Stress Detection via Soft Keyboard Typing Behaviour using Smartphone Sensors and Ensemble Learning

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I. Motivation

Stress is how the body responds when we are facing a strenuous and challenging situation. This induces anxiety and pressure. The clinical definition of stress states that it is a state of extreme discomfort and distress.

The challenging situations are often referred to as ”stressors”. This is an event an individual is in which would lead to a heightened levels of stress in the body. Particularly in this fast-paced digital era an individual faces more of these challenging situations be it in real life or online. The information overload along with high-demand schedules has led to an alarming rise in stress levels among individuals. This rise in stress levels has been particularly high after the COVID-19 pandemic. If the feelings of stress left unattended can have a profound impact on both the mental and physical health of an individual [1].

Recognising the gravity of the issue, we need innovative solutions for detecting high levels of stress and then take proactive measures to alleviate it. For this, machine learning algorithms and smartphone technology has provided a promising avenue to detect stress.

The advancements in the smartphones has transformed them into an integral part of our daily routines. As of 2024, 91% of college students world-wide own a smartphone. And by the end of 2024 the number of smartphone users would reach 7.1 Billion[1].

Since the increase in the availability of these devices, smartphones can be utilized to detect stress levels in the users by collecting the data from the inbuilt sensors. In this project the main focus would be to collect data from two sensors, namely, accelerometer and gyroscope sensors in the devices. By utilizing the smartphones, this gives a non-invasive, readily available method to detect stress. But more research is needed in this particular field to achieve high precision of intrusive methods.

[1]https://whatsthebigdata.com/smartphone-stats/

II. Research Question

How can ensemble learning techniques, coupled with various feature selection methods, improve the performance of stress detection technique based on smartphone accelerometer and gyroscope sensor data derived from user’s soft keyboard typing behaviour?

III. Initial Review

This section briefly summarizes the work that has been done in the field of stress detection and the various methodologies leveraged by the researchers.

In [2], the authors conducted a survey on the application of machine learning in the systems that detect emotional and mental stress. They explored the connection between human biological features and mental stress and emotions and researched various machine learning algorithms employed for emotion and stress detection. Including feature extraction, datasets and class labels.

Elzeiny and Qaraqe [3] in their study developed and application to gather smartphone sensor data. The research focused on the accelerometer data only and was conducted on 30 participants to discern stress behaviour in their daily work setting. The users were asked to self-assess their stress levels as well on a 5-point scale throughout the standard office hours. 4 to 5 signified high levels of stress while 3 indicated moderate and 1 or 2 suggested low stress. The sampling rate for the sensor was limited to 5 samples per second to preserve battery life of the smartphones. They implemented Naive bayes and decision tree classification on the 34 features that were extracted from the the raw sensor data.

Using the smartphone sensors, [4] study worked on the ”StudentLife” dataset, which consisted of sensing data collected from smartphones of college students. They collected diverse data including audio recordings of surrounding noise, periods of silence, accelerometer data, along with a survey response of stress levels. The main focus of their research was to develop a stress detection model capable of classifying students’ perceived stress. For the classification they utilized random forest and Support Vector Machine (SVM) algorithms.

In [5] to tackle the issue of data scarcity while training machine learning models they proposed an approach of semi-supervised, ensemble methods and transfer learning to develop models for limited data. Their study involved 30 employees across two organizations. They concluded that moving away from intrusive high precision methods, smartphones sensors can effectively be used to detect stress of the user.

In the study conducted by Ahuja and Banga [6] focused on the stress in students leading up exam period. The data was sourced from the Jaypee Institute of Information Technology which included 206 participants. They implemented four different classification algorithms namely, Linear Regression, Naive Bayes, Random Forest and SVM and the performance of these algorithms were further enhanced by 10-fold cross validation. The performance was measured using, but not limited to, parameters like sensitivity and specificity. They concluded a high correlation between stress, internet usage and exam pressure, with the SVM model yielding the highest accuracy of 85.71%.

Focusing on the gyroscope and accelerometer data from the smartphones, the study conducting by Yuksel et al. [7] proposed a classification system using various machine learning techniques including ANN, k-nearest neighbours, random forest and SVM. Similar study was conducted by Sagbas et al. [8] collecting the data from the smartphone accelerometer and gyroscope data.

