



HUMAN STRESS DETECTION BASED ON SLEEPING HABITS USING MACHINE LEARNING ALGORITHMS

¹ Lakshmi Shree M S, ²Ranjitha M, ³Rebecca D, ⁴Shirisha H N, ⁵Shradha Sania J E

¹Assistant Professor, ²Student, ³Student, ⁴Student, ⁵Student

¹ Department of CSE,

¹ Cambridge Institute of Technology, Bangalore, India

Abstract: Stress, which is a more and more common part of contemporary life, can have a serious negative effect on a person's physical and mental health. Determining and tracking stress levels is therefore essential to improving general health and quality of life. The "Human Stress Detection Based on Sleeping Habits Using Machine Learning with Random Forest Classifier" project offers a cutting-edge and successful method for determining a person's degree of stress by looking at how they sleep. Utilizing the robust features of the Python programming language, the research makes use of the Random Forest Classifier algorithm, which is renowned for its adaptability and precision in classification assignments. This project's primary objective is to develop a reliable stress detection system that can provide insightful data about people's stress levels, enabling timely interventions and promoting improved mental health. Numerous significant variables related to stress levels and sleep patterns are included in the dataset that was carefully chosen for the study. The user's snoring range, respiration rate, body temperature, limb movement rate, blood oxygen levels, eye movement, heart rate, number of hours slept, and stress levels—which are divided into five classes—are among these parameters. The classes are 0 (low/normal), 1 (medium low), 2 (medium), 3 (medium high), and 4 (high). By including these several criteria, a thorough examination of sleep patterns and their relationship to stress levels is ensured. The model was able to learn complex patterns from the dataset and forecast stress accurately based on the user's sleeping patterns, as seen by the high accuracy that was attained. Research and treatments in medicine as well as personal health monitoring are just a few of the many possible uses for this stress detection system. People can take proactive steps to reduce stress, enhance sleep quality, and promote general well-being by using the system to analyze their sleep patterns and receive insights into their stress levels.

Index Terms - Random Forest Classifier algorithm ,Decision Tree

I. INTRODUCTION

An essential aspect of human existence, stress is a complex reaction to a range of internal and external pressures that disturb a person's emotional, physical, or mental balance. Humans face several stressors as they make their way through the complexity of daily life. These stressors might include financial constraints, personal relationships, professional pressures, health-related issues, and more. Although stress is a necessary survival mechanism that primes the body for fight-or-flight reactions in life-threatening circumstances, chronic or extreme stress can be harmful to one's general health. The stress response, sometimes known as the "fight-or-flight" response, is the body's physiological and hormonal response to stress. The adrenal glands release cortisol and adrenaline while under stress, which raises blood pressure and causes a rise in heart rate and behavioral responses to stress. Machine learning algorithms, such as Random Forest Classifier and Naive Bayes, offer powerful tools for analyzing these data and predicting stress levels based on various parameters.

Technological and data analytic advancements have created new avenues for stress identification and management. Large-scale data collection on people's physiological and behavioral reactions to stress is now feasible because to wearable technology and health monitoring systems. Strong tools for evaluating these data

and forecasting stress levels based on several criteria are provided by machine learning algorithms like Naive Bayes and Random Forest Classifier. Finding out how human stress varies according to sleeping patterns is the main objective of this study. The particular goals also include how human stress and sleeping habits are related, what primary sleeping behaviors influence a person's stress level, what methods are available for detecting human stress, and lastly, how to detect human stress based on sleeping habits. In order to better understand the relationship between stress levels and sleep patterns, the study "Human Stress Detection Based on Sleeping Habits Using Machine Learning with Random Forest Classifier" looks at this relationship. The project aims to develop an accurate and efficient stress detection system through the use of sleep-related data and machine learning techniques. The project's findings can furnish individuals with significant information regarding their stress levels, so enabling prompt interventions and proactive stress management.

