Analysis of Factors Affecting Stress Using Feature Selection and Classification Techniques

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***Abstract*—In the current Anthropocene era many people are suffering from stress due to our current lifestyle. Long-term stress that isn't managed properly might cause major health issues. It is very dangerous and can lead to some major conditions like cardiovascular disease, depression, suicidal activities and many. Early identification of mental stress can help to avoid number of serious health problems. There are several methods that can be helpful in recognizing stress like our behavior, speech, facial expression, physiological signals, questionnaire based detection and so on. In this paper, we propose to identify the features which have significant contribution towards stress. For this we will be using the observations from two devices RespiBAN and Empatica E4.**

***Index Terms*—Classification algorithms, Feature extraction**

I. INTRODUCTION

A person's mental and physical status might influence their way of living. A nice and healthy lifestyle can start with a good mental and physical state. A person may experience stress in their daily life as a result of our hurried routine. The stress level can be determined using physiological signals such as ECG, EEG, GSR, and HRV that are not easily intervened by humans. The accurate detection of stress can help prevent various harmful diseases and also aid in proper management of stress. Various machine learning and deep learning technique can help us to achieve high accuracy in recognition of stress.

Most of the works done till now have focused on predicting the stress condition of the subjects using the available features. However, to the best of our knowledge very few studies are done on finding the features causing stress condition. We propose to find the major contributors by reducing the number of features in the dataset while keeping the detection accuracy equal to that of the previous contributors. .

Philip Schmidt, et al. [1] had introduced WESAD dataset for the purpose of wearable affect and stress detection and made it available to the public. For collecting this data, they had chosen 15 people and recorded the physiological data such as three-axis acceleration, electrocardiogram, blood volume pulse, body temperature, respiration, electromyogram and electrodermal activity by putting wearable devices – RespiBAN Professional and Empatica E4 on the chest and on the wrist respectively.

II. LITERATURE REVIEW

The WESAD Dataset is a widely used dataset for diagnosing depression. Philip Schmidt et al. [1] first proposed it. A total of 15 participants' physiological data was gathered, including three-axis acceleration, electrocardiogram (ECG), blood volume pulse (BVP), body temperature, respiration, electromayogram (EMG), and electrodermal activity (EDA). Empatica E4 and RespiBAN are used to gather data on the wrist and chest, respectively. They've divided stress into categories including baseline, amusement, and stress. They also compared the results of five machine learning algorithms for detecting stress in various states: Linear Discriminant Analysis, K-Nearest Neighbor, Random Forest, AdaBoost, Decision Tree. For three-class and binary classification, respectively, accuracy of 80.34% and 93.12% was attained. .

Another deep learning framework proposed by Giorgos Giannakakis at el. [2] for recognizing stress. A multi-kernel 1D convolution neural network is used in this study. In the study they have used various types of kernel to compute complex features and made a multi-level modelling for stress identification of unique heart rate variables. They have performed comparison between 6-fold cross-validation and single kernel in which cross-validation outperform the single kernel with accuracy of 99.1%. .

Khalid Masood and Mohammad A. Alghamdi [3] have presented a Deep Learning technique for modelling mental stress. They used deep CNN algorithms using a triplet loss function in this study. The data was separated into two groups. 70% of the was used in training, while 30% was used in validation and testing. Nearly 90% labelling accuracy was attained. .

Six machine learning techniques such as Random Forest, Decision Tree, AdaBoost, KNN, LDA and Kernel Support Vector Machine along with deep learning approach ANN were compared in study conducted by Pramod Bobde and Vani M [4]. They have computed various statistical features on raw signal and data. In the experiment they have classified individuals by two methodologies three class classification and binary classification. In the end of study, they have achieved SVM with highest performance in machine learning classifiers whereas ANN attain overall best performance.

