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Rahata - Stress Detection by Monitoring Physiological Data

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***Abstract-* Human health effects of mental stress have been recognized for decades. Early detection of high levels of stress is necessary to stop detrimental effects. In order to prevent stress-related issues, it is crucial to identify them early on. This can only be done through continuous stress monitoring. This study examines the methods for detecting stress that are used in conjunction with sensory devices such as blood oxygen levels, body temperature, and respiration rate. Many researchers and scholars today use the data they gather from the internet to help in detecting stress. In order to resolve the issue of detecting stress, Once more, I am applying machine learning model to identify that a person is stressed or not. These training models takes a sample data and train itself for detecting stress and give the output of stress level ranging from 0 to 4.**

***Indexed Terms-* Stress Prediction, physiological data, Machine Learning.**

I. INTRODUCTION

Stress from daily living is a significant issue in our contemporary society. It is a problem that is becoming worse and is now inescapable in our daily lives. Stress can cause major health problems if it is not effectively managed. Stress is more well studied because its symptoms are more obvious than those of chronic disease. Stress is a heightened psycho-physiological bodily state that arises in response to a demanding or difficult event. Stress is brought on by environmental factors known as stressors. Extended exposure to numerous stressors acting at once can have a negative impact on a person's physical and mental health, which can further contribute to chronic health issues. If you experience a lot of stress on a daily basis, your health is at risk. Stress is detrimental to your physical and mental wellbeing. You have a finite capacity for clear thinking, effective work, and enjoyment. It could seem impossible to find ways to reduce your stress. The bills won't stop coming in, there won't ever be more hours in the day, and your obligations to your family and job will always be demanding. But contrary to what you might believe, you have a lot more power. In this study, we created a physiological signal-based system for automatically detecting stress levels. Our plan can also be used in people's daily lives.

II. LITERATURE SURVEY

In recent years, efforts have been put forth of using machine learning models which are developed by utilising physiological reactions to emotional and stressful stimulito automate the detection and prediction of stress.

For the purpose of wearable affect and stress detection, Philip Schmidt, et al. established and made public the WESAD dataset. RespiBAN Professional and Empatica E4 wearable devices were placed on the chest and wrist of the 15 participants, respectively, to record physiological data such aselectrocardiogram, blood volume pulse, three-axis acceleration, respiration, body temperature, electromyogram and electrodermal activity. They exposed the test subjects to a range of stress situations, including baseline, fun, tension, meditation, etc. Five machine learning methods, including K-Nearest Neighbour (KNN), Linear Discriminant Analysis (LDA), Random Forest (RF), Decision Tree (DT), and AdaBoost, were utilised, and their performance was compared (AB). By combining common features with traditional machine learning techniques, they were able to achieve classification accuracy of up to 80% and 93% for the three class (amusement vs. baseline vs. stress) and binary (stress vs. non-stress) classification problems, respectively.

In order to identify mental stress, Jacqueline Wijsman, et al. investigated physiological data. They measured the individuals'skin conductance, ECG, EMG and respiration and from those measurements they derived a total of 19 physiological characteristics. Out of these 19 characteristics, a subset of 9 features was chosen for further research. These 9 features were then normalised, studied for correlations, and utilising principal component analysis, downsized to 7 characteristics. The 80% accuracywas achieved between a person's stress and non-stress circumstances by combining these variables with various classifiers, including Fisher's Least Square Linear Classifier, K-Nearest Neighbours Classifier, and Linear Bayes Normal Classifier. With the exception of the participant count and the features retrieved, this experiment is almost identical to what already performed. They compared their findings to earlier articles relating to stress classification that utilised just one kind of stressorand three different stressors was also used in their study.

And Saskia Koldijk, et al. created a brand-new multimodal dataset called SWELL Knowledge Work (SWELL-KW) dataset for user modelling and research on stress. This dataset was gathered using 25 persons who were engaged in routine knowledge tasks including searching, reading, writing etc. The working settings were manipulated utilising the stressors of time constraints and email interruptions. Body postures, facial expressions, computer logging, skin conductance, and heart rate are among the recorded data. All users have access to this dataset, which includes both raw and pre-processed data with extracted features. Validated questionnaires pertinent to task load, mental stress and other factors were used to evaluate the dataset on working behaviour and affect. This study didn't employ any machine learning methods for the benchmark, but it did provide a new stress-related data set to the body of literature.

Wearable technology called the BioNomadix type BN-PPGED from Biopac was used to detect physiological reactions. Two electrodes were placed on the participant's non-dominant hand's to measure the signals from the pulse plethysmograph (PPG) and electrodermal activity (EDA). Additionally, AcqKnowledge software was used to exfoliate the PPG autocorrelation signal and Heart Rate Variability (HRV).

To categorise people as stressed or not stressed, a support vector machine (SVM) was employed, with an 82% accuracy rate.

Saskia Koldijk, et al. developed automatic classifiers to examine the relationship between working conditions and mental stress-related conditions from sensor data, including body postures, facial expressions, computer logging, and physiology (ECG and skin conductance). This was done in response to the employees' reports of stress at work. They found that the performance of the specialised model is almost always equal to or better than a generic model when similar users are sub-grouped and models are trained on particular subgroups. The most important information among the most practical modalities is provided by posture, which can be used to distinguish between stressful and non-stressful working environments. By including information regarding one's facial expressions, performance might be enhanced even more. They attained 90% accuracy using an SVM classifier.

