2023 International Conference on Sustainable Emerging Innovations in Engineering and Technology (ICSEIET) | 979-8-3503-2919-3/23/$31.00 ©2023 IEEE | DOI: 10.1109/ICSEIET58677.2023.10303348

Mental Stress Prediction using Wrist Wearable through Machine Learning Approaches

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***Abstract* - Stress is one of the mental health issues that people face today. In reality stress is the primary cause of many conditions, such as heart disease, migraines, infertility, obesity, insomnia, and a host of others. In this scenario, stress prediction is crucial at an early stage so that we can protect ourselves against future issues. For identifying the stress, method of connecting sensors to multiple data gathering units using traditional technologies typically involved electrodes, wires, and sensors, was uncomfortable. Smart watches, on the other hand, are designed to be worn on the wrist and have sensors integrated into them that can measure heart rate and activity levels. Here, we report on our smart watch's highest level of stress prediction accuracy. We have used random forests, decision trees, support vector machines, naive bayes , logistic regression, and k-nearest neighbor models with k-fold cross-validation and voting ensemble learning to predict stress using data from smart watches (Fit bit).The support vector machine model had a binary class prediction of stress accuracy of 94%, which was the highest. Our findings suggest that the support vector machine and voting ensemble combination may be more effective at identifying stress using smart watches. Our study closes a variety of methodological shortcomings in previous studies on the automatic stress prediction using smart watches. It has also been noted that the model performs better when ensemble learning techniques are used.**

Keywords -mental stress, voting ensemble, wrist worn wearable, machine learning, smart watch

I. INTRODUCTION

Now a day's people are stressed due to their living styles and working culture. Mental and Physical, both illnesses can occur if someone continuously be in stressful situation. Stress is the response to various deadlines and requirements that every person uses to face in their day to day activities. Stress condition can be initiated due to different factors and which can create problem differently for each individual. Some people can feel more stress with little problem and some can feel less stress for the same; therefore, how each person manages stress differs. Several typical causes of stress include: Expanding workload stress, can be caused by pressing deadlines and demanding work. Long work hours, employment uncertainty, and a competitive job market may make this worse. For people and families, main causes of stress can include financial obligations, debt, job loss, and economic distress. Relationship disagreements, whether they include a spouse, family, or friends, may be emotionally taxing; Breakups, divorces, and the loss of a loved one may also be extremely stressful situations [13]. Stress levels may be influenced by a busy schedule, a lack of work-life balance, poor diet, insufficient sleep, and a sedentary lifestyle.

Stressful situations can be defined into different categories like physiological, behavioral, emotional and psychological. Physiological symptoms can be like body ache, digestive problem, migraine, joint pain, increased heart rate elevated blood pressure, etc. And psychological problems can be like anxiety, bipolar disorder, depression, mood swings, difficulty in making decisions and concentration etc. Behavioral changes in appetite, social withdrawal, neglect of duties, decreased productivity, increased use of alcohol and tobacco, difficulties unwinding or finding delight in activities are only a few examples.

In a cause and effect relationship, cortisol and stress are tightly linked. The body's stress response system is triggered when a person is under stress, whether that stress is physical, psychological, or emotional. This body system is known as hypothalamic-pituitary-adrenal, in short HPA, causes the adrenal glands to produce cortisol. The brain's hypothalamus recognizes the stressor and alerts the pituitary gland when a person is in a stressful circumstance. The pituitary gland releases adrenocorticotropic hormone (ACTH) into the bloodstream in response to a signal from the hypothalamus. The adrenal glands, which are situated above the kidneys, are visited by ACTH, which prompts them to manufacture and release

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cortisol into the blood. Through the mobilization of energy reserves, a boost in glucose production, and an improvement in brain function, cortisol aids the body's response to stress. Additionally, it inhibits non-essential processes including the immunological and reproductive systems to focus energy on coping with the stressor. Cortisol elevation that is severe or sustained can be harmful to the body. It can disrupt sleep, weaken the immune system, cause weight gain, and raise the risk of mental health problems.

