JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

Machine Learning based Stress Detection using Multimodal Physical Data

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Abstract – The detection and monitoring of stress have a significant impact on one's physical, mental, and social wellbeing. Currently available techniques for categorizing emotional states rely on traditional machine learning algorithms that compute features from a variety of sensor modalities. A new machine learning algorithm called Extreme gradient boost algorithm has been proposed and it does not require the computation of any features. This method for stress identification on individuals delivers improved results and yields the highest accuracy, 97.8%, when compared to the existing methods, using a multimodal dataset recorded via wearable physiological and motion sensors. Three separate physiological states—relaxed, alert, and stressed—are represented by the sensor data in the Wearable Stress and Affect Detection (WESAD) dataset.

Index Terms*: - WESAD, Machine Learning Classifiers, ACC, BVP, EDA.*

1. INTRODUCTION:

Communication between humans and computers, affective computing has emerged as a new area of study. Machines with empathy are able to read the emotional state of their human operators, modify their 'behaviour' accordingly, and even display emotions of their own. Stress, which can be thought of as the body's "nonspecific response to any demand upon it," is an intriguing affective state from a medical perspective. The negative effects of longterm stress, which can include anything from headaches and insomnia to an increased risk of cardiovascular disease. British government agency Health and Safety Executive (HSE) estimates that 37% of all cases of work-related ill health in 2015/16[2] can be attributed to stress. One definition of stress is "the change from a state of calm to an excited state that triggers a cascade of physiological response," which accurately describes the body's reaction to perceived physical or psychological threats. There has been a consistent annual increase in the percentage of people reporting stress-related health problems such as headaches and insomnia in the United States of America, where roughly 77% of the population experiences such symptoms. Further, stress is a major contributor to a wide range of health issues, including but not limited to depression, anxiety, hypertension, cardiovascular disease, and stroke. An individual's capacity for making decisions, paying attention, learning, and solving problems are all impacted by stress. Personal, occupational, and social well-being are all affected by stress levels, making stress detection and monitoring an active area of study. Early diagnosis and monitoring of stress may reduce the risk of developing potentially fatal stress-related illnesses. Our method is on par with other cutting-edge approaches and overcomes many problems seen in previous studies.

The rest of the paper will progress as follows. In Chapter 2, discussed about the stress detection and monitoring literature review. The proposed methodology of stress detection is discussed in Section 3. Section 4 presents the results of the experiments conducted, and compares the efficiency of the proposed methods to that of the currently used ones.

2. LITERATURE SURVEY

Pramod bobade et.al [1] describes an accuracy for three-class (amusement, baseline, and stress) and binary (stress, non-stress) classifications were evaluated and compared using machine learning techniques like K-Nearest Neighbour, Linear Discriminant Analysis, Random Forest, Decision Tree, AdaBoost, and Kernel Support Vector Machine. For these binary and three-class classifications introducing a straightforward artificial neural network for deep learning. In the study, deep learning obtains an accuracy of up to 84.32 percent and 95.21 percent, whereas machine learning techniques reached an accuracy of up to 81.65 percent for three-class classification problems and 93.20 percent for binary classification problems.

Mike Thelwall et.al [2] demonstrates an improved method for detecting signs of stress and relaxation in internet posts. TensiStrength is the first dictionary-based algorithm to distinguish between stress and relaxation, and this approach leverages word sense disambiguation using word sense vectors to increase the system's precision. The author also provide a cutting-edge approach for determining where stress and anxiety come from.

Huijie Lin et.al [3] explores the relationship between users stress levels and social interactions using a sizable dataset gathered from active social media networks. The author proposed an unique hybrid model that combines a factor graph model with a convolutional neural network for the purpose of detecting stress using tweet content and social interaction data.

Mike Thelwall et.al [4] describes a technique for spotting overt and subtle signs of anxiety or calm while travelling. The usefulness of Tensistrength is challenged by tweets that contain a lot of phrases connected to stress. Utilizing machine learning strategies will enhance Tensistrength's performance.

Michael Gamon et.al [5] had proposed crippling medical illness known as depression has a significant impact on one's ability to work, study, eat, sleep, and have fun. A system that employs SNS as a data source and screening tool was proposed in order to categorise the user with AI in line with the UGC on SNS. The main goal is to investigate how social media posts can be used to classify individuals based on how they are feeling emotionally.

