International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 8s
DOI: https://doi.org/10.17762/ijritcc.v11i8s.7217
***Article Received**: 28 April 2023 **Revised:** 15 June 2023 **Accepted:** 30 June 2023*

Machine Learning based Stress Detection using Keyboard Typing Behavior

Abhishek Chunawale[1], Dr. Mangesh Bedekar[2]
[1]School of Computer Engineering and Technology
Dr. Vishwanath Karad MIT World Peace University
Pune, India
e-mail: abhishek.chunawale@mitwpu.edu.in
[2]School of Computer Engineering and Technology
Dr. Vishwanath Karad MIT World Peace University
Pune, India
e-mail: mangesh.bedekar@mitwpu.edu.in

Abstract—Emotion detection is one of those areas where technological advances have brought about significant changesin the human lifestyle. During COVID-19 pandemic, due to the work from home culture, use of computers and laptop was suddenly increased. Introduction of digital environments gave it a whole new dimension. Emotion detection is a virtual or computerized way to detect stress. People suffer from various kinds of stress in day to day activities and it is directly connected to their performance. The stress factor can be expressed through a number of ways and human behavior. The way in which humans interact with the computer can reveal the emotional state of the user, mainly the stress. Keyboard typing behavior or characteristics can be used for stress detection. This paper focuses on understanding typing behaviour of human and indicate their stress level. Relevant features are extracted from typing behavior of a user and used for training machine learning models for detection of stress. K-Nearest Neighbor algorithm gave highest accuracy of 84.21% with dimensionality reduction approach.

Keywords- Machine Learning; Stress Detection; Emotion Recognition; Keyboard Typing Behavior

I. INTRODUCTION

Stress detection in human beings is nowadays a very important research topic. It also resulted in a noteworthy rise in the search for applications and devices to detect and measure real time stress. Affective Computing provides a platform for stress detection, where stress can be assessed and accordingly the person will be given a response to reduce stress.

A lot of research has been carried out to detect human emotion through implementation of various methods, such as physiological signals, human body parameters and facial expressions. These methods need specific hardware devices and sensors for data capture and experimental setup. A new approach for measuring stress is to monitor human behaviors that are influenced by stress without disturbing the normal activities. Some researchers suggested easier methods such as use of mouse and keystroke analysis for detecting human affective and emotional state, specifically the stress [1].

Monitoring computer mouse and keyboard dynamics can be used to measure stress. Mouse dynamics cover speed, number of clicks and frequency of movement. It was observed that during stressed situations, the mouse speed and acceleration is increased, which causes less precise movements. Keyboard dynamics depend on latencies of the typing and keystrokes. Every individual shows different typing behaviors over time that are also affected by stress. Thus, mouse and keyboard dynamics reveal ample behavioral information about the emotional/affective state of the user [2].

This paper focuses on extracting some interesting features from the typing pattern of users through the keyboard that can be utilized for detecting stress, specifically the cognitive stress produced at the time of some mental activity for example; solving mathematical calculations in some restricted time limits. This is just for understanding the relation between user behavior and keyboard typing characteristics, because when there is pressure to solve the mathematical questions in a given time duration, the person will be stressed out and normal typing patterns will get changed. Thus human stress can be identified from keyboard input when some sort of typing work is going on.

II. LITERATURE SURVEY

The authors of [3] explored an alternate method to stress detection which is unobtrusive and cost-effective. Cognitive stress is monitored through keyboard interactions of the user to detect subsequent changes in cognitive and physical state of that user. Participants of the study were made to write paragraphs when they are and are not stressed and the machine learning models were trained according to the data recorded during stressed and non-stressed states. Algorithms used in

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 8s
DOI: https://doi.org/10.17762/ijritcc.v11i8s.7217
***Article Received**: 28 April 2023 **Revised:** 15 June 2023 **Accepted:** 30 June 2023*

their experiments included Support Vector Machine (SVM), K-Nearest Neighbor (KNN), and Decision Tree.

Another paper mentioned an e-learning system consisting of learner and agent. The agent responds to the learner based on activities of the learner. For instance, the agent may use music, animations, etc. to try to make the learner calm if it notices that they are becoming fatigued; and thus alert a disengaged learner. The pedagogical agent would periodically ask for vocal feedback while also continuously monitoring the learner's mental state through keyboard usage and mouse clicks during the learning process. After that, it would give instructions tailored to the subject's mental state. For instance, if the learner is feeling tired out, the agent will ask him/her to take a break or rest [4].

