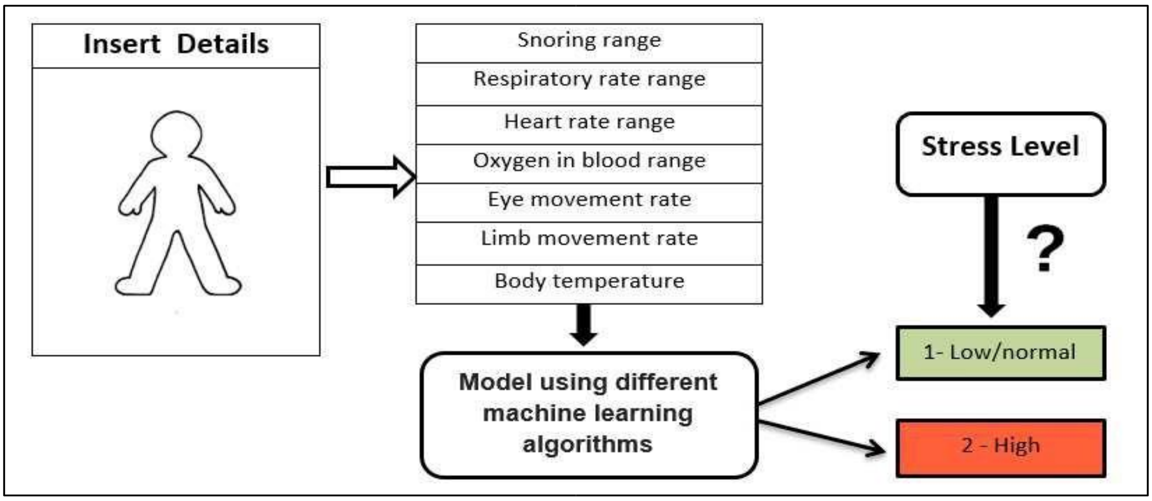



**Fig.** 3. **Process of getting results**

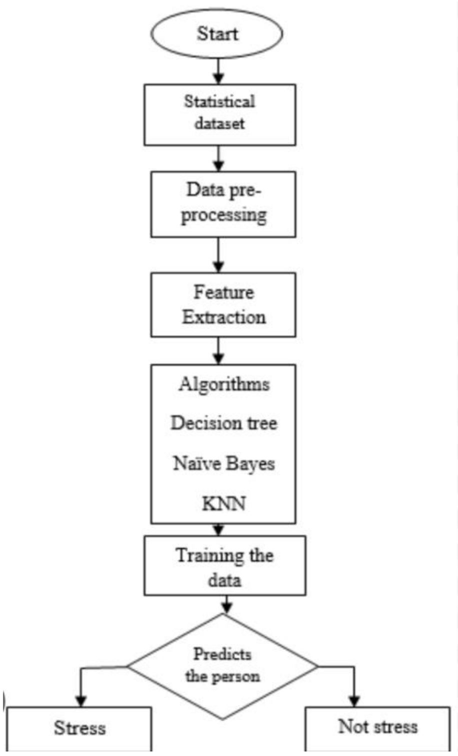



**Fig 4 – Flowchart**

## RESULT

Human stress is depending on the different criteria and it is important to understand the human stress level to avoid some unnecessary problems. The purpose of this study is to detect how human stress change based on sleeping habits. Also, we identified the benefits of using a model to detect human stress and the connection between human stress and sleep. For this purpose, we collected data including human stress levels and seven habits as the variables through sleep. We used six alternative machine learning algorithms such as Random Forest, MLP, Logistic Regression, Decision Tree, Naïve Bayes, and SVM were evaluated using sleeping habits and human stress level. The evaluation is done 10-fold crossvalidation. Based on the evaluation results, Naive Bayes outperforms the other five algorithms, and it is the most effective in forecasting human stress. The best recall, precision, and f-measure values, as well as a lower error rate in MAE and RMSE values, go hand in hand with the Naive Bayes method's 91.27% accuracy. When discussing the usability and potential applications of this work, we may utilize this model to detect the stress level of the people by adding their sleeping habits to the model, which served as the study's independent variables. Based on the result of stress level, we can deal with that person.

In the future, to increase the accuracy of the results, we intend to multiply the data and employ the ensemble learning method, which combines all six algorithms. Because of the less data we could not use the neural networks and deep learning techniques here. Therefore, we intend to apply those algorithms by expanding our dataset, and then it uses to boost the existing accuracy.

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