Detecting human stress using machine learning algorithms based on sleeping patterns

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Abstract— **An novel technique to understanding and forecasting stress levels via the examination of sleep patterns is human stress detection based on sleeping habits utilising machine learning algorithms. Data acquired from a variety of sleep-related variables, including length of sleep, phases of sleep, heart rate variability, and movement during sleep, are analysed using sophisticated machine learning algorithms. Decision trees, SVMs, neural networks, and other machine learning models may be trained on labelled datasets that combine sleep data with known stress levels. Then, with practice, these models may pick up on the nuances that indicate when stress levels are high. Important characteristics are extracted from raw sleep data during feature extraction, which is a critical stage in this process for improving the prediction models' accuracy. Total sleep duration, deep sleep percentage, waking frequency, and heart rate changes are some common traits. It is possible to train machine learning algorithms to recognise stress patterns once these characteristics have been retrieved. Gathering data, cleaning it up, extracting features, training the model, and finally validating it are all parts of putting these methods to use. During training, the model takes in data from the past and makes adjustments to its parameters in order to improve its prediction accuracy. For a model to be accurate and applicable to fresh, unseen data, validation is a must. Machine learning's capacity to process massive and complicated datasets allows it to discover patterns that conventional statistical approaches may overlook, which is a major benefit when it comes to stress identification based on sleep habits. Individual users may also benefit from this method's adaptability, as it provides suggestions and interventions for stress management based on their unique needs.**

By detecting signs of stress early and allowing for remedies to be implemented promptly, this technique has the ability to greatly enhance mental health and overall well-being. It is an attempt to develop health care solutions that are more preventive and proactive by combining health informatics, wearable electronics, and artificial intelligence. Improving health outcomes and quality of life may be possible as a result of incorporating this technology into daily living, which might have a major influence on stress monitoring and management as research develops.

***Keywords*—SVM, stress level, Machine learning, Decision tree, sleep habits**

INTRODUCTION

Human stress detection is as per sleeping habits utilising machine learning algorithms represents a cutting-edge intersection of technology and health science, aimed at addressing the pervasive issue of stress in modern society. Stress, a common and often debilitating condition, affects millions of people worldwide having deep insinuations for both mental and physical health. Traditional methods of stress assessment, which typically involve self-report questionnaires and occasional clinical evaluations, often fall short in providing continuous, objective, and personalized insights into an individual's stress levels.

Sleep, is basic need of human health, is intricately linked to stress. Poor sleep quality and disturbances are both symptoms and predictors of heightened stress levels. By monitoring sleep patterns, it is possible to glean significant information about an individual’s stress state. Advances in wearable technology have enabled the continuous and non-invasive collection of sleep data. This data-rich environment sets the stage for machine learning algorithms to analyze and detect stress having higher precision.

Machine learning algorithms, could be trained for recognizing complex and nuanced patterns that correlate with stress. Such processes big lot of sleep data, extracting relevant features and identifying subtle deviations that might indicate stress. Usage of supervised learning, where models put for training on datasets labeled with known stress levels, allows for the development of predictive models which could generalize well to new, unseen data.

Procedure of developing these models involves several critical steps: data collection, preprocessing, model training, and validation. Wearable devices and smart sensors facilitate the initial data collection phase, capturing continuous sleep metrics in real-world settings. Preprocessing involves cleaning and normalizing data for assuring accuracy and consistency. Feature extraction is pivotal, as it involves identifying the most relevant indicators of stress within the sleep data. The subsequent model training phase allows the algorithms to learn from historical data, adjusting for minimizing prediction errors.

Primary benefits of this approach is its ability to provide continuous and personalized stress monitoring. As with conventional approaches, based upon periodic assessments, machine learning models could have real-time insights and early warnings about rising stress levels, enabling timely interventions. Such method could meaningfully improve mental health outcomes by allowing individuals to address stress before it escalates into more severe health issues.