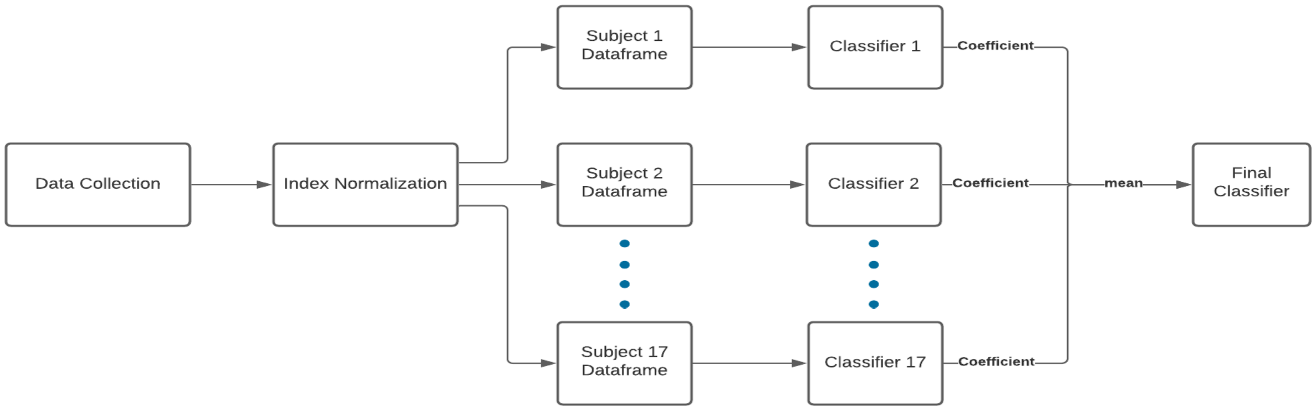

Fig. 1. Process Diagram

III. Methodology

A. Dataset

To best of our proposed approach we find WESAD dataset to be most relevant. The dataset contains physiological data of 17 subjects gathered in a laboratory setting by Philip Schmidt, et al. [1]. RespiBAN (Chest-worn) and Empatica E4 (Wrist-worn) devices were used to collect signals. RespiBAN collected three-axis acceleration (ACC), electrocardiogram (ECG), body temperature (Temp), respiration (Resp), electromyogram (EMG) and electrodermal activity (EDA) sampled at 700Hz. Moreover, the Empatica E4 on the wrist collected blood volume pulse (BVP @64Hz), Electrodermal Activity (EDA @4Hz) and three-axis acceleration (ACC @32 Hz). Furthermore, the readings corresponds to 5 mental conditions of the subjects namely Transient, Baseline, Stress, Amusement and Meditation. For collecting the readings for each subject, a certain time interval was observed between two consecutive conditions.

B. Approach

We tried multiple approaches to best fit the data and get the maximum accuracy possible. As a first step of any of these approaches we performed index normalization on the dataset.

In the first approach we pre-processed the dataset in terms of the classes. We created five records for each subject representing the five classes and the mean of the features were calculated. We then applied classification algorithms like KNN and Logistic regression to examine our approach. We also tried finding the correlation between the features and removed the features with low correlation values to improve the accuracy of the algorithm.

Since the accuracy from the previous approach didn't match our expectation we tried training a binary classifier instead of multinomial classifier. For this we treated stress condition as one class and all other conditions as another class.

Finally, we trained a different classifier for each of the subjects. In this approach we used the raw readings from the sensors and didn't find the mean of the features. Only index normalization was performed. Once all the classifiers were trained the means of the coefficients were used to determine the coefficients of our final classifier. Fig 1 demonstrates the system overview of our approach.

IV. Justification

The readings of RespiBAN were sampled at 700 Hz but the readings of Empatica E4 were sampled at different frequencies. Moreover, the labels in the dataset were sampled at 700 Hz. So, to use the readings from both the sensors together there was a need to normalize the readings. We used the index to normalize the readings by repeating the readings of lower frequencies to the match the number of readings of higher frequency using the below formula:

$$index_n = index/(higher\_freq/lower\_freq) \qquad (1)$$

In our first approach we calculated the mean of the features corresponding to each class for each subject. Since we were concerned about predicting the mental condition of the subjects we kept the classes as single source of truth and the features as the driving factor. Also, the number of readings for each of the features were too high to consider as independent features, hence we decided the mean to be a suitable operation to perform.

