HUMAN SLEEP STRESS DETECTION USING MACHINE LEARNING ALGORITHMS

Authors:

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Abstract

Machine learning (ML), a new technique, allows computers to simulate human behaviour. It may provide significant benefits for a variety of industries, including industry, agriculture, and medicine. This article's main focus is the healthcare sector, namely the identification of human stress when we sleep. Stress may be classified as either eustress or distress. Persistent discomfort may lead to serious health problems. The hormones cortisol and adrenaline are involved in the body's stress response. Reliable detection methods are necessary for stress management to be successful. The objective of our study is to assess stress levels based on human criteria using a machine-learning algorithm. By comparing the outcomes of machine learning models such as Random Forest Classifier, Naive Bayes, and K-Nearest Neighbour with those of individual variables such as age, sex, cp, trest bps, FBS, respect, thali, old peak, slope, ca, thal, and target, we shall ascertain if stress is present in people. If we want to achieve even greater benefits, future research may concentrate on feature engineering and ensemble techniques.

Keywords: Machine learning, human stress, Random Forest Classifier, Naive Bayes, and K- Nearest Neighbour

1. Introduction

Depression, anxiety, stress, and related illnesses are rising worldwide [1]. Stress is unhealthy mentally and physically. Stress may weaken the immune system; and induce drug addiction, diabetes, cancer, stroke, and cardiovascular disease [2]. Creating reliable real-time stress detection and monitoring systems is essential. Stress detection is hindered by physiological and psychological factors. Both traits are difficult to assess and are affected by many factors. Wearable sensor technology makes physiological stress measurements easier in daily life.

Psychological assessment questionnaires are the most common way to measure daily stress. The questionnaires only record stress at a given moment, not continuously. Since questionnaire-based evaluations are time-bound and hard to define the particular task or activity that caused stress, verifying innovative stress monitoring systems is challenging. The data-driven stress model [3] uses wearable sensors to standardise continuous stress monitoring. Participants completed an Ecological Momentary Assessment (EMA) questionnaire 15 times a day at random hours for this study. The EMA self-report was used to validate stress. The stress model addressed EMA self- report stressor recording unpredictability. Many supervised learning methods have been developed for stress detection and categorisation [4]. Several machine learning methods include logistic regression, Gaussian Naive Bayes, Decision Tree, Random Forest, AdaBoost, and K- Nearest Neighbours. The measured driver stress using HRV-generated ECG features. The best recall score was 80% after many supervised machine-learning approaches [5].To identify driver stress using GSR data and supervised ensemble and unsupervised learning classifiers. The recommended model recognised stress 90.1% correctly. Respiration, heart rate, skin conductance, temperature, and galvanic skin reaction are stress indicators. Supervised learning requires classifier training labels, which are typically unavailable or incorrect in real-time data collection. Labelling stress states is problematic and must be overcome for sensor-based stress monitoring. The lack of reference data and human bias have led to the exploration of unsupervised machine-learning algorithms for stress identification and monitoring.

2. Related Works:

The authors of the previously cited research [6] calculated stress using heart rate, electromyography (EMG), GSR data from the hands and feet, and breathing and concluded that it is a necessary component of stress. Using electrocardiogram (ECG) data, the authors of the previously cited work [7] created a technique to predict stress. Stress was calculated by the authors of the research [8] using information from EEG, GSR, EMG, and SpO2. Several pattern recognition techniques are being used to achieve automated stress detection. Every sensor reading is compared to an index value to determine stress. The J48 algorithm, SMO, and Bayesian Network technique were utilised in a paper [9] to predict stress using data collected from 16 people in four different stressful scenarios. In a research publication, the degree of stress was predicted using an electroencephalogram (EEG) signal and an HRV characteristic [10]. The electrocardiogram (ECG), heart rate variability (HRV), and other signs are used to estimate the level of stress. A dataset derived from two experiments that were deemed inadequate in the paper was subjected to the decision tree technique [11]. At the start and finish of every semester, we do a stress test for the students. The study found that there was greater tension towards the conclusion and less stress at the start [12]. Prior research mostly concentrated on creating standardised stress measures, such as tracking brain activity or assessing people's lives in both urban and rural areas, but none of these techniques provided a way to identify stress early. These study papers go into great detail on a variety of studies that include capturing brain signals or measuring them in different circumstances as possible means of enhancing the precision of these brain measures.

3. Methods:

3.1 Exiting Methods:

Naive Bayes classification, WEKA SVMs, data preparation, and performance estimations were modern strategies. It's used temporarily. Pictures, text, and images are missing.

They used these approaches in current procedures: A wi-fi community sensor platform monitors heart rate, skin and pore conductivity, and breathing disorders. CNN-based dataset validation and teaching enhance awareness of difficult tasks. Brain parameters improved accuracy significantly, whereas assessing strain with the simplest reduction frame parameters was comfortable but dependent on numerous factors.