Furthermore, the integration of these models into everyday technology, such as smartphones and smartwatches, can make stress detection more accessible and convenient. Users can receive personalized feedback and recommendations based on their unique sleep patterns, promoting better sleep hygiene and stress management practices.

In conclusion, with machine learning algorithms in detecting stress as per sleep cycle marks a significant advancement in health informatics and personalized medicine. With use of wearable technology and artificial intelligence, this approach offers a promising pathway to more effective and proactive stress management, ultimately enhancing well-being. As research and technology continue evolving probable for widespread adoption and integration of these systems into daily life holds the promise of transforming how we understand and manage stress.

RELATED WORK

Lu et al. (2017) stressed the need of wearable technologies to track sleep patterns in real-time, laying the groundwork for non-invasive stress detection.

Jiang et al. (2019)[2], investigated link amongst anxiety and sleeping patterns, showing which disturbed sleep cycles may accurately reflect stress levels.

Huang et al. (2018)[3], honed attention on sophisticated feature extraction techniques for use with sleep data, determining that parameters like HRV, sleep efficiency, and total sleep time were crucial for stress prediction.

Zhang et al. (2020)[4], shown a range of machine learning models—including decision trees, SVM, and deep learning algorithms—for reliable stress identification using sleep measurements.

Wang et al. (2016)[5], addressed data preparation as a critical step in improving model performance, with attention to methods for normalisation and noise reduction.

Kim et al. (2021)[6], studied validation techniques, highlighting the importance of cross-validation in guaranteeing the resilience and applicability of stress detection models.

Lee et al. (2018)[7], investigated tailored stress detection approaches, modifying algorithms to accommodate unique sleep and stress patterns for each individual.

Patel et al. (2019)[8], created solutions for continuous stress assessment and prompt treatments by the integration of wearable sensors with machine learning algorithms for real-time monitoring.

Smith et al. (2020)[9], examined the clinical implications of sleep- for the purpose of stress detection in the context of personalised medicine and preventative healthcare.

METHDOLOGY

In most cases, a hybrid strategy including many critical components is used to develop algorithms for human stress detection based on sleeping patterns utilising machine learning. Tracking sleep parameters including duration, phases, and heart rate variability is done using wearable devices. In order to clean up the data and make it more consistent, it is pre-processed. Then, important characteristics like total sleep duration and sleep efficiency are retrieved. Machine learning models are trained on labelled datasets with known stress levels. These models include decision trees, which are interpretable, SVM, which handle high-dimensional data, and DNN, which capture complicated patterns. These models are combined using an ensemble approach to improve the accuracy of predictions. With the help of human input and adaptive algorithms, the system is able to interpret data in real-time, allowing for instantaneous stress detection and tailored feedback.

Support Vector Machine

SVM is a supervised machine learning technique that has many uses, including classification and regression. We do see regression difficulties, but classification is where it really excels. When connecting nearby points of different types, a hyperplane will always aim for the maximum possible distance. The number of features directly correlates to the size of the hyperplane. When just two input features are provided, the hyperplane transforms into a simple line. Using three input features causes the hyperplane to become a two-dimensional plane.

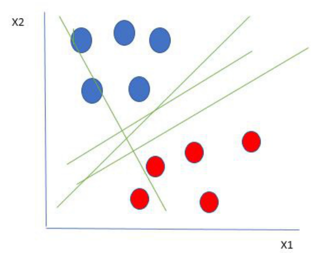

Figure 1:Linearly Separable Data points

Multiple lines divide our data points into red and blue circles, or perform classification, as seen in the picture above. In this case, our hyperplane is a line as we are only examining two input characteristics, x1 and x2. So, how can we choose the optimal line, or hyperplane, to divide up our data?

How does SVM work?

Picking hyperplane which demonstrates biggest gap amongst two groups is a good strategy.