In the above approach we split the dataset into 5 classes and calculated the mean for each of the features. This resulted in very less number of samples for each of the classes. So, while training the classifier we didn't get the desired accuracy. Hence, we decided to train a binary classifier for which we considered the stress condition as one class and the rest as non-stress class. The classifier trained with this dataset provided good accuracy but it was over fitting the non-stress condition as the number of samples for this class were too high when compared to the stress condition. In both of these techniques the means readings were treated as features i.e. columns of the dataframe.

Finally, we trained different classifier using different subjects. In this approach instead of finding the mean of the readings we considered the actual raw readings as samples which

Model	Accuracy	F1 Score
Logistic Regression	76.14	0.756
KNN	99.82	0.995
Decision Tree	99.30	0.992

TABLE I

resulted in very high number of samples. In this approach the readings were treated as samples i.e rows of dataset instead of columns of dataframe. Due to computational constraints we could not coalesce the entire dataset into one dataframe and used multiple dataframes to train multiple classifiers. At last, the coefficients of these classifiers are used to find the final coefficients.

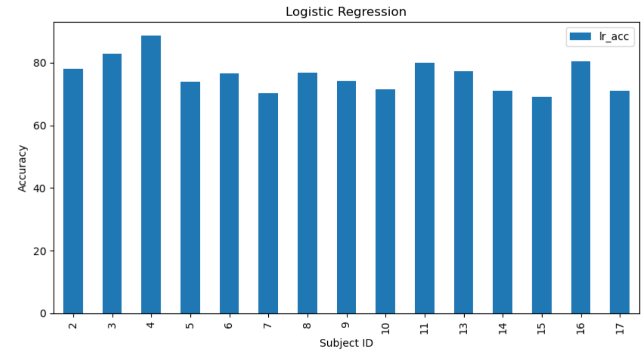

Fig. 2. Logistic Regression Accuracy

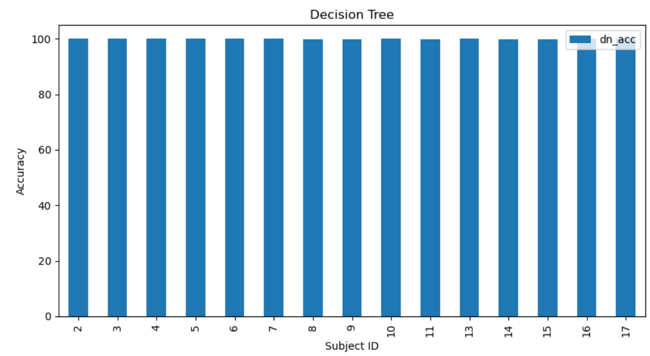

Fig. 3. Decision Tree Accuracy

V. Experiments

A. Training model using mean of features

We started with splitting each subject into 5 records corresponding to each of the stress conditions. For features we calculated the mean of the features and populated them against each class. This way be formed a dataframe of shape (90, 12). Using the transformed data we trained two classifiers using KNN and logistic regression. Using this approach we achieved a testing accuracy of 25%. This is because the number of samples required for training a 5 class classifier (as mentioned in section III.A) is higher than then what we had.

B. Training a binary classifier

To improve the accuracy of classification we treated stress condition as one class and all the rest as another class and trained a binary classifier. We achieved a higher accuracy of 85% using this approach, but the classifier was over-fitting the non-stress classes as the number of samples corresponding to non-stress classes were much higher than the stress condition.

C. Training a separate model for each subject

Since by calculating the mean of the features the number of samples were getting significantly reduced, we tried training multi-class classifiers using the raw dataset. While training a model without mean calculation we got a very high number of samples for each class but the memory requirement for training this classifier was much higher than what we had in our implementation environment i.e Google Colab. Hence, we trained different classifiers for different subjects and calculated the mean of accuracy to get the final performance of our classification. We trained three classifiers for each subject based on KNN, Logistic Regression and Decision Tree approach.

D. Features affecting stress class

We also tried to determine the factors which are contributing most towards the stress condition. For find these features we calculated the co-variance and correlation matrices. Using the values of correlation matrix we determined the major factors for stress and cross-validated using findings in [7].