II. LITERATURE SURVEY

A technique for identifying and managing physiological stress related to eating habits on the Internet of Medical Things (IoMT) has been presented in the study. Additionally to these pieces, they provide SaYoPillow, a device that tracks and regulates a person's stress levels while they slumber. The primary goal of SaYoPillow is to accomplish "Smart-Sleeping," which is a thorough sleep that meets the ideal body requirements for sleep. SayoPillow proposed a real-time physiological signal detecting to adjust the quality of sleep by considering parameters like heart rate range, snoring range, respiratory rate range, number of hours of sleep, oxygen in blood range, eye movement rate, duration of Rapid Eye Movement (REM), change in body temperature, and limb movement rate. Any snoring rate more than 50dB increases the risk of tension and other health problems. 15 to 17 breaths per minute (bpm) are considered to be a good breathing rate. When a person is sleeping, their heart beats five to ten times slower than usual. Due to the detrimental effects of sleep deprivation on one's health, adults should aim for at least 7 hours of sleep each night. Next, it is advised that 20–25 percent of the total amount of sleep be spent in rapid eye movement (REM), which equates to about 90 minutes for 7-8 hours of sleep. When oxygen saturation drops below 90%, it is deemed abnormal and stressful.

348 men and women, working and unemployed, performing a variety of tasks from housework to professional responsibilities, between the ages of 20 and 60, participated in the study ML framework for the monitoring mental stress at multiple levels. According to their findings, Random Forest scored 90% for stress and Naive Bayes for depression, giving them the highest f1 score.

An ML framework based on the electroencephalogram (EEG) signal analysis of stressed individuals was presented in the study. In the lab, stress was created using a well-liked evaluation technique based on the Montreal Imaging Stress Task. The objective feedback and work performance both corroborated the introduction of stress. The EEG feature extraction and selection (using the t-test, ROC curve, and Bhattacharya distance), logistic regression, regression analysis, SVM classification, and Naive Bayes models were all included in the proposed machine learning model. The results showed that the suggested framework produced multiple-level detection accuracy of 83.4% and level-two stress detection accuracy of 94.6%.

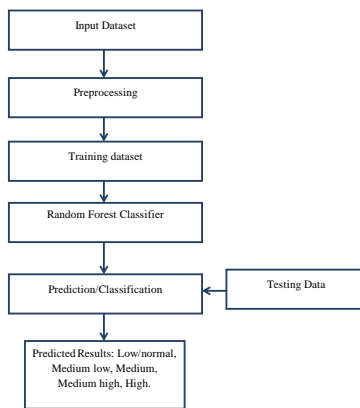
The galvanic skin response (GSR) is the most common physiological marker for identifying stress, according to studies. GSR has been connected to physiological and psychological arousal. Skin conductance rises as a result of increased sweat gland activity brought on by ANS arousal. They underlined how crucial it is in this situation to track stress continuously. They looked into the tracking, study, and stress prediction methodologies. They also talked about past studies that used an edge computing framework to track stress in real time.

The study discovered that physiological sensor analytics is becoming an essential tool for health monitoring as wearable, sensor-enabled portable, and implantable device prevalence rises in the expanding Internet of Things (IoT). Prior studies using multiple sensors have identified stress through physiological processes. They focused on ECG monitoring, which is now feasible utilizing slightly intrusive wearable patches and sensors, in order to develop a dependable and efficient system for accurate stress identification. Eight distinct types of input data are considered: breathing, intermittent heart rate (IHR), foot galvanic skin response (GSR), electromyogram (EMG), ECG hand marker, and GSR time stamp.

According to the study, a technique for assessing pilgrims' stress levels involves examining their patterns of sleep at night and determining which sleep metrics are most important for identifying stress. Using bio-physiological indicators such as respiration, body temperature, GSR data, and upper body position sensors and accelerometers on the arms and body, they develop and assess various classification models. Using the classification models, they were able to develop person-independent models that differentiated between three stress levels: low, moderate, and high. Out of all the algorithms, SVM produced the best classification accuracy of 73%.

III. METHODOLOGY

The primary goal of the study is to forecast human stress by analyzing sleep-related behaviors. There are five suggested approaches. They are Data Collection, Dataset, Data Preparation, Splitting the Dataset and Model Selection. An explanation of the study's architecture is provided after Fig. 1.



3.1 Data Collection

Data Collection: Human Stress Detection Based on Sleeping Habits's first module To obtain the input dataset, we created the system using machine learning algorithms. The process of gathering data is the initial step in the actual building of a machine learning model. This is a crucial stage that will have a cascading effect on the model's quality; the more and better data we collect, the more capable our model will be. There are various methods for gathering the data, including manual interventions and online scraping. Our dataset may be found in the model folder of the project. The dataset is sourced from Kaggle, a widely used standard dataset repository that is used by academics worldwide. There are numerical data in the dataset.