Buckley et.al [6] had discussed recently created algorithm can be used to detect sentiment and sentiment strength in unstructured English text. You should therefore concentrate more on fixing spelling mistakes than grammatical ones. The author has shown that the SentiStrength baseline implementation outperforms cutting-edge machine learning methods. Additionally, it was mentioned that researchers would soon be able to automatically distinguish between good and negative attitudes in online talks using the sentiment strength detection method.

Apoorva Inamdar [7] had introduced the power shift can be attributed to teenagers' increased use of social media. Twitter users moods and behaviours are a well-known but little-studied subject of research. The extensive data set on tweets, retweets, and comments in Twitter can be used for human sentiment analysis and behavioural research. Twitter users' moods and behaviours are a well-known but little-studied subject of research.

Huayang Xie et.al [8] developed the distinguishing stressed speech in New Zealand English, using the descriptors. The speaker-independent feature values produced when these features are normalised and scaled can be utilised to determine whether a specific vowel segment should be stressed or unstressed. The method starts by separating the vowel segments from the speech signal and then extracts prosodic and vowel quality information from those segments. On 60 adult female utterances with 703 vowels, the method's maximum accuracy of 84.72 percent was attained.

3. STRESS DETECTION METHODOLOGY:

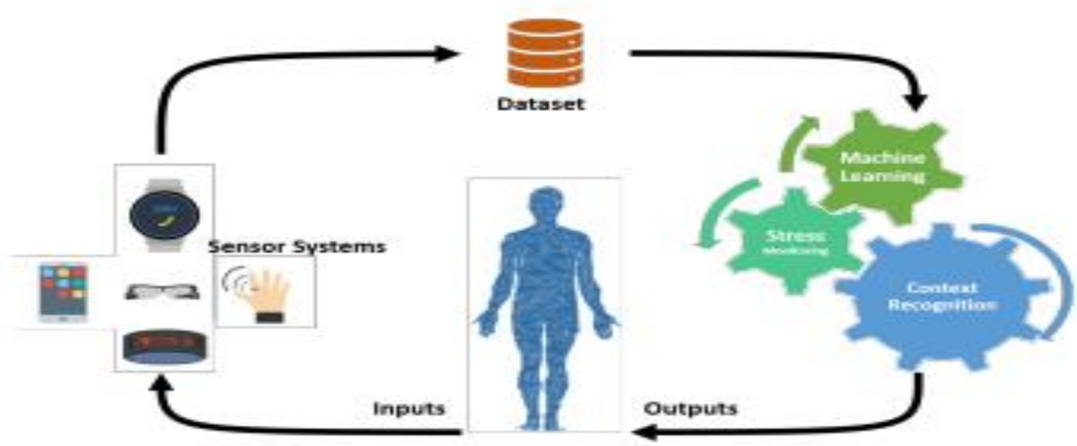

Fig. 1. A stress detection and context recognition framework using sensor systems and machine learning algorithms

In this fig1, data is gathered from the subject's human being and then sent into a network of sensor systems, which in turn sends the information to a dataset. From that database it is going to applying the machine learning technique. The user can obtained the required data from these sources.

3.1 Data Set Information:

The Wearable Stress and Affect Detection (WESAD) is available to the public. This multimodal dataset was collected from a laboratory study, and it includes physiological and motion data from 15 participants recorded by a wrist-worn and a chest-worn device. All of the following sensor modalities (blood volume pulse, electrocardiogram, electrodermal activity, electromyogram, respiration, temperature, and three-axis acceleration) are included. Additionally, the dataset contains three distinct affective states, which helps to close the gap between stress and emotion research conducted in the laboratory (neutral, stress, amusement).

3.2 Attribute Information:

Two devices, one worn on the chest (a RespiBAN) and one on the wrist, recorded raw sensor data (Empatica E4). ECG, EDA, EMG, respiration, temperature, and three-axis acceleration are just some of the sensor data provided by the RespiBAN device. A 700 Hz sample rate is used for all signals. Data from the following sensors are provided by the Empatica E4 device: blood volume pulse (BVP, 64 Hz), electrodermal activity (EDA, 4 Hz), body temperature (BVT, 4 Hz), and three-axis acceleration (32 Hz).

3.3 Classes:

Baseline condition: 20 minutes of standing or sitting reading Magazines.

Amusement condition: The subjects in the amusement condition watched eleven comedic videos.

Stress condition: The Trier Social Stress Test (TSST) is a demanding exam that includes both a public speaking and arithmetic section.