Taking a different approach, Yasufuku et al. [9] employed temperature sensors to gauge stress levels from the nasal skin temperature leveraging on the knowledge that the nasal skin temperature decreases with increase in stress due to the reduced blood flow from constricted blood vessels. They utilized the accelerometer along with three tempeature sensors in glasses to capture the relevant data.

In [10], the study proposed employing supervised learning for identification of stress levels in drivers. They utilized a dedicated sensing device, Skin Potential Response (SPR) and used Electrocardiogram (ECG) from the chest to collect the data from drivers during situations involving high levels of stress. To further enhance the machine learning performance they also implemented a motion artifact removal algorithm. Their research attained an accuracy of 88.13% in stress recognition through the LSTM model.

IV. Data Sources and Statistics

The data used for this project was sourced from a study conducted by Sagbas et al. [8]. The data collection process and subsequent data processing is meticulously detailed in their work. The raw data is publicly accessible though the google drive link. The accelerometer and gyroscope sensors in a smartphone along with touchscreen interactions are utilized to gauge user's stress levels based on the soft keyboard typing behaviour. This subsection details the sensors used and subsequently the methodologies employed by the original researchers in collecting and storing this raw data from the sensors.

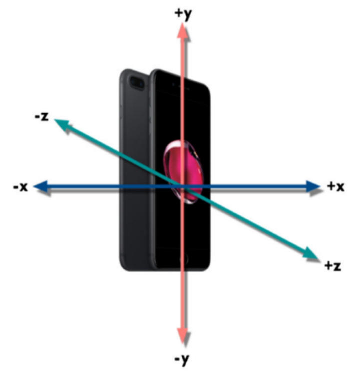

Fig. 1. Accelerometer Orientation [8]

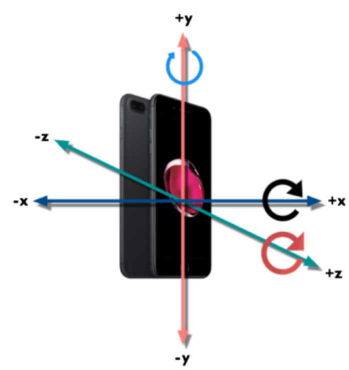

Fig. 2. Gyroscope Orientation [8]

The accelerometer measures the acceleration that is being applied to the smartphone and does so along the X, Y and Z axes. The units for this measurement is in m/s^2. Fig. 1 shows the direction and orientation of these axes with respect to the smartphone. The gyroscope measures the rotation along the same X, Y and Z axes. Fig. 2 describes the orientation of the spin and the axis direction. The raw data collected from the gyroscope in the three X, Y, Z planes is rad/s (radians/s) [7].

To collect the data, the original researchers designed a dedicated application for android smartphones. It comprised of four stages where the user had to complete specific tasks. These four stages are Non-stressful state from which the data is collected and stored, which is followed by the Stressor task, then the data collected from the stress state and finally Ground truth survey. The raw data is categorised for each participant (user) and stored in csv format.

Fig. 3 shows a screenshot of one of the stressor task to be completed by the participant in the allotted time.

The participants age and gender was also collected by the original authors. Fig. depicts the the age distribution of the participants. From the graph we can infer that majority of the participants for this study were in the age bracket of 18-24.

The original authors have made the raw data collected publicly available. For further data analysis in this project, the data data would be processed to create datasets that would be used for training the machine learning models. This raw data is split into separate csv files for each participant per each

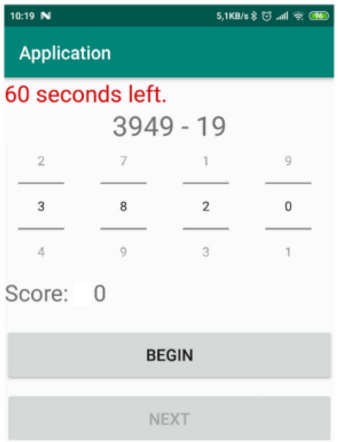

Fig. 3. Application screenshot [8]