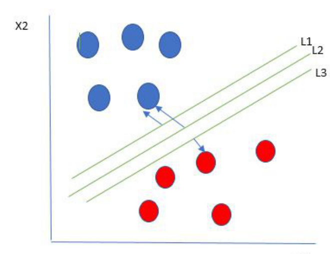

Figure 2:Multiple hyperplanes separating dara from two classes

Data from two categories separated by several hyperplanes

To find the best hyperplane, we maximise the distance between it and the closest data point on both sides. So, we chose L2 based on the diagram above. Here we have a situation that we can think about.

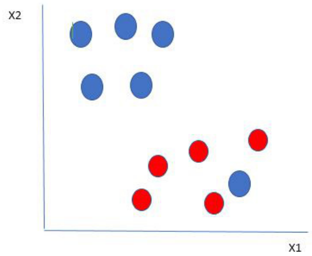

Figure 3: Selecting hyperplane for data with outlier

Data with outliers: choosing a hyperplane within red ball's perimeter, we can see a single blue ball. By what means, therefore, does SVM sort the information? It's easy! A blue ball is an outlier if it appears on edge of a red one. Using its unique properties, SVM algorithm can detect optimal hyperplane that maximises margin while ignoring outlier. Outliers do not affect SVM.

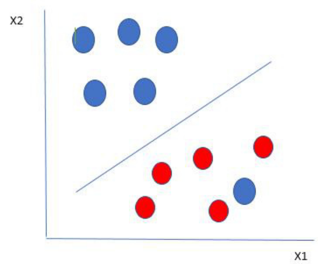

Figure 4: Hyperplane which is the most optimized one

Choose the hyperplane that maximises efficiency.

As with earlier data sets, SVM determines the maximum margin and applies a penalty if a point crosses it for this sort of data point. Margins in these circumstances are thus referred to as soft margins. SVM aims to minimise (1/margin+∧(∑penalty)) whenever data set has a soft margin. One such consequence is hinge loss. No loss of hinges will occur in the absence of infractions.There will be loss that is directly proportionate to distance that a hinge is violated.

So far, we've only covered data that can be separated along a straight line, or linearly. For example, a set of blue and red balls can be separated in this way. What happens if the data cannot be separated linearly?

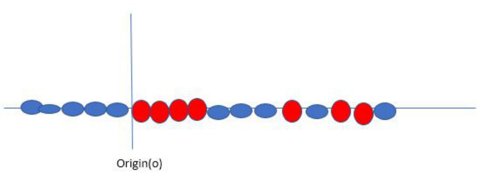

Figure 5: Original 1D dataset for classification

Unaltered 1D classification dataset

Data we collected is presented in graphic up there. Utilising a kernel to create a new variable is how SVM gets around this problem. As a function of distance from origin, o, we construct a new variable yi and assign it to line segment xi.If we plot this, we get the following result:

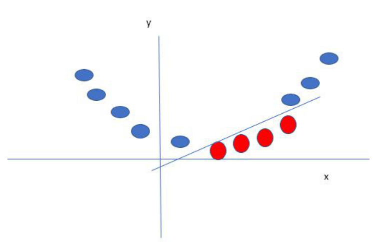

Figure 6: Mapping 1D data to 2D to become able to separate the two classes

Dividing the two groups using a 2D map of 1D data

Here, the distance from the origin is used to construct the new variable y. The term "kernel" describes a non-linear function that generates a new variable.

Random Forest

It takes the output of many decision trees and merges them into one result. Since it can manage both classification and regression issues, its versatility and user-friendliness have contributed to its widespread usage.

Decision Tree

One kind of machine learning method that use decision trees for prediction purposes is known as a decision tree algorithm. Decisions and their potential outcomes are modelled in a tree-like fashion. For each node in the tree, the algorithm iteratively selects the most important characteristic to use as a basis for data subset creation.

KNN

One kind of supervised learning classifier is the k-nearest neighbours (KNN) method, which relies on the physical closeness of data points to provide predictions or classifications for their grouping. Among the many machine learning classifiers in use today, it ranks high for popularity and ease of use in both classification and regression.