The modules will be executed in the following order: dataset and data loading, cross validation loader, network architecture, model training, visualization, and evaluation.

3.4 Exploring the Dataset:

To ascertain which labels were made available, the dataset will examine the pickle files it has been given. Prior to training, neural networks allow for calculation for a single subject. The interesting aspects of the accelerometer data will be computed simultaneously with the electrodermal activity (EDA) and temperature features.

A machine learning algorithm called XG boost is proposed here. It's important to note that machine learning falls under the umbrella of AI. Also used ensembled techniques to argue the performance of preexisting models, which us call "boosting." Boosting is a popular method for improving the accuracy of ensemble classifiers. The primary goal of boosting is to mitigate bias within the underlying model. Classification tasks with structured and tabular data are best handled by the XGBoost classifier, a machine learning algorithm. The XGBoost algorithm is a very powerful gradient increaser. XGBoost can handle large, complex datasets.

The performance of proposed methodology is evaluated by using the following parameters:

1. Accuracy:

Accuracy of a particular approach defined as the proportion of true positive predictions out of all true positive predictions. The equation for accuracy is

$$\textbf{Accuracy} = \frac{True\,positives + True\,Negatives}{Total\,Population} \qquad \text{------------------ (1)}$$

2**. Precision:**

A method's precision is defined as the number of true positives over the number of how many correct predictions it makes relative to the total number of observations.

$$\textbf{Precision} = \frac{TP}{TP+FP} \qquad \text{------------------ (2)}$$

3.Recall:

Recall (R) is calculated by dividing the number of True Positives (TP) to the sum of False Negatives (FN) and true positives.

$$\text{Recall} = \frac{TP}{TP+FN} \quad \text{------------------ (3)}$$

4.F1 Score:

An approach's F1 score is calculated as a harmonic mean of its precision and recall. Here is the formula for determining an F1 score:

$$\text{FI Score} = 2.\frac{Precision.Recall}{Precision+Recall} \quad \text{------------------ (4)}$$

Confusion matrix:

		Actual values	
		Positive values (1)	Negative values (0)
Predicted values	Positive values (1)	TP	FP
	Negative values (0)	TN	FN

TP=TRUE POSITIVES
TN=TRUE NEGATIVES

FP=TRUE NEGATIVES
FN=FALSE NEGATIVES

Using the confusion matrix here calculating the accuracy, precision, recall and f1 score.

4. Results and Discussion:

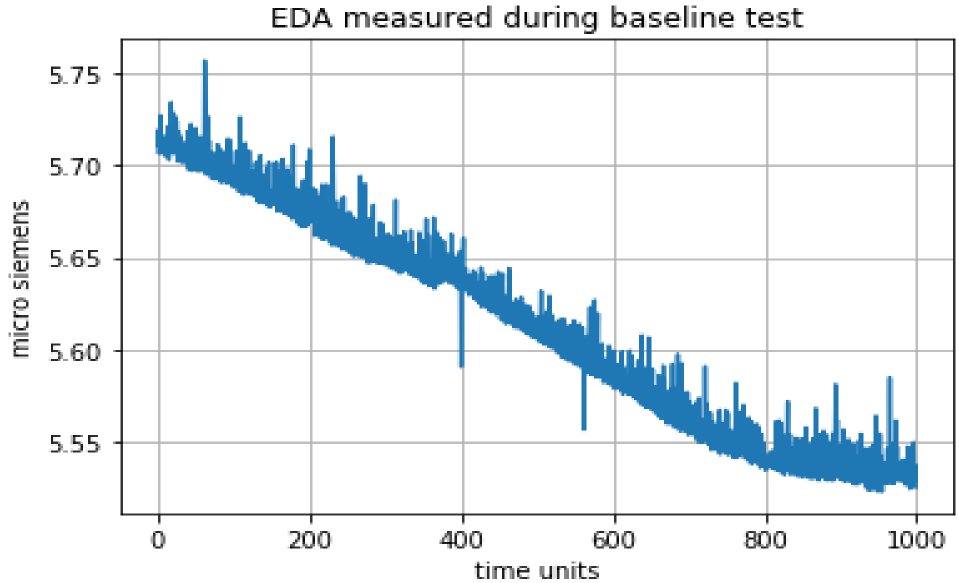

FIG 2: EDA Measured during baseline test

Fig2 depicts that EDA is measured in Siemens. It shows whether the person is in relax or amusement condition. when the microsiemens is above 5.5 and the time unit is in 500 above the person states that is in amusement condition.