Heart disease, diabetes, and diminished cognitive function have all been linked to persistently increased cortisol levels. Regulating cortisol levels and reducing the harmful effects of extreme stress on the human body can be achieved by using stress reduction techniques such as relaxation, physical activity, meditation, mindfulness, and yoga. Prior to recovering from stress, we must first identify and detect it. The ability to recognize stress is essential for managing and recovering from it. We may take charge of our health and move towards a healthier, more balanced lifestyle by recognizing and dealing with stress.

II. LITERATURE SURVEY

Researchers have created a variety of techniques for analyzing physiological data obtained from sensors attached to human bodies in order to identify stress and categories emotions [11].A computer science-based study of linked studies on stress recognition reveals that the emphasis switches from stress prediction in a confined utilizing less comfortable sensors in an environment to detect stress in an unconstrained environment using more comfortable sensors that are cozy. Later on, physiological sensors can be used to identify stress. Even though there are several stress detection systems, there are only a few studies that show DSS that can support an online stress diagnosis, and they are mostly created for clinical use [12].

The approach previously required invasive wires and electrodes, may finally be executed painlessly, thanks to the advancement of technology gadgets equipped with physiological sensors. In recent decades, improvements in sensor technology, processing capacity, and concomitant growth of machine learning (ML) techniques have made automatic and data-driven stress detection possible [14]. Numerous experiments have been done to achieve stress prediction using a signal processing and machine learning combination. The majority of them made use of information from sensors for respiration, electrocardiogram, heart rate, acceleration, electro dermal activity, blood volume pulse, and electromyogram. Many studies have also used questionnaires; however the findings from these data might not be very reliable because the validity of the questionnaires participants fill out cannot be verified.

This study investigated a small sample of research publications and methods to identify stress from the recent body of work on stress analysis using machine learning algorithms.

TABLE 1. STRESS PREDICTION USING MACHINE LEARNING

S.No	Author	Methods	Used Sensors	Accuracy
1	Ahuja, R and Banga, A(2019) [1]	RF, SVM, LR, NB	Perceived Stress Scale (PSS) test	(SVM) 85.71%
2	Albertetti et al.,(2021) [2]	RNN	Empatica E4 signals, Questionnaire	71%
3	Can, Y. S et al.,(2020) [3]	DEEP MLP, DEEP CNN FOR BINARY AND 3 CLASS CLASSIFICATION	Physiological Signals	99.80% , 99.65% AND 99.55%, 98.38% resp.
4	Priya, A et al.,(2019) [4]	DT, RFT, NAÏVE BAYES, SVM, KNN	Questionnaire	Highest Accuracy- NB,RF-BEST
5	Aristizabal, S et al.,(2021) [5]	DEEP NEURAL NETWORK	Skin Temp. , Heart Rate Measurement, Elelectrodermal Activity	96%
6	Sagbas et al.,(2020) [6]	DT, Bayesian Network, KNN	Accelerometer, Gyroscope Sensor	74.26%, 67.86%, 87.56%
7	Campanella,S et al.,(2023) [7]	RF, SVM,LR(Chi-Test Method	Empatica Signals	75.7%,73.9%,72.8%
8	Almadhor, A et al.,(2023) [8]	Federated Learning-Based Technique on DNN,	Wearable Stress & Affect Detection (WESAD)	86.82%
9	Rashid N et al.,(2023) [9]	DT, RF, AdaBoost AB, LDA, KNN	wrist-based sensors- ACC, BVP, ECG,EMG, EDA, temperature, RESP	86.34% , 94.12%

10	Bin Heyat et al.,(2022) [10]	DT, RF,NB, LR	DASS TEST, ECG	DT-93.30%, Classification DT- 94.10%

III. PROPOSED WORK

In this system, we use signals from wearable devices like the Fitbit to anticipate stress. The factors used by this approach for prediction are SO2, sleep duration, ECG, weight, BMI, and HIIT, resting heart rate, age.