Figure 1: Architecture of the study

3.2 Dataset

The dataset consists of 630 individual data. There are 9 columns in the dataset, which are described below.

SR - Snoring Range.

RR - Respiration Rate.

T - Body Temperature.

LM - Limb Movement Rate.

Bo - Blood Oxygen.

REM - Eye Movement.

SR1 - Number of Hours Sleep.

HR - Heart Rate.

SL - 0- Low/Normal, 1 – Medium Low, 2- Medium, 3-Medium High, 4 –High.

3.3 Data Preparation

Sort through data and get it ready for training. Clean up anything that could need it (get rid of duplicates, fix mistakes, handle missing values, normalize, convert data types, etc.). Data can be made random to eliminate the impact of the specific order in which it was gathered and/or prepared. Use data visualization to carry out additional exploratory analysis or to identify pertinent correlations between variables or class imbalances (bias alert!). Divided into sets for training and assessment

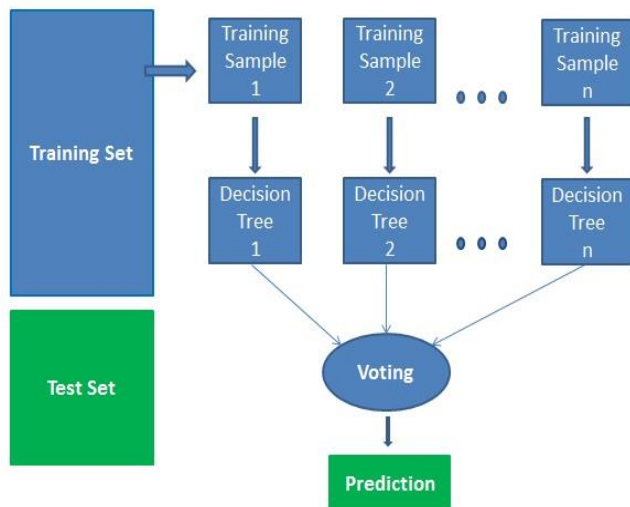
3.4 Splitting the Dataset

In this module, the image dataset will be divided into training and testing sets. Split the dataset into Train and Test. 80% train data and 20% test data. This will be done to train the model on a subset of the data, validate the model's performance, and test the model on unseen data to evaluate its accuracy. Split the dataset into train and test. 80% train data and 20% test data.

3.5 Model Selection

We used Random Forest Classifier machine learning algorithm, we got a accuracy of 97.6% on test set so we implemented this algorithm.

The Random Forests Algorithm:



A group of decision-making trees cooperating to generate predictions is how the random forest classifier functions. To make its choice, every tree in the forest considers a random subset of information and a random collection of characteristics. Next, every tree casts a vote to choose the winning forecast. It leverages several trees, which makes it effective in processing large and complex data sets. However, it occasionally has a slowdown and performs poorly with noisy data. All things considered, it's a well-liked and effective machine learning tool.

The Random Forest Classifier facilitates the identification of the most relevant characteristics that contribute to stress level forecasts by offering a measure of feature importance. By ensuring that only major and pertinent features are taken into account, this feature selection procedure improves the effectiveness of the model and lessens the influence of unimportant traits. Random Forest is renowned for its ability to withstand outliers, reducing the potential for disruption in its ability to anticipate stress levels. When working with real-world sleep data, which occasionally contains outliers owing to a variety of reasons, this feature is really helpful.

Figure 2 : Random Forest Classifier Diagram

IV. RESULTS AND DISCUSSION

In machine learning, prediction is the process of employing a trained model to infer probabilities or estimates regarding novel, unseen data points by applying patterns discovered during training from a labeled dataset. Initially, input data with features comparable to those in the training data are given to the model. Before the input data is fed into the model, it is preprocessed to extract pertinent features. Subsequently, the model employs the patterns it has learnt to provide predictions. These predictions might be class labels for classification tasks or continuous values for regression tasks. The model's performance is assessed using a variety of indicators once it has made predictions. Once it has been verified, the model can be used for practical purposes.

Prediction

Snoring Range (0-100):

Respiration Rate (0-1): Value must be less than or equal to 100.