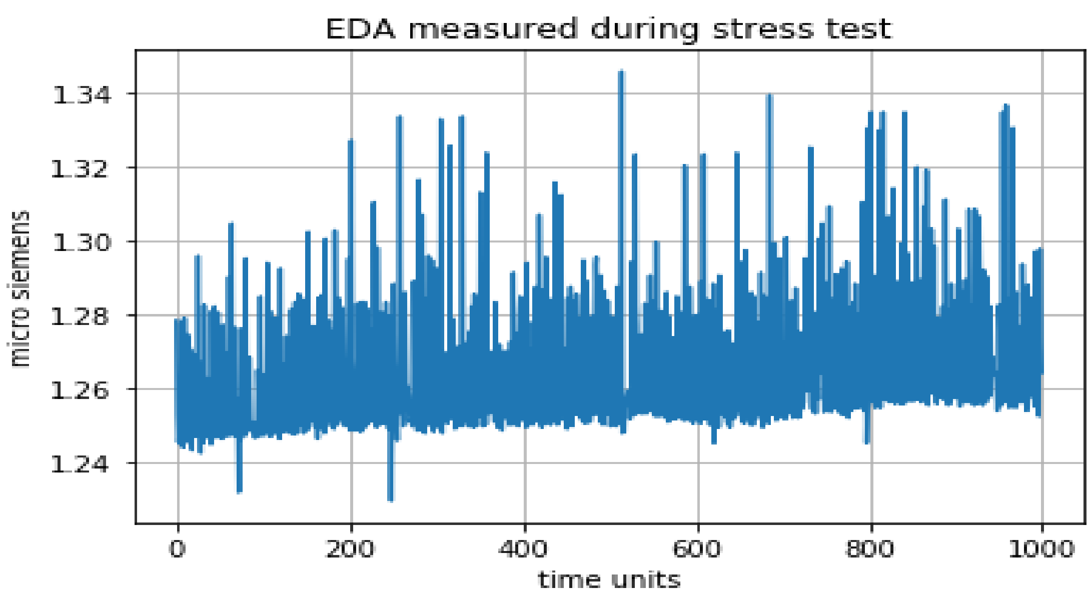

FIG 3: EDA measured during stress test

Fig3 depicts that EDA is measured during whether the person is stressed or unstressed. When the time unit is reaches the point as 500 above and microsiemens is above 1.3 range . It shows the person is having high stress.

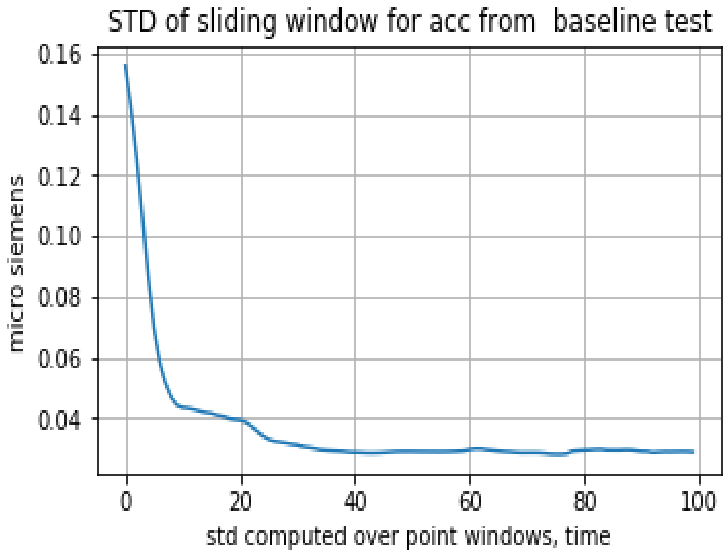

FIG 4: STD sliding window for acc from baseline test

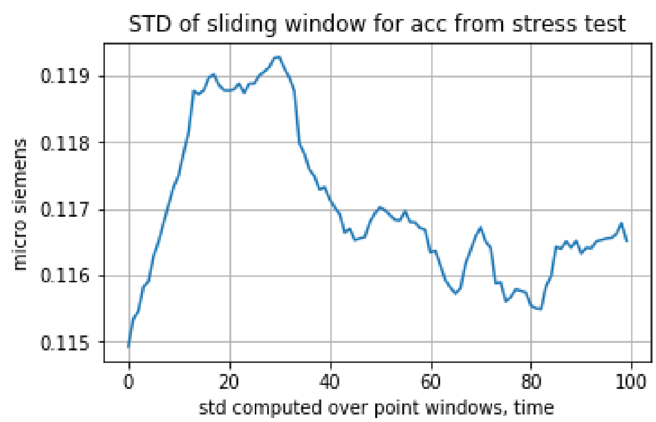

FIG 5: STD Sliding window for acc from stress test

The sliding window technique is a computational technique that tries to replace nested loops with a single loop in order to reduce time complexity. The following steps of the STD sliding window is:

1. Add the first K components and store the result in the current Sum variable. The first sum is also the current maximum, so it should be stored in the variable maximum Sum.

2. It shifts the window to the right by one position and calculate the sum of the items within the window; the window size is K.

3.If the current Sum is greater than the maximum Sum, then you should update the maximum and continue with step 2.

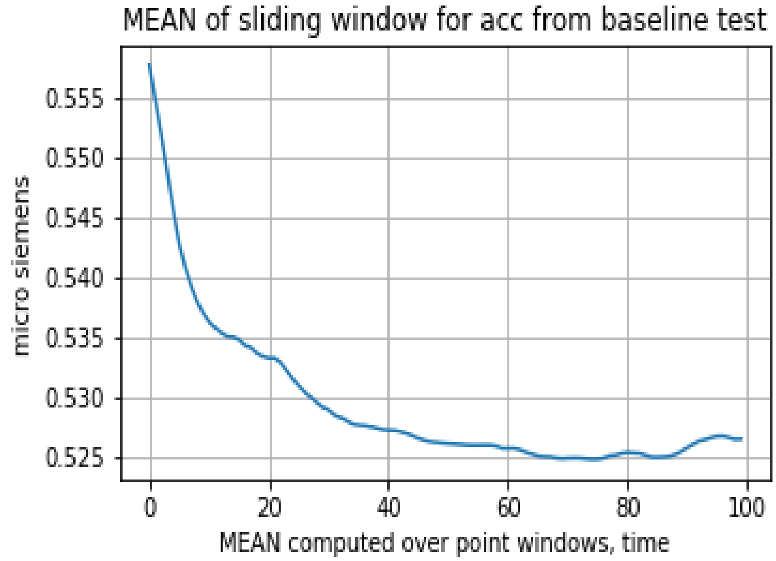

FIG 6: Mean sliding window for acc from baseline test

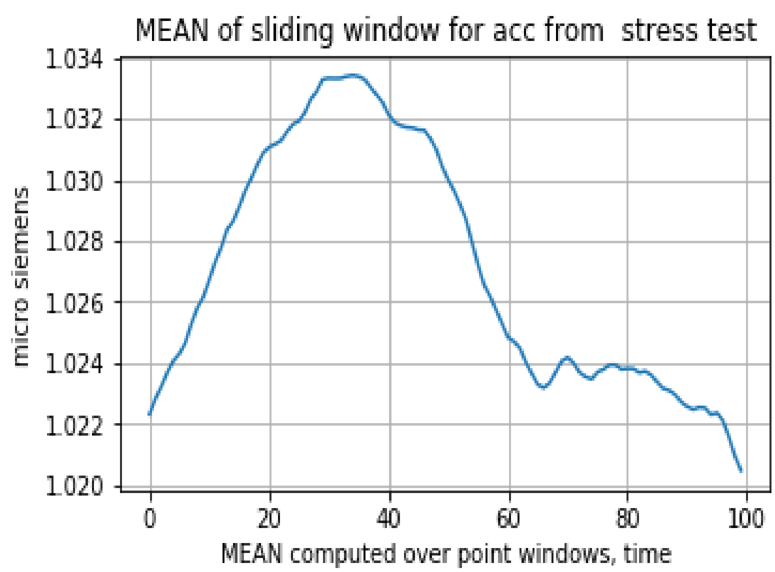

FIG 7: Mean Sliding window for acc from stress test

Fig 6 and 7 graphs depicts that the algorithm is based on a Mean sliding window that runs over an active power consumption curve by using the Extreme gradient boosting (XGB) algorithm.