Authors of paper [5] used Fuzzy logic to build an intelligent emotion extraction engine that is able to identify complex emotional states from the textual contents. The engine was built on real-world vocabularies and keyword tagging that can categorize happiness, sadness, surprise, fear, disgust and anger.

The paper [6] consists of a survey of newly emerging stress assessment methods and approaches focusing particularly on those that are suited for the workplace which is one of the major sources of stress. The analysis of the keystroke dynamics, or rhythm of typing pattern, on a conventional keyboard, is used to solve the challenge raised above. The study of keyboard typing habits of people when using computers is known as keystroke dynamics. Additionally, keystroke timing parameters like typing speed, key press duration, the interval between key presses, etc. are extracted. While experiencing an unpleasant emotion, typing speed decreases for an individual.

Some approaches categorize the text by understanding its context or meaning. A user's emotional state (e.g. stress) can also be identified through keyboard typing patterns.

The authors of [7] have done emotion recognition by using a soft-keyboard available in smart phones by collecting sensor data when a user is actually typing on a soft-keyboard. While typing, a user was prompted to state his/her current emotional state and sensor data from the smart phone was simultaneously tagged with the existing emotional state of that particular user. After collecting sufficient data, machine learning classifiers were modeled to predict the user's current emotional states based on their current typing pattern. Authors derived a set of feature vectors such as average acceleration, average time lag between letter typing, number of times backspace key pressed and the related user emotion from the typing pattern of each user. The acceleration and time lag were calculated from sensor data of smart phone.

The authors of [8] used a multi-task learning based neural network which is trained to identify different emotions using the representation automatically learned from the raw keyboard interaction pattern. They collected interaction data from 24 subjects through a customized keyboard and captured touch speed, error rate, pressure and emotion category (happy, sad, stressed and relaxed) reported by the users. Authors achieved an average accuracy of 84% for distinguishing different emotions.

The study mentioned in [9] included keyboard and mouse data collected from 62 volunteers through a web application, developed specifically to cause stress by challenging each user to do 8 computer-related tasks under various stressful circumstances. Random Forest (RF) classifier was used for classifying 3 classes of stress-level from keyboard with accuracy of 76% and mouse with 63% accuracy.

III. PROPOSED SYSTEM

Our proposed solution is a web-application for users that they open on their laptop/computer, select stress level and type meaningful paragraphs for data collection. The typed data is used to calculate features like pause rate, shift key rate, positive words, negative words, adjectives etc. After data collection and feature extraction, Machine Learning models are trained for stress prediction and finding the accuracy. Lastly, we integrate the trained model with our web application to alert the user whenever typing behavior suggests he/she is under stress. Figure 1 shows the proposed system for stress detection through the keyboard.

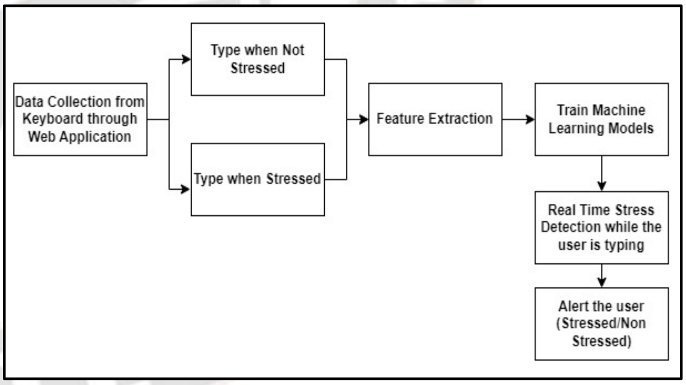

Figure 1. Proposed system for stress detection through keyboard

A. Data Collection

We have taken care related to following points while collecting data:

1. *User has a laptop/desktop with a functional keyboard.*
2. *User will converse in English.*
3. *Users do not have a problem with being cognitively drained during data collection.*
4. *User selects the stress level properly and honestly.*
5. *User does not give his account to some other person to type on his/her behalf.*

6. *Users agree to share their information insights with us.*
7. *Willing participants of different gender and age groups who were ready to volunteer for the process of data collection.*

Since we need the user's typing pattern when under stress too, we also provided certain tasks he/she can do in order to feel cognitively stressed and speed up the process of stress induction rather than depending on natural processes. Machine Learning models are needed that are personalized based on each user's input. Hence, to get personalized recommendations, training the models by identifying which user has input which data, a login system is needed.