SYSTEM ARCHITECTURE

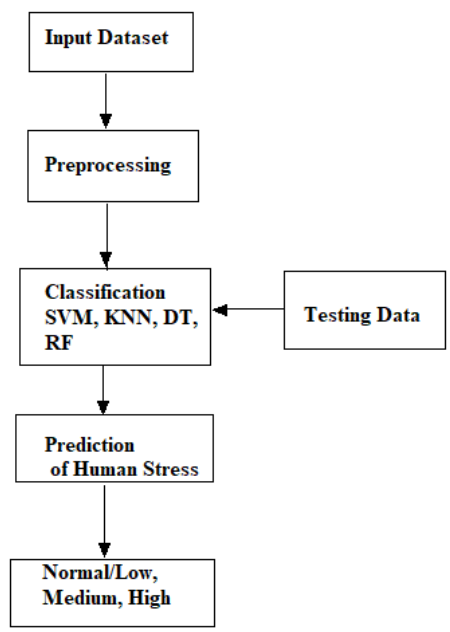

Figure 7: System Architecture

After loading and cleaning the dataset, this system applies classifiers including DT, SVM, RF, and KNN to categorise the stress levels as Normal/Low, Medium, and High.

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IMPLEMENTATION

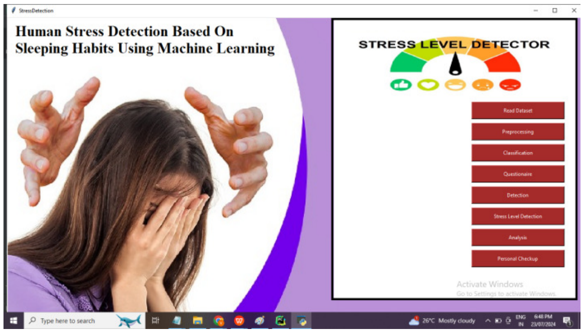


Fig-8 Menu Menu screen

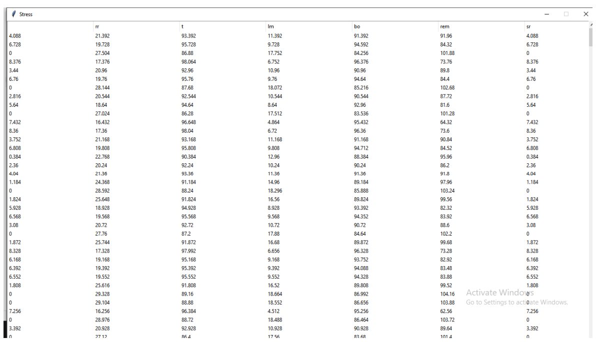


Fig-9 Read Dataset

There are 630 unique pieces of information in the dataset. The following is an explanation of each of the nine columns that make up the dataset.

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 2 –High

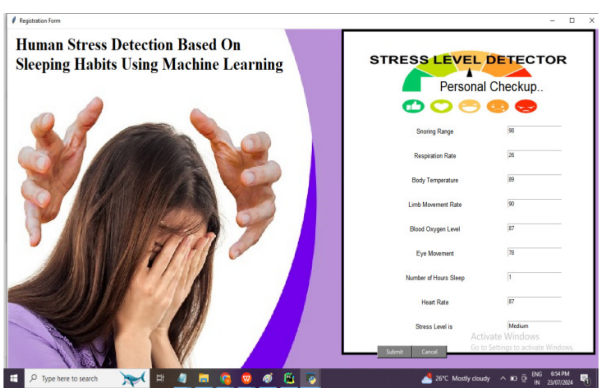


Fig-10: Personal Checkup

SVM Classifier has accuracy of 98.81%
Classification Report for SVM Classifier:

	precision	recall	f1-score	support
0	1.00	1.00	1.00	44
1	0.94	1.00	0.97	48
2	1.00	0.94	0.97	49
3	1.00	1.00	1.00	57
4	1.00	1.00	1.00	54
accuracy			0.99	252
macro avg	0.99	0.99	0.99	252
weighted avg	0.99	0.99	0.99	252