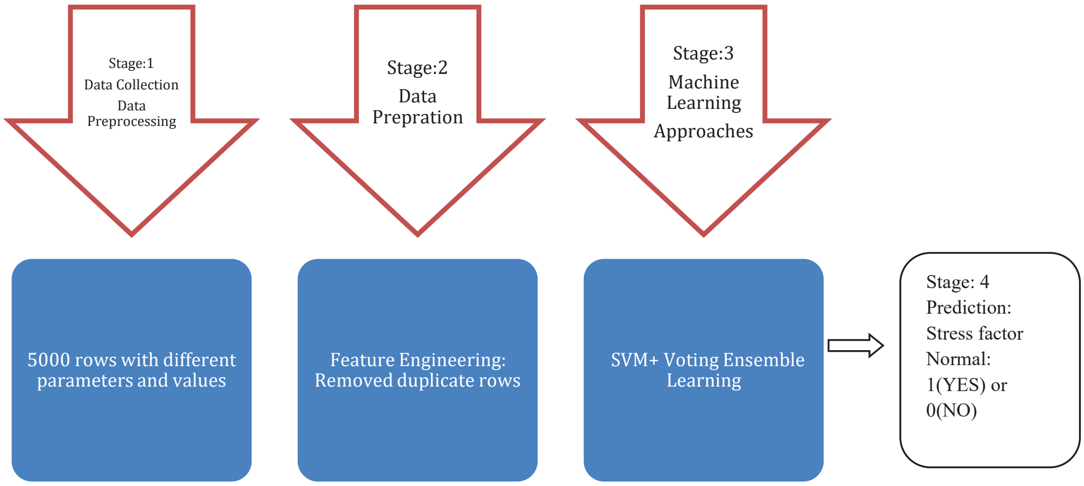

Fig. 1. The several steps of our approach to automatically forecast stress using machine learning model.

A. Data Collection and Data Preprocessing

This project used data from the Kaggle database. There were 5000 rows at first, but after removing duplicate rows, there were only 1000 rows in the final data.
Data set link: Fitbit Dataset | Kaggle

B. Data Preparation

We examined the data and discovered that some values are categorical and others are numerical; therefore, the data was converted or transformed from categorical to numerical in accordance with the specifications and model training.

C. Machine Learning Classifier Algorithms

For the aim of stress foretelling, we used various machine learning classification approaches in this work. Random Forest, Logistic Regression, Decision Tree, Naïve Bayes, Support vector Machine, K-Nearest Neighbor are used. The aforementioned algorithms were picked since they are the most reliable and conventional algorithms. The model was set up for training with a 75/25 split between the training and test sets. In order to leverage additional data for training, the K fold cross method was also applied. As it exposes our model to various subsets of the data, it also aids in overcoming the issue of overfitting.

D. Computations to Improve Accuracy

The goal of including various algorithms is to discover the one with the highest accuracy. Began with the Decision Tree algorithm, but since those results were unsatisfactory, we switched to logistic regression. We used parameters to apply logistic regression, which had an accuracy of 70%. We then used scaling on the same technique, which increased accuracy to 80%. Accuracy of 80% was also unsatisfactory, so we used Random Forest, K-Nearest Neighbor, Naive Bayes, and Support vector machine to improve our findings. All produce unsatisfactory results. We now use the voting ensemble method to improve the model's accuracy of KNN and SVM. SVM is one of the best performing algorithm as compare to SVM and has improved accuracy from 89% to 94%.We are using binary classification in this project. Each input sample is categorized into one of two types in binary classification. These two categories typically receive names like 1 and 0, or positive and negative. The machine learning techniques for the model evaluation were put to the test using the 10-fold cross-validation configuration setting. The accuracy % obtained uses the available subsamples as validation data and is the average over the 10 iterations. In a binary classification exercise, one's capacity to classify something as either present or absent of stress was evaluated using the accuracy, precision, recall, and F1 score performance indicators for classification. We utilize the confusion matrix to assess the effectiveness of the classification model. The matrix shows the total amount of true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN) that the model on the test data has produced.