B. Interactions

The user would first have to create an account by signing up. Then they can login and a web token is created that stores the user's info. This token is stored in the browser's local storage. It expires in 7 days and hence the user does not have to login again for the next 7 days ensuring a smooth user experience. Figure 2 shows the user interface to choose between cognitive stress induction or typing data or stress detection.
After logging in, the user is given three options:

1. *To perform a stress inducing task*
2. *To type data under their current level of stress*
3. *To type data which will be used for stress prediction*

Figure 2. Option to choose between cognitive stress induction or typing data or stress detection

If the user chooses to perform a stress inducing task, they are taken to a different screen where they are made to play a cognitively intensive arithmetic game which is likely to increase their stress level. Then the user can go back to the type data screen in order to record new data under their new level of stress. Figure 3 shows instructions for a user undergoing a stress inducing task.

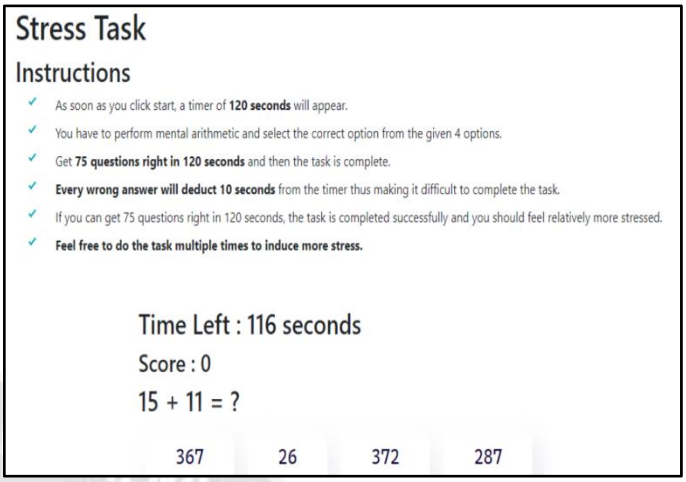

Figure 3. A user undergoing a stress inducing task

If the user chooses to type data, they are taken to a new screen where they can select their level of stress by a slider bar and then type data in the text box provided as shown in Figure 4. Their data is recorded and once they hit the "submit" button, a POST request is made to the backend where the user's data is sent in the request body. More features are calculated based on the user's data and are stored as an entry into the database.

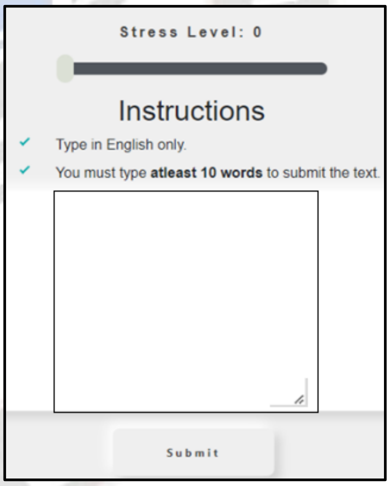

Figure 4. Option to select cognitive stress level and typing data under selected stress level

After sufficient data collection, entries from the database can be extracted as a csv file and this csv can be used to train Machine Learning models so as to predict stress occurrence in the future. Whenever stress is detected, the user will be alerted. If the user chooses the stress detection option, he/she will type the data in the text box provided and using the features that are calculated in the backend and the Machine Learning model, his/her stress level will be displayed as an alert in the User Interface as shown in Figure 5 below.

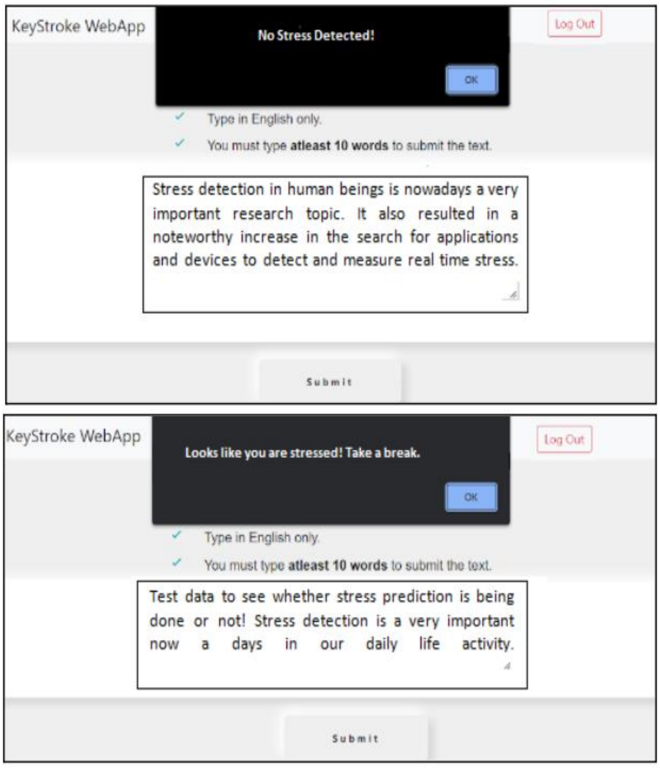

Figure 5. Testing typed data for stress detection and displaying alert with the prediction