VI. Results and Discussion

Table 1 illustrates the accuracy we achieved with different techniques. We achieved higher accuracy using KNN and Decision tree as compared to logistic regression. Decision tree of depth 33 and 2785 leaves gave the highest accuracy for dataset of shape (3663100, 10). But, since we took the training and testing samples from the same dataset, it over-fitted the dataset. KNN provided equivalent accuracy when compared to the Decision tree but the prediction time was significantly higher. Figure 2, 3 and 4 illustrates the subject wise prediction accuracy for Logistic Regression, Decision Tree and KNN respectively.

Furthermore, using the correlation matrix as depicted in figure 5, chest ACC, chest TEMP, wrist TEMP are the major factor affecting the stress condition.

VII. Conclusion

Using the WESAD dataset we trained multiple classifiers to predict the different stress conditions. We found provided the best accuracy when considering although the prediction time was relatively higher. Accuracy achieved with decision tree was also comparable to that of KNN but it over-fitted the training set. Also, we found the features (chest ACC, chest TEMP and wrist TEMP) which are affecting the stress condition the most.

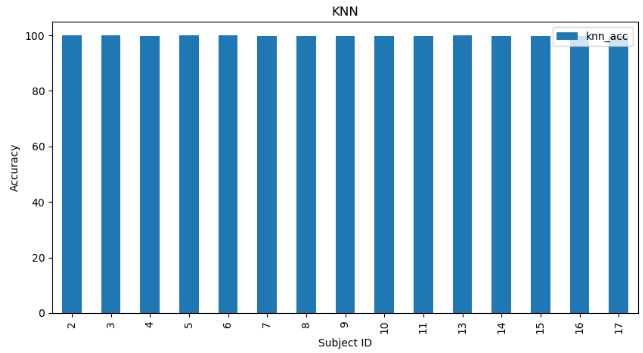

Fig. 4. KNN Regression Accuracy

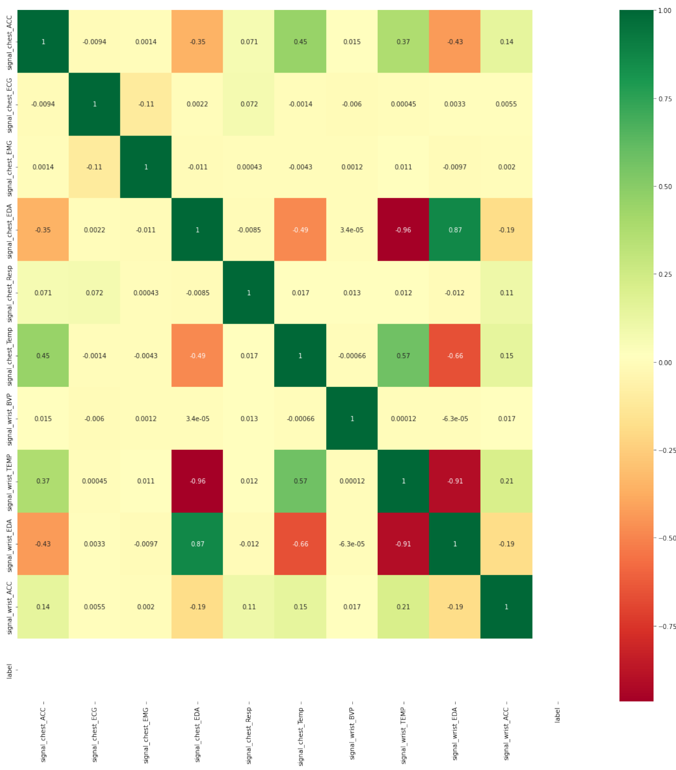

Fig. 5. Stress Condition correlation

VIII. Future Work

Although, we achieved highest accuracy with KNN, the prediction time is considerably high. In future, decision tree approach can be used with properly segregated training and test dataset so that it does not over-fit the training set. Also, the depth of the decision tree can be reduced after analysing all the internal nodes.

We trained different classifier for different subjects. Methods can be explored to combine these classifiers and generate a single final classifier which has the knowledge of all these pre-trained classifiers. Last, new classifiers can be trained using the features which affecting stress condition the most and verify if the original accuracy is preserved.

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