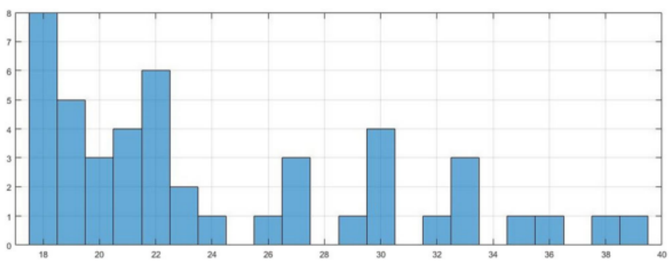

Fig. 4. Age distribution [8]

task, with the sample rate from the sensor being 20 samples per second.

For creating the datasets, they could be split into range of time windows i.e. 5s, 10s and 15s and the performance results would be compared for each of these datasets.

V. Machine Learning Methodology

For this project the focus in on the implementation of ensemble learning for the task of classification of stress. Different algorithms would be used including but not limited to random forest, k-nearest neighbours, logistic regression, SVM. Support vector Machine (SVM) is effective in handling non-linear relationships and it's versatility in datasets with high feature dimensions, along with this the logistic regression performs well by focusing on the contribution of individual features. While the k-NN would provide diversity by it's performance being high in localized patterns.

There has been work done to detect stress using smartphone sensors, the goal for this project is to improve the performance of these detection methods when combined together in ensemble techniques. Ensemble learning provides a diverse baseline of models and thus reduces the risk of overfitting. There are various methods for combining the models like bagging, averaging, boosting [11].

In recent years there have been an increase in research being done using ensemble learning techniques due to the high

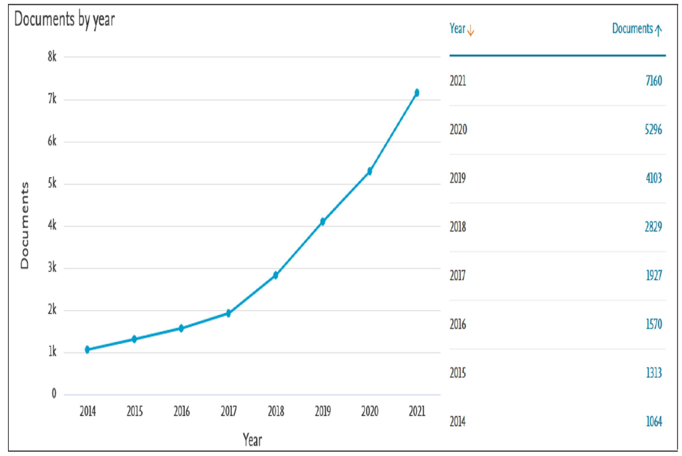

Fig. 5. Trend of search of "Ensemble learning" in "Scopus" from 2014 to 2021 [11]

effectiveness that is provides. Fig. 5 shows the increase in the search of the term "Ensemble Learning" in "Scopus".

The first stage of the project would include the implementation of these machine learning algorithms on the data and the performance gauged. The second step would be to use the combination of these above mentioned algorithms.

VI. Evaluating Strategy

The primary method for evaluating the performance of the model in this project would be a comprehensive set of predictive performance metrics. Along with accuracy, precision and recall, specificity and f-measure metrics would also be used. The following are the formulas for the above mentioned metrics:

$$\text{Accuracy} = \frac{\text{True Positives} + \text{True Negatives}}{\text{Total Population}} \tag{1}$$

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives + False Positives}} \tag{2}$$

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives + False Negatives}} \tag{3}$$

$$\text{F-measure} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision + Recall}} \tag{4}$$

$$\text{Specificity} = \frac{\text{True Negatives}}{\text{True Negatives + False Positives}} \tag{5}$$

Further, specificity would be able to access the model's ability to identify negative instances from all the actual negative instances. This metric would compliment the recall by having a main focus on the accurate identification of the negative instances. And F-measure would offer a consolidated metric for both precision and recall. These together would give a balanced evaluation and avoid undue emphasis on any one single metric. By this, the model's performance will be evaluated from various dimensions.

For sampling the data to measure and train the model there are various ways including n-fold cross validation and random subsampling.

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