IV. RESULTS

Machine Learning models were trained based on dimensionality reduction and feature engineering. The features that are extracted from the typed data are as follows:

Conjunction Rate, Positive Word Rate, Adjective Rate, Arrow Key Rate, Average Pause Length, Noun Rate, Punctuation Key Rate, Lexical Diversity, Sentence Ending Punctuation Key Rate, Verb Rate, Pause Rate, Adverb Rate, End Key Rate, Space Key Rate, Total Input Time, Shift Key Rate, Time Per Keystroke, Average Sentence Length, Negative Word Rate, Average Word Length, Other Key Rate, Adjusted Time Per Keystroke, Enter Key Rate, Backspace Key Rate.

Stress detection and typing behavior are very much related to each other, because when a person is stressed out, normally that person is quite angry, and in that situation, either the person presses the keyboard keys very hard as well as makes many mistakes while typing. So ultimately, the typing pattern of the person also changes. Figure 6 shows heat map for above mentioned features to understand correlation between them.

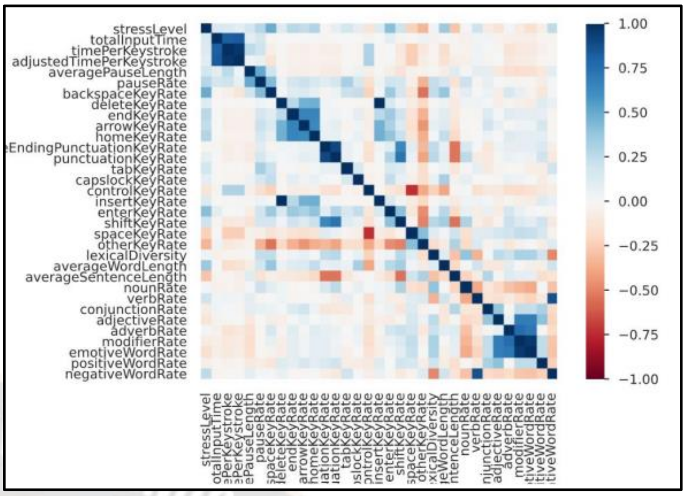

Figure 6. Heat map for features

Moreover, to solve the correlation issues of data points in the features, we performed principal component analysis (n_component = 20) to reduce the dimensions as well as interaction between features in the same data plane, therefore reducing overfitting and making the execution more concrete. Figure 7 shows correlations between features.

Figure 7. Correlations image from data report

Based on all the extracted features and trained machine learning models, we tested our model for real time data. The accuracy that we obtained for various machine learning models are as mentioned below in Table 1 and 2. Accuracy comparison graph of KNN, Logistic Regression (LR), RF and SVM is presented in Figure 8. Best accuracy yield is achieved from KNN algorithm. By analyzing the data, we came across most important features that would yield best results by dimensionality reduction.

TABLE I. ACCURACY OF DIFFERENT MODELS IMPLEMENTED USING PRINCIPAL COMPONENT ANALYSIS (DIMENSIONALITY REDUCTION)

Sr. No.	Machine Learning Model	Accuracy
1	KNN	84.21%
2	LR	78.94%
3	RF	52.63%
4	SVM	78.94%

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 8s
DOI: https://doi.org/10.17762/ijritcc.v11i8s.7217
***Article Received**: 28 April 2023 **Revised:** 15 June 2023 **Accepted:** 30 June 2023*

TABLE II. ACCURACY OF DIFFERENT MODELS IMPLEMENTED USING FEATURE ENGINEERING

Sr. No.	Machine Learning Model	Accuracy
1	KNN	70.45%
2	LR	61.36%
3	RF	68.18%
4	SVM	56.81%