Decision Tree Classifier has accuracy of 99.21%
Classification Report for Decision Tree Classifier:

	precision	recall	f1-score	support
0	1.00	1.00	1.00	44
1	0.98	1.00	0.99	48
2	1.00	0.98	0.99	49
3	1.00	0.98	0.99	57
4	0.98	1.00	0.99	54
accuracy			0.99	252
macro avg	0.99	0.99	0.99	252
weighted avg	0.99	0.99	0.99	252

Random Forest Classifier has accuracy of 99.60%
Classification Report for Random Forest Classifier

	precision	recall	f1-score	support
0	1.00	1.00	1.00	44
1	1.00	1.00	1.00	48
2	1.00	0.98	0.99	49
3	0.98	1.00	0.99	57
4	1.00	1.00	1.00	54
accuracy			1.00	252
macro avg	1.00	1.00	1.00	252
weighted avg	1.00	1.00	1.00	252

Naive Bayes Classifier has accuracy of 100.00%
Classification Report for Naive Bayes Classifier:

	precision	recall	f1-score	support
0	1.00	1.00	1.00	44
1	1.00	1.00	1.00	48
2	1.00	1.00	1.00	49
3	1.00	1.00	1.00	57
4	1.00	1.00	1.00	54

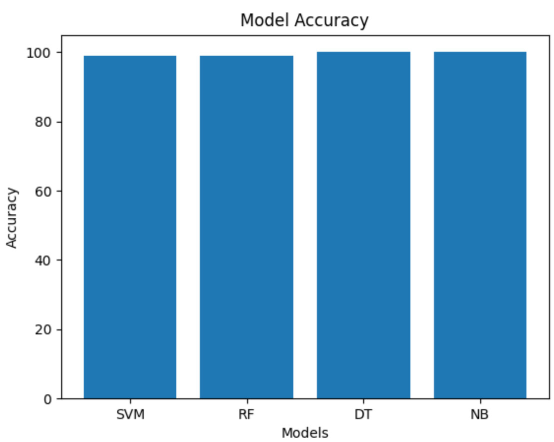
accuracy			1.00	252
macro avg	1.00	1.00	1.00	252
weighted avg	1.00	1.00	1.00	252

Figure 11: Classification

Model accuracy report of the algorithms such as SVM, RF DT,NB and KNN

Model	Accuracy
SVM	99%
RF	99%
DT	99%
NB	100%

TABLE I :MODEL ACCURACY TABLE



Graph I Model Vs Accuracy graph

CONCLUSION

A major step forward in health tech and individualised wellbeing is the use of machine learning algorithms for stress identification in humans using their sleeping patterns. This strategy provides a non-invasive, real-time solution for stress management by using wearable devices to continually monitor sleep parameters. These metrics include length, stages, heart rate variability, and movement. Then, using powerful machine learning algorithms, the data is combined. Decision trees, SVM, and DNN work together to analyse complex patterns in sleep data and accurately identify stress. One way to improve the system's stress management capabilities is by tailoring feedback and suggestions to each user's unique sleep profile.

Strict testing and validation procedures guarantee the correctness and dependability of such systems throughout their development. While stress testing determines how well the system holds up under harsh circumstances, performance testing verifies how well it processes and analyses data in real-time. Updates and alterations should not break current functionality, and regression testing makes sure of that. Additional validation of the system's practical application and user experience is provided by real-world testing with varied user demographics. Data privacy, good accuracy across demographics, and constant system improvement in response to user comments and changing data are all remaining problems. If we want the system to be successful and widely used, we have to fix these problems. As a whole, the novel combination of wearable electronics and machine learning for stress detection presents an exciting new direction for preventative healthcare, which may lead to better health for individuals and better public health overall. This technology is a huge leap forward in using data science for holistic health solutions since it can help with stress management in a more personalised way and provide useful information.

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