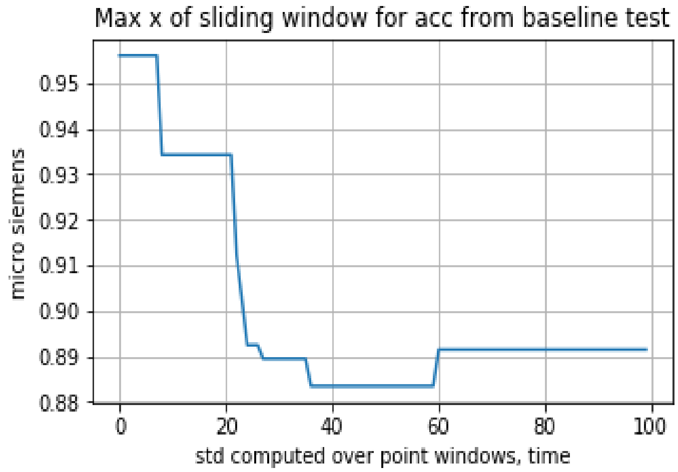

FIG 8: Max X of Sliding window for acc from baseline test

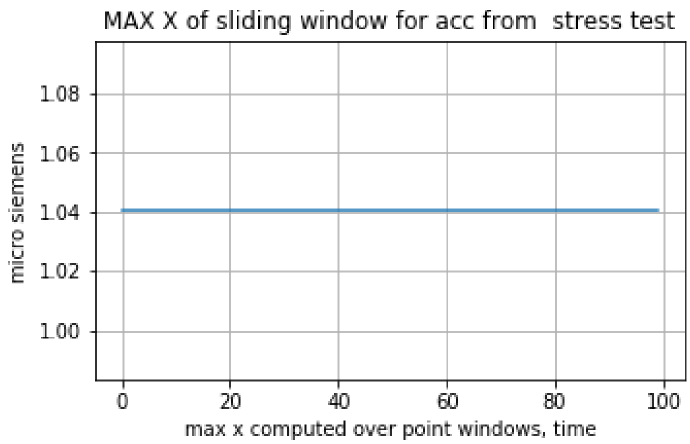

FIG 9: Max X of Sliding window for acc from stress test

Fig 8 and 9 depicts that giving an array of samples, there is a sliding window of size k which is moving from the very left of the array to the very right. You can only see the k numbers in the window. Each time the sliding window moves right by one position by using the Extreme gradient boosting (XGB) algorithm.

	precision	recall	f1-score	support
0.0	0.9801	0.9839	0.9820	245889
1.0	0.9994	0.9425	0.9701	10734
2.0	0.9755	0.9539	0.9645	63716
3.0	0.9821	0.9811	0.9816	47585
4.0	0.9704	0.9910	0.9806	52168
accuracy			0.9788	420092
macro avg	0.9815	0.9705	0.9758	420092
weighted avg	0.9789	0.9788	0.9788	420092

FIG 10: Simulation result of Proposed method

After the simulation in XGB machine learning algorithm gives an accuracy 97.8% .

TABLE: Performance comparison of different machine learning algorithms:

S.NO	Model	Accuracy	Precession	Recall	F1- Score
1	LR(1)	82.2	0.82	0.89	0.85
2	KNN	85.5	0.92	0.82	0.87
3	DT	93.7	0.96	0.92	0.94
4	XGB(proposed)	97.8	0.98	0.98	0.95

LR- LOGISTIC REGRESSION

KNN- K NEAREST NEIGHBOUR

DT- DECISION TREE

XGB- EXTREME GRADIENT BOOSTING

From the above table the proposed XGB gives an highest accuracy compared to the existing methods. The difference between the Logistic Regression to the Extreme Gradient Boosting algorithm the accuracy is increased by 15.6%.

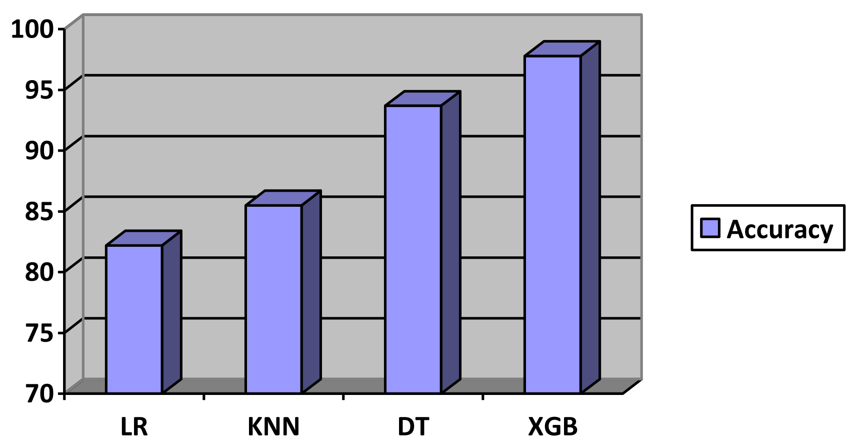

FIG 11: Accuracy shown for different machine learning models

Comparing all the machine learning algorithms, XGB algorithm reaches the highest accuracy upto 97.8%.