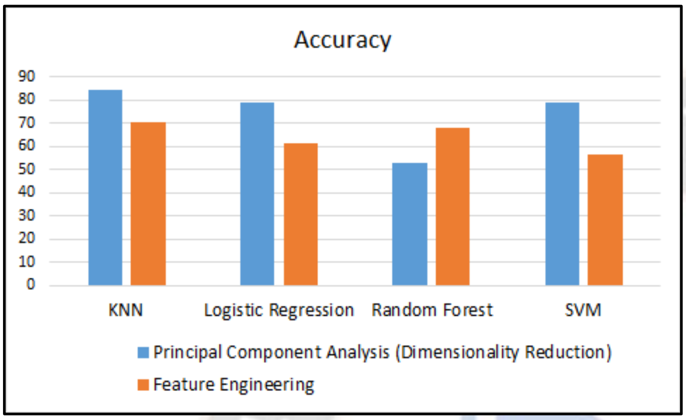

Figure 8. Accuracy Comparison of KNN, LR, RF and SVM

V. CONCLUSION

Research indicates that a person's typing behavior can be analyzed to detect stress at early stages. As stress increases, performance generally increases and then decreases. Keystroke based stress detection is cost effective as well as unobtrusive as compared to other techniques. The features that we extracted from typing behavior analysis were correlated with each other. We used KNN, Logistic Regression, RF and SVM algorithms for training and testing. We also used Principal Component Analysis for dimensionality reduction and it was observed that it gave better results than feature engineering. Out of the algorithms, KNN gave the highest accuracy of 84.21%. Our proposed work is aimed at detecting only cognitive stress. Future work can focus on recognizing physical stress as well as a plethora of other emotions. It can also be integrated into daily activities through monitoring devices to detect early signs of stressed conditions or emotional uncertainty of a person.

REFERENCES

[1] Zimmermann, Philippe, et al. "Affective computing—a rationale for measuring mood with mouse and keyboard." International journal of occupational safety and ergonomics 9.4 (2003): 539-551.

[2] Hernandez, Javier, et al. "Under pressure: sensing stress of computer users." Proceedings of the SIGCHI conference on Human factors in computing systems. ACM, 2014.

[3] Vizer, L. M., Zhou, L., & Sears, A. (2009). Automated stress detection using keystroke and linguistic features: An exploratory study. International Journal of Human-Computer Studies, 67(10), 870-886.

[4] Kumar, N. V. M. ., Raju, D. N. ., PV, G. ., & Subhashini, P. (2023). Real-Time User-Service Centric Historical Trust Model Based Access Restriction in Collaborative Systems with Blockchain Public Auditing in Cloud. International Journal of Intelligent Systems and Applications in Engineering, 11(2s), 69–75. Retrieved from https://ijisae.org/index.php/IJISAE/article/view/2509

[5] B. Kabi, A. Samantaray, P. Patnaik and A. Routray, "Voice Cues, Keyboard Entry and Mouse Click for Detection of Affective and Cognitive States: A Case for Use in Technology-Based Pedagogy," 2013 IEEE Fifth International Conference on Technology for Education (t4e 2013), 2013, pp. 210-213, doi: 10.1109/T4E.2013.57.

[6] S. B. Sadkhan and A. D. Radhi, "Fuzzy Logic used in Textual Emotion Detection," 2017 Second Al-Sadiq International Conference on Multidisciplinary in IT and Communication Science and Applications (AIC-MITCSA), 2017, pp. 242-245, doi: 10.1109/AIC-MITCSA.2017.8722967.

[7] Carneiro, D., Novais, P., Augusto, J. C., & Payne, N. (2017). New methods for stress assessment and monitoring at the workplace. IEEE Transactions on Affective Computing, 10(2), 237-254.

[8] I. Zualkernan, F. Aloul, S. Shapsough, A. Hesham, and Y. El-Khorzaty, "Emotion Recognition Using Mobile Phones", Department of Computer Science and Engineering American University of Sharjah, UAE, Computers and Electrical Engineering, vol.60, pp., 1-13-2017.

[9] S. Ghosh, S. Goenka, N. Ganguly, B. Mitra and P. De, "Representation Learning for Emotion Recognition from Smartphone Keyboard Interactions," 2019 8th International Conference on Affective Computing and Intelligent Interaction (ACII), 2019, pp. 704-710, doi: 10.1109/ACII.2019.8925518.

[10] L. Pepa, A. Sabatelli, L. Ciabattoni, A. Monteriù, F. Lamberti and L. Morra, "Stress Detection in Computer Users From Keyboard and Mouse Dynamics," in IEEE Transactions on Consumer Electronics, vol. 67, no. 1, pp. 12-19, Feb. 2021, doi: 10.1109/TCE.2020.3045228.