We used the following formulas to access accuracy, recall, precision and F1 score

$$\text{Accuracy} = (TN + TP) / (TP + FN + FP + TN) \quad (1)$$

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

$$\text{F1 score} = 2*((\text{Precision} * \text{Recall}) / (\text{Precision} + \text{Recall})) \quad (3)$$

$$\text{Recall} = TP / (FN + TP) \quad (4)$$

TABLE 2. ABBREVIATIONS

HRV	Heart Rate Variability
ACC	Accelerated Hypertension
SVM	Support Vector Machine
RF	Random Forest
KNN	K- Nearest Neighbor
LDA	Linear Discriminant Analysis
MLP	Multi-Layer Perceptron
CNN	Convolutional Neural Network
DT	Decision Tree
SGDM	Stochastic Gradient Descent Method
ANOVA	Analysis Of Variance
PSS	Perceived Stress Scale
LR	Logistic Regression
OSN	Online Social Networks
ACTH	Adrenocorticotropic Hormone
HIIT	High Intensity Interval Training
BMI	Body Mass Index
DASS	Depression Anxiety Stress Scale

The Main Contribution is:

- The proposed system's experimental examination was carried out exclusively using signals from a smart watch.
- The Support Vector Machine Algorithm and Voting Ensemble Learning were used to conduct the experimental investigation of the suggested system.
- With smart watch signals, the proposed system had the maximum accuracy of 94% in predicting stress.

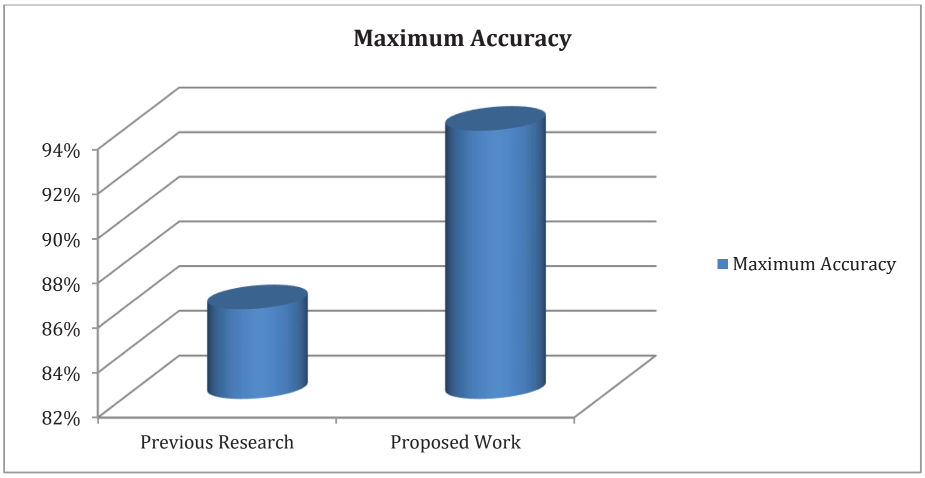

Fig. 2. Previous research and current research maximum accuracy for stress prediction on smart watches.

IV. RESULT AND DISCUSSION

The performance and prediction results of the two-level stress classification are summarized in a matrix and shown in a table and a graph. Six different machine-learning classifiers were employed for the aforementioned binary classification, and each of them was trained using a 10-fold cross-validation technique. As a result, each algorithm's accuracy, precision, recall, and F1 score were assessed. The following table presents the findings. These measurements can be affected by the size and caliber of the dataset, the model's attributes, and the specific technique employed.

TABLE 3. PERFORMANCE MATRICES

	Logistic Regression	**Support Vector Classifier**	**Decision Tree**	**Random Forest**	**K nearest neighbor**	**Gaussian Naive Bayes**	**Best Score**
Accuracy	0.868005	0.897037	0.823979	0.914021	0.928035	0.835011	K nearest neighbor
Precision	0.863891	0.949366	0.826720	0.917832	0.923290	0.838288	Support Vector Classifier
Recall	0.873876	0.837780	0.821715	0.909854	0.933902	0.831803	K nearest neighbor
F1 Score	0.868236	0.889125	0.823367	0.913386	0.928289	0.833677	K nearest neighbor

The comparison of the whole set of feature results shows that accuracy, recall, and f1 Score are all higher for KNN, but precision is higher for SVM.