CNN-MDRP, the Multi-modal Disease Risk Prediction algorithm, leverages Chinese hospital SQL and JSON data. CNN-UDRP is slower than the standard illness risk prediction method.

A sensor (hardware circuit), a microcontroller-linked gadget, a smartphone app to display findings, and cloud storage to save data are other modern methods. Stress may be indicated by EEG brain waves. It warns users of their stress levels via mobile app at any time. The system needs datasets and machine learning.

3.2 Proposed Methods:

This research was able to anticipate the amount of stress that students will face in the future, detect pupils whose stress levels were rising, and prevent major harm by using machine learning (ML).

Students are assessed on the exam in several scenarios. We gave our approval for the project's execution. Gathering PSS datasets, performing pre-processing and feature extraction, and comparing three machine learning algorithms Random Forest Classifier, Naive Bayes, and K-Nearest Neighbour based on performance measures are all part of the model's setup, as shown in Figure 1.

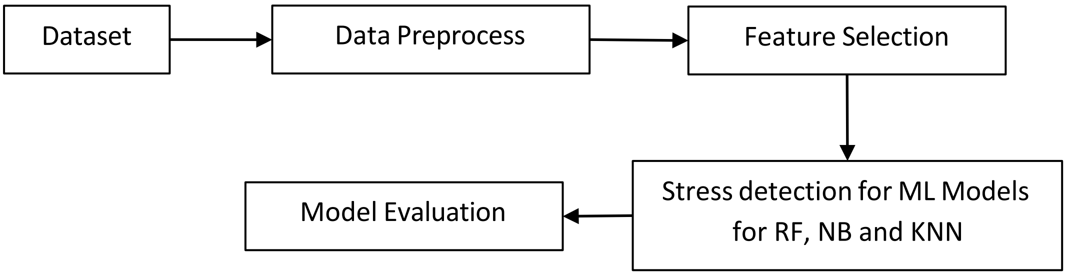

Figure 1: Proposed System Architecture

3.2.1 Dataset:

The dataset used in this research includes several physiological variables, such as heart rate, snoring rate, respiration rate, body temperature, limb movement, blood oxygen levels, eye movement, and sleeping hours, in addition to stress levels as the target variable. After preprocessing, the data is prepared to be analysed using machine learning. Detection of Human Stress in and Through Sleep is the title of the dataset. You can obtain the dataset at: https://www.kaggle.com/code/mustafacihadgoktepe/human-stress-detection-in-and-through-sleep/notebook.

3.2.2 Data Preprocess:

The primary goal of its development was to assess people's resilience and the kinds of stressful events they can handle. The levels are meant to represent the randomness and helplessness that individuals face regularly. To gauge the relationship between everyday stress and participants' mental health, it also prompted them to reflect on incidents that had occurred over the last week.

In general, the questions are designed to elicit responses that demonstrate a level of care towards some common topics. Find out how they are feeling and how stressed out they are. In preparation for training the model, the dataset has been through preprocessing procedures to fill in missing values and normalise features.

3.2.3 Feature Selection:

To determine the most crucial components of our model, we have investigated the link between the qualities and the dependent variable using techniques such as Mutual Information and Correlation analysis.

3.2.4 Machine Learning Models:

To determine the best model for stress prediction, many machine-learning methods were considered. These algorithms were k-Nearest Neighbours, Random Forests, and Naive Bayes.

3.2.4.1 k-Nearest Neighbours:

This adaptable approach, which is dependent on the value of k, is used to carry out the categorisation procedure. It makes use of the closest neighbour approach. When it comes to detecting stressful situations that happen while a person is sleeping, the K-Nearest Neighbors Classifier is a blessing. It enables the various identification of stress in a range of physiological indicators.

3.2.4.2 Random Forests:

As an ensemble method, RFC does very well on difficult classification problems, and decision trees are part of it. The random forest classifier can gather comprehensive stress patterns for stress detection and lower the chance of overfitting, making it helpful for stress detection during sleep.

3.2.4.3 Naive Bayes:

Among probabilistic classifiers, the Naive Bayesian classifier stands out. A directed acyclic graph (DAG) used in Naive Bayesian (NB) theory has one unseen parent node and several visible children. Predictor is a common name for Naïve Bayesian classifiers since they operate on the strong premise that each child node is completely separate from each parent node.

3.2.5 Model Evaluation:

A. ***Accuracy***

The accuracy of a classifier measures how well it achieves its objective. The degree to which a predictor correctly forecasts the value of an attribute given new data—in this case, the class label—is known as its accuracy.

$$AC = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

B. ***Precision***

One way to define precision is as the proportion of genuine positives to the sum of all positive and negative outcomes respectively.

$$Precision = \frac{TP}{TP + FP} \quad (2)$$

Where,

TN: True

Negative FN:

False Negative

TP: True

Positive FP:

False Positive

C. ***Recall***

Calculating recall is as simple as dividing the number of observed occurrences by the number of projected outcomes. In the context of binary classification, "recall" and "sensitivity" are often considered synonyms. You might say that the chance of the request succeeding is the same as the chance of the request returning the correct record.