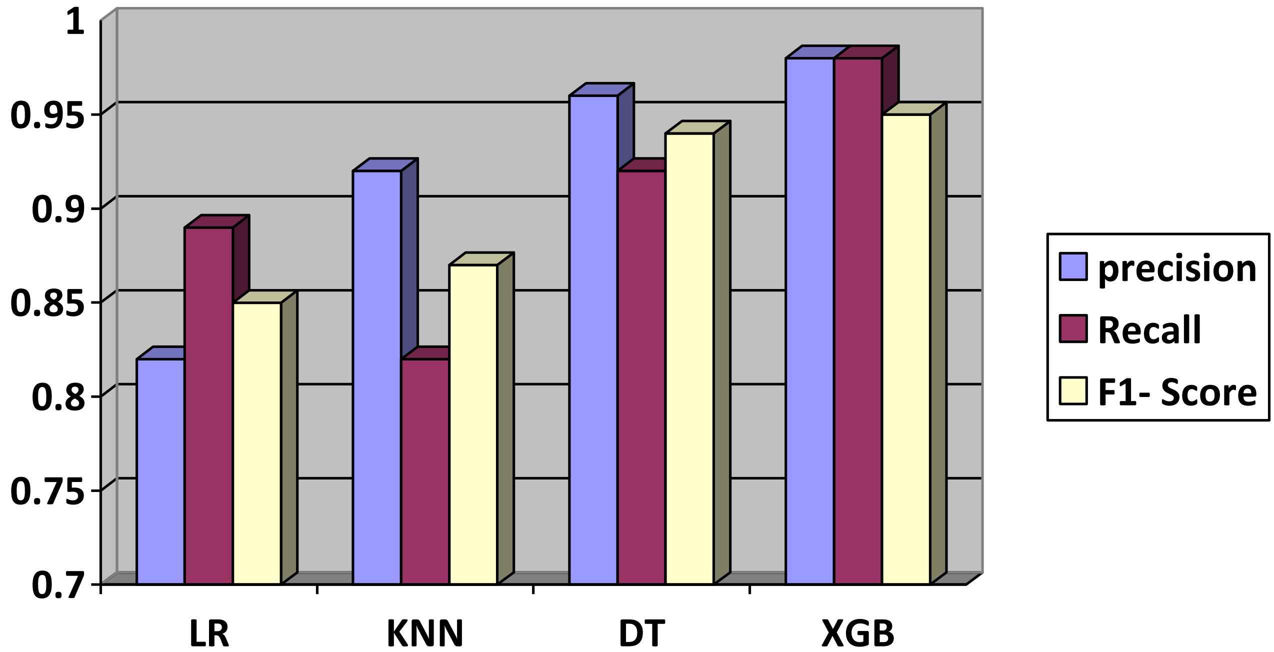

FIG 12: Precision, Recall & F1- Score shown for different machine learning models

Comparing all the machine learning algorithms, XGB algorithm reaches the highest precision, recall and F1 Score as shown in graphical order.

6. CONCLUSION:

The proposed research has deciphered the WESAD dataset's structure and format, transformed the raw data into a form suitable for machine learning and deep learning classification methods, explored those methods, constructed various classification models, and compared them. This work is suitable for the detection of stress in humans because the WESAD dataset includes data from multiple physiological modalities, including three-axis acceleration (ACC), respiration (RESP), electrodermal activity (EDA), and electrocardiogram (ECG), that are not available in other datasets. In this paper, proposed a machine learning method called XGB algorithm for detecting and classifying stress based on raw data from EDA sensors, eliminating the need for feature computation and selection. Since EDA is the most reliable indicator of stress, it was analysed using that data. Future work will make use of the subjects' own self-reports within the dataset, which were gathered through a slew of well-structured questionnaires. Physiological data can be combined with other types of information collected in different studies (such as facial cues, logs, audio/video recordings, FITBIT data, etc.).

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