Body Temperature (30-45):

Limb Movement Rate (0-100):

Blood Oxygen Levels (40-120):

Eye Movement (0-100):

Number Of Hours Of Sleep (0-24):

Heart Rate (30-180):

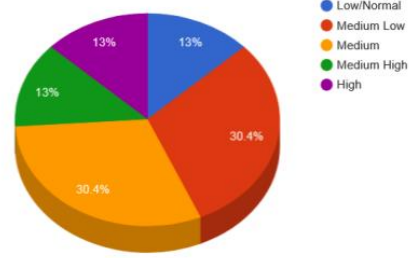


Figure 3 : Prediction

Figure 4 : Prediction chart

Prediction

Snoring Range:

Respiration Rate:

Body Temperature:

Limb Movement Rate:

Blood Oxygen Levels:

Eye Movement:

Number Of Hours Of Sleep:

Heart Rate:

Stress Levels is : High

Prediction

Snoring Range:

Respiration Rate:

Body Temperature:

Limb Movement Rate:

Blood Oxygen Levels:

Eye Movement:

Number Of Hours Of Sleep:

Heart Rate:

Stress Levels is : Low/Normal

Prediction

Snoring Range:

Respiration Rate:

Body Temperature:

Limb Movement Rate:

Blood Oxygen Levels:

Eye Movement:

Number Of Hours Of Sleep:

Heart Rate:

Stress Levels is : Medium Low

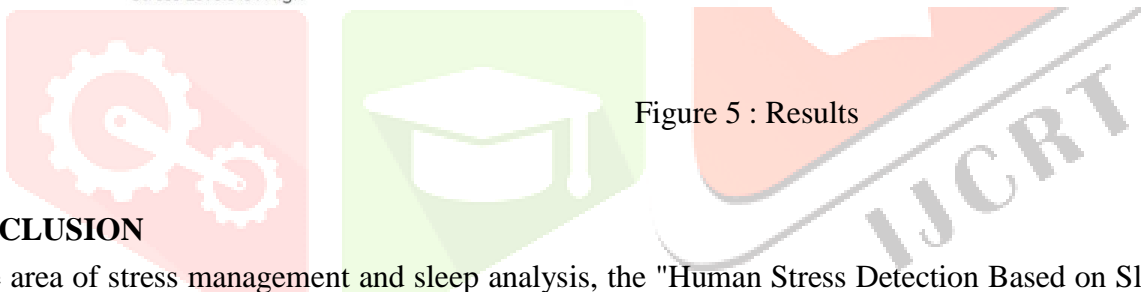


Figure 5 : Results

CONCLUSION

In the area of stress management and sleep analysis, the "Human Stress Detection Based on Sleeping Habits Using Machine Learning with Random Forest Classifier" study is significant. The research attempts to accurately estimate human stress levels based on sleeping habits by implementing the Random Forest Classifier algorithm and carefully taking into account various sleep-related data. Better accuracy, resilience to outliers, and the capacity to manage non-linear correlations between stress levels and sleep metrics are just a few of the benefits that the suggested approach offers over the current one. Utilizing feature importance analysis and continual learning, the system guarantees flexibility to evolving sleep patterns over time and offers insightful predictions of stress levels. The initiative streamlines the data through a number of clearly defined modules. At the heart of the system is the Random Forest Classifier module, which uses a group of decision trees to classify stress levels in an accurate and well-informed manner. The system's performance is thoroughly evaluated by the project's assessment module, which makes sure that the accuracy attained is in line with the goals and anticipated results of the project. Additionally, the visualization module makes it easier to convey the data, improving the interpretability of the system and making it easier to understand how stress levels and sleeping patterns relate to one another. To sum up, the initiative offers insightful information on sleep analysis and stress detection, which could transform stress management techniques and improve people's general well-being.

The project gives people the ability to take proactive measures towards stress reduction and better mental health by giving them an easily available tool to track and comprehend their stress levels based on their sleep patterns. Although the project's execution and results have shown encouraging results, it is important to recognize that more research and development in the areas of machine learning and stress detection will improve the system's functionality and usefulness. The system's ability to adjust to new developments in technology will be essential to keeping it current and functional. All things considered, the project "Human Stress Detection Based on

"Sleeping Habits Using Machine Learning with Random Forest Classifier" has a lot of promise to improve people's lives, make stress management easier, and promote a healthier society.

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