D. ***ROC***

Visualizing the clinical specificity and sensitivity of a test or set of tests at different cut-off points is possible using ROC curves. Analyzing the ROC (receiver operating characteristic) curve provides further evidence for the use of the tests stated before.

4. Results and Discussion:

To get the desired result, the dataset and user inputs may be analysed after the training phase is over. Its potential accuracy increases with the number of tests carried out inside the ruleset. Since the facts depend on the regulations regulating effective implementation and the production of the chosen output, the accuracy of testing inputs may vary for different algorithms.

Table 1: Performance Results

Algorithm	Accuracy	Precision	Recall	F1-Score
Random Forest	0.98	0.87	0.91	0.91
K-Nearest Neighbour	0.98	0.87	091	0.91
Naïve Bayes	0.99	0.89	0.92	0.91

Figure 2 and Table 1 compare Random Forest, Naïve Bayes, and K-Nearest Neighbour (KNN), three machine learning models, according to their accuracy, precision, recall, and F1-score. As can be shown from the blue accuracy bars, all models work admirably. The top two, Random Forest and Naïve Bayes, achieve an accuracy of about 0.98. A possible decrease in false positives is shown by the fact that all models exhibit considerably lower accuracy (red bars). While Naïve Bayes doesn't perform as well as Random Forest and KNN, recall and F1-Score remain highly consistent. Regardless of the metric, Random Forest outperforms KNN overall. In certain application circumstances, the somewhat lower Precision and Recall shown by Naïve Bayes might be considered a trade-off, considering its accuracy. Random Forest outperforms the other algorithms in this test when it comes to balanced classification tasks.

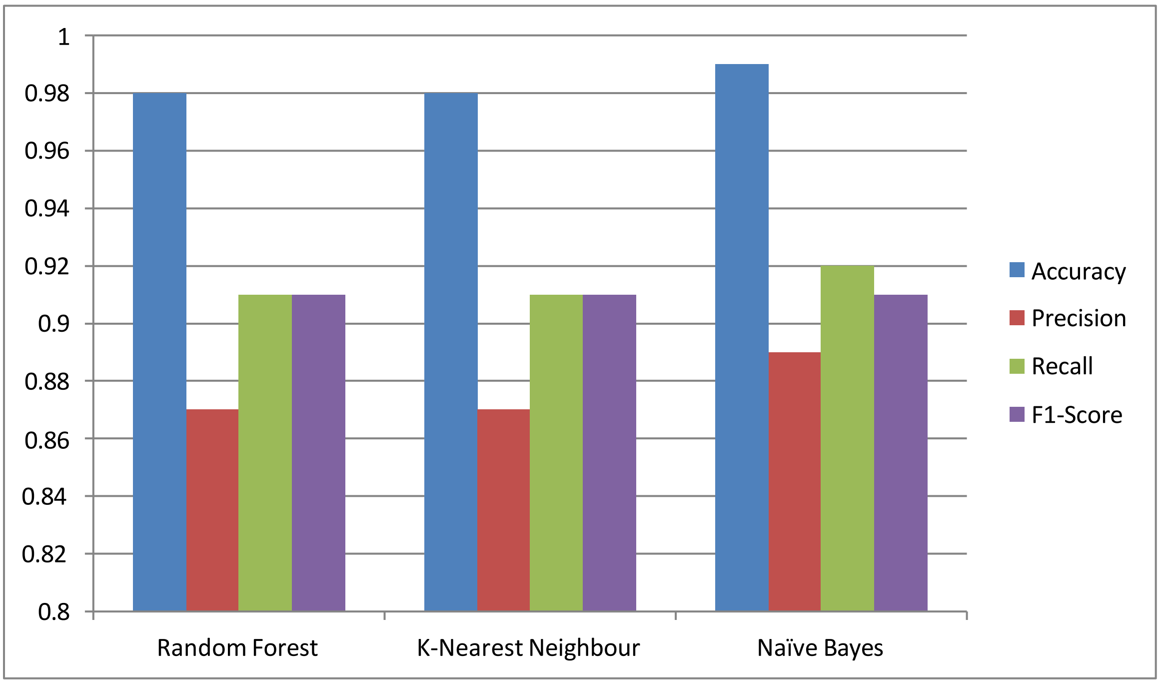

Figure 2: Performance Metrics

5. Conclusion:

Based on our findings, there were a few models that achieved remarkable overall performance, showing excellent accuracy, recall, and F1-score across several classes and folds. As a result of outstanding performance, every class in every fold was able to attain accuracy, as well as perfect precision, recall, and F1 score. Using user input and qualities, modern research may identify stressed people and provide findings tailored to their specific needs. Whether we add in additional variables, we can tell whether a person is sick or just stressed out; a shift in the value of a single metric, for instance, may indicate that someone is sick or just stressed out. As a result, we have used machine learning algorithms to detect stress signs, and we have achieved a 99% success rate in this regard.

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