Another important component that might identify someone's stress is facial clues. In addition, G. Giannakakisa, et al. created a framework for identifying and interpreting emotional states of stress and anxiety using video-recorded facial clues. Mouth activity, eye events, camera-based photoplethysmographic heart rate estimate, and head action parameters were the features that were examined. In front of a computer monitor with a built-in camera, candidatewere required to sit few cm apart. There were several techniques employed and tried, a classifier called AdaBoost, the Naive Bayes classifier, Support Vector Machines, and the Generalized Likelihood Ratio. In the social exposure procedure, the Adaboost classifier's accuracy of 91.68% led to the best classification outcomes.

For the classification of stress conditions, Md Fahim Rizwan et al. used the ECG feature among the numerous bio-signals that were available. ECG was chosen as the main choice due to methods for extracting ECG features and the availability of numerous portable clinical grade recorders, making its recording easily accessible. ECG is more advantageous since it can identify respiratory signal information using the EDR technique (i.e., ECG derived Respiration), which eliminates the requirement for a separate respiration measurement sensor system.

They were able to reach an accuracy of about 98.6% by combining the SVM classification approach with the, QT interval, EDR data and RR interval. However, this conclusion is unsatisfactory since it only took into account one signal, the ECG, and ignored other vital bodily signals that are also vital for inducing stress.

The current study aims to identify an individual's stress-related status by analysing bio signals using machine learning and deep learning models. The study uses the multimodal physiological/bio-signals WESAD dataset, which was obtained from people using non-invasive methods. Subjects are categorised based on their stress levels using machine learning techniques. This can relief a psychiatrist or doctor from having to do it manually. A person can receive the appropriate counselling or, if necessary, stress-relieving drugs after classification, if it is determined that they are stressed.

III. PROPOSED METHODOLOGY/PROJECT IMPLEMENTATION

The dataset used for this investigation is from Kaggle. Attila Reiss, Philip Schmidt, et al. first presented and made this dataset available to the public in 2018. This multimodal dataset assembles mobility information and physiological characteristics from 15 subjects using the wrist- and chest-worn sensors. Through several study protocols, the subjects' physiological signals were recorded, including preparation, baseline condition, amusement condition, stress condition, meditation, and recuperation.

The measured ECG, Blood oxygen, Respiration Rate, Body Temperature, Heart Rate etc. All signals were sampled at 700 Hz. For feature extraction, we employed a variety of modalities from the WESAD dataset.

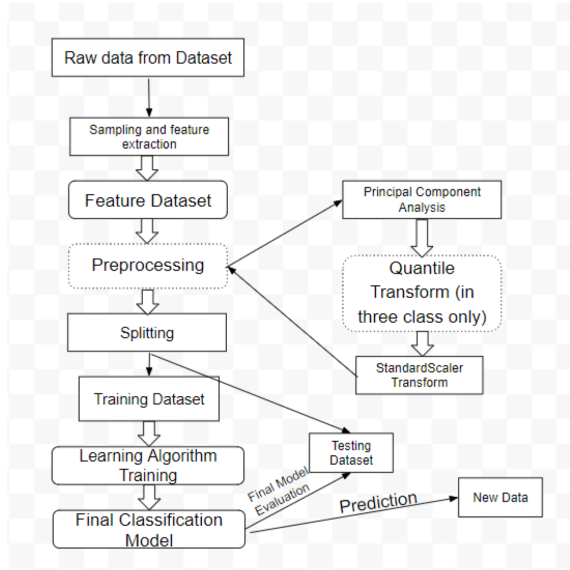

Fig.Schematic flow diagram of Stress Detection Methodology.

A deep learning Artificial Neural Network (ANN) and a few machine learning techniques (Random Forest, Decision Tree, AdaBoost, k-Nearest Neighbor, Linear Discriminant Analysis, and Kernel SVM) were utilized, and their performances were compared. The retrieved features are preprocessed to determine their eligibility for the classification methods, as described above.

For Random Forest classifiers, the least number of samples needed to split a node was set at 10 and the maximum depth for three-class classification was set at 4 and 9, respectively. The maximum depth was set to the default settings in the categorization case (nodes are expanded until all leaves are pure or until all leaves have less samples than the number for breaking a node).The minimal number of samples for splitting a node in the Decision Tree, which served as the base estimator for the AB ensemble learner, was set at 5 for three-class classification and 10 for binary classification, respectively. In both classification tasks, the kNearest Neighbor method's maximum number of neighbours was set at 9.

IV. RESULT

Above mentioned classifiers are used and their performances are compared,

Techniques	Accuracy
DT	87.59
ANN	89.53
AB	91.06
LDA	90.15
KNN	87.92
SVM	93.20
RF	95.21

By comparing all of them, DT (Decision Tree) classifier reached the lowest classification accuracy. From Table, it can be concluded that the DT performed the poorest overall, whereas SVM performed the best among all machine learning classifiers, and RF(Random Forest) performs the good overall from all of the classifiers. These outcomes surpass those of Philip Schmidt et al. , who reported accuracies ranging from 80.34% to 93.1%.

CONCLUSION

The publicly available WESAD dataset's format and structure have been understood by the proposed research work. The data have also been cleaned and transformed into a set that can be used to build machine learning and deep learning classification methods. Various classification models have also been investigated, built, and compared.

Dataset contains data from multiple physiological modalities like ECG, Blood oxygen, Respiration Rate, Body Temperature, Heart Rate, Limb Movement, Random Eye Movement, Sleeping Hours which is not available in any other

Data files, it qualifies this work for identifying stress in people.

Accuracy of 84.32 to 95.21 has achieved by this model.

Future research can be done by taking self-reports which were gathered via a number of structured questionnaires. Facial cues, logging data, audio and video recordings, FITBIT data and other senses that are used in different studies independently can be combined with physiological data to create a new dataset. As nearly all of the factors required to induces stress in humans are present in such a dataset, it can be utilised for stress detection with greater accuracy.

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