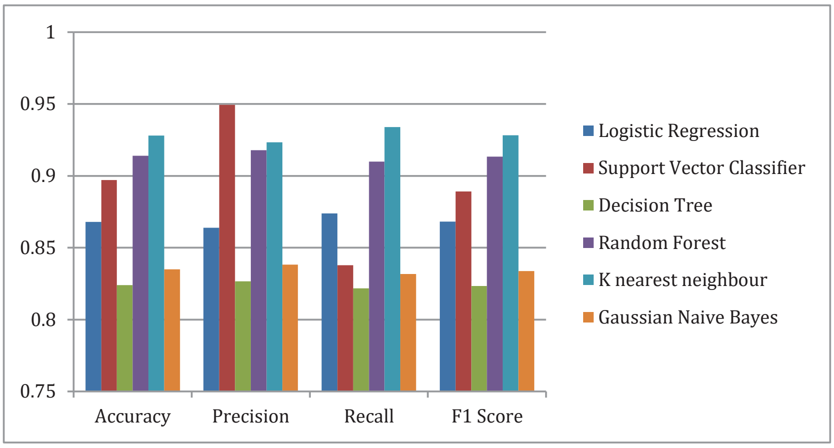

Fig. 3. Comparison among ML algorithms according to performance metrics

Even though KNN outperformed SVM in terms of performance metrics and is also depicted in the graph, after applying the ensemble technique to both algorithms, SVM performed better with 94% accuracy while KNN outperformed SVM with 92% accuracy.

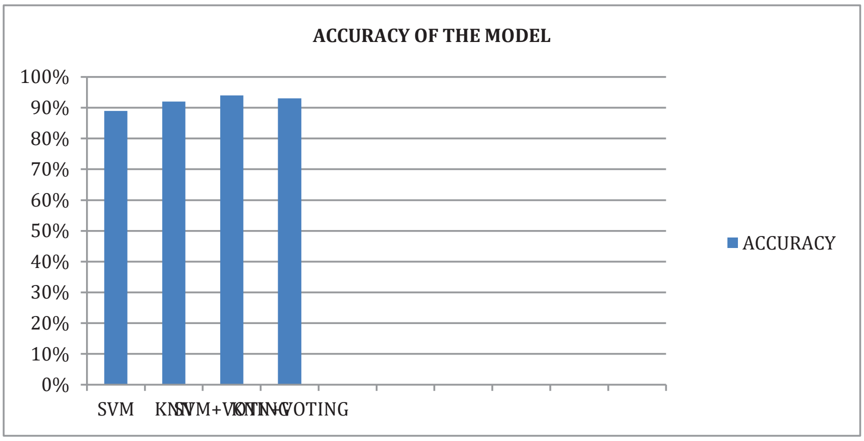

Fig. 4. Accuracy after implementing ensemble voting technique.

V. CONCLUSION

This study's goal was to determine whether it is possible to recognize stress using some feasible devices without any issues related with wearing gadgets. Traditional devices frequently include electrodes, wires, sensors, and connections to link the sensors to a different data collection unit. Smart watches, on the other hand, are designed to be worn on the wrist and have sensors integrated into them that can measure heart rate and activity levels. They are frequently more comfortable to wear and may continuously gather data throughout the day with little user involvement. As a result, many people pick smart watches when they want to assess their stress levels and other health data in a more connected and user-friendly way. Although there are many wrist wearable on the market today, the measurement of stress is still not very precise. Utilizing smart watches and bands, we offered new models and techniques for enhancing the real-life system of stress prediction. Our results are in line with those that have been reported in the literature, and they indicate that mental stress raises salivary cortisol levels to handle stress. We started our study with an open source dataset that has a variety of factors on which to base our model, including body weight, BMI, oxygen saturation, and HIIT. We used a variety of models to forecast stress, and they produced a range of outcomes. We chose two of them that are accurate and used the voting ensemble procedure on them once more. As a result, we achieved the highest accuracy of SVM above KNN, which is 94%.

The study comes to the conclusion that wearable technology enables accurate and persistent data analysis, and that this information can be used to track a variety of elements of human health, including levels of stress. Wearable tech can benefit users effectively manage stress by tracking irregular heartbeats, sleeping habits, and exercise. The easier it is to treat a disease, the sooner it is identified. More significantly, these results demonstrate that machine learning techniques enable the combination of smart watch measures into a single, superior model. A tiny dataset might not be accurate and be prone to errors because it might be affected by outliers or data anomalies. It also might not be representative of the larger population. Future research might add more stimuli to get over this restriction and more closely mimic real-world settings.

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