Advances in Computer Engineering and Science (ACES)
(2026)
Volume -1, Issues – 1

A Real-Time Personalized Stress Detection System Using Keystroke Dynamics

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***Abstract*: Stress at the workplace is a growing issue in the contemporary digital world where people spend a great deal of time communicating with computers. The constant stress may have a detrimental impact on the productivity, ability to make decisions, and well-being. Conventional stress detection methods are usually based on web sensor or web-based questionnaires which can be obtrusive, costly or inappropriate to monitor continuously. To overcome these shortcomings, this study suggests a real-time stress detection system using keystroke dynamics and machine learning methods. The types of behaviour analysed by the proposed system include key hold duration, speed of typing, latency between typing and error frequency to determine patterns of typing with regard to stress conditions. The behavioral characteristics are fed into and trained with machine learning models that are able to differentiate stressed and non- stressed states. A real time monitoring dashboard is also created to visualise stress indicator and give meaningful insight on user behaviour. The system is non-intrusive and scalable to stress monitoring as it can be run without the need of extra hardware. Experimental assessment reveals that typing behavioral analysis is viable in identifying stress patterns and aiding in early stress detection of mental strain among computer-based work set ups.**

KEYWORDS

Keystoke Dynamics, Psychological stress Detection, Machine Learning Classification, Behavioral Biometrics, Real-Time User Monitoring, Huma-Computer Interaction

I. INTRODUCTION

Psychological pressure has become a usual phenomenon in the contemporary electronic work environments where people spend much of their time in contact with a computer. constant workloads, multi-tasking demands and tight deadlines may cause psychological stress. Unless stress is detected at an early age, it can have a harmful impact on the productivity, decision-making capacity, and well-being of the individuals in general. Hence, the creation of effective ways of tracking and identifying the stress levels among the computer users has emerged as a major area in research. The traditional stress detection method predominantly uses a physiological sensor which could be heart rate monitors, electroencephalography, or skin conductance sensors. These techniques might be used to give dependable measurements but they typically need more hard ware equipment and can be uncomfortable to usability when used in long term measurements [1].

Also, stress assessment is often conducted in the form of questionnaire-based tests. Nevertheless, such mechanisms are disruptive to user interactions, and rely extensively on subjective reactions, which can make them less accurate and less useful in real-time contexts. According to recent developments in the field of behavioral analytics and human-computer interaction research, typing behavior could be used to obtain rich information about the cognitive and emotional state of a user typing. keystroke dynamics. The study of typing patterns, including the length of key presses, time interval between consecutive key presses, typing rhythm, and typing speed. These patterns can vary to reflect variations in mental workload and stress level. As the keyboards are already a part of the modern computer usage, the analysis based on the keystroke is an anon-intrusive and cost-effective alternative to monitor the stress, without any extra sensors. In this research. A keystroke dynamic and machine learning-based stress detection system is proposed as real-time. It captures typing information in the course of regular computer use and extracts behavior features which are patterns of interaction between the user. Machine learning algorithms are then used to analyze these

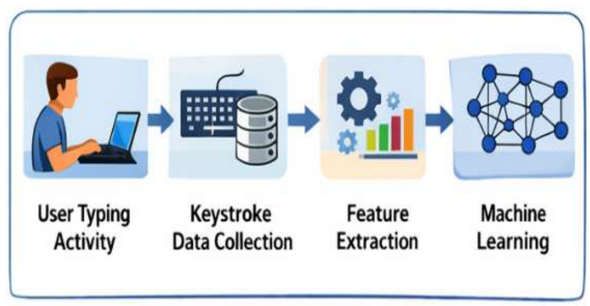

Figure 1 : Framework of proposed research work

features to classify stress conditions. Moreover, real-time monitoring dashboard is implemented to help visualize stress indicators and generate meaningful insights to users and administrators. The proposed solution is expected to offer a scalable and effective solution to the long-term monitoring of stresses in online environments. Through behavioral data analysis and machine learning models, the system will be able to recognize patterns of stress with high accuracy and user privacy without causing overload to the system [2].

II. LITERATURE REVIEW

Stress detection has been widely studied in recent year due to the growing impact of mental stress on productivity and health. Researchers have explored several approaches to identify stress levels using physiological signals, behavioral analysis, and machine learning techniques[3]. Early studies mainly focused on physiological signal analysis to detect stress conditions. Methods based on heart rate variability, electroencephalography (EEG), and skin conductance. Have shown promising results in identifying stress level. These techniques can provide accurate measurements of physiological changes associated with stress. However, they often Require wearable sensors or specialized medical devices, which may cause discomfort to users and limit their usability in everyday working environments. With the advancement of human-computer interaction research, behavioral biometrics have gained attention as an alternative approach for stress detection. Among these techniques, keystroke dynamics has widely studied because it reflects subtle changes in a user's Cognitive and emotional state. Researchers have observed that typing behavior, including typing speed, key hold duration, and time intervals between keystrokes, tends to vary when individuals experience stress or increased mental workload.

Several machine learning techniques have been applied to analyze typing patterns for stress detection. Traditional algorithms such as support vector Machines[4], Decision Trees, and Naïve Bayes classifiers have been used to classify behavioral date collected from keyboard interactions. These models can identify patterns in typing rhythm and error frequency to differentiate between stressed and non-stressed conditions. More recent studies have explored the use of advanced machine learning and deep learning techniques to improve classification accuracy. Models such as Random Forest, Gradient Boosting, and Neural Networks have demonstrated better performance in handling complex behavioral datasets. These approaches can capture non- linear relationships between typing features and stress levels, making them suitable for behavioral data analysis[5].

Despite these advancements, many existing systems focus primarily on offline analysis and experimental datasets. In practical environments, continuous real-time monitoring is required to provide timely insights into user stress levels. Additionally, many systems use generalized models that do not consider individual differences in typing behavior, which may reduce prediction accuracy. To address these limitations, this study proposes a real-time stress detection system based on keystroke dynamics and machine learning techniques. The proposed approach focuses on analysing typing behavior in real time while adapting predictions to individual user patterns. By integrating data collection, machine learning analysis, and visualization through a monitoring dashboard, the system aims to provide a scalable and non-intrusive solution for stress monitoring in computer-based work environments[6].

III. PROPOSED SYSTEM

The proposed system seeks to identify the level of psychological stress of computer users based on the typing behavior in real-time. The system makes use of keystoke dynamics and machine learning to detect changes in typing patterns, which can be used to show stress condition. In comparison to the classical methods of stress detection relying on either physiological devices or questionnaires, the suggested framework is completely software-based, and it does not involve the use of additional hardware. The design of the proposed system is made up of several functional units that collaborate to obtain typing data, process behavioral

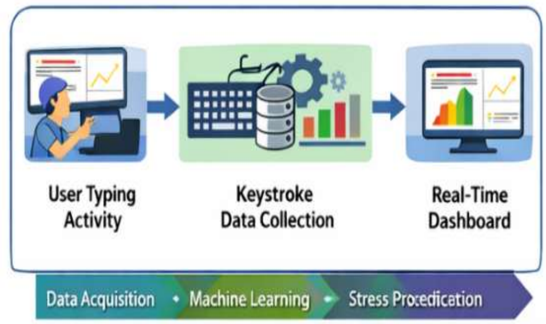

Figure 2 : Overview of proposed work

features, and produce stress prediction. The first is a lightweight background module which captures events of keyboard interaction during normal computer usage. It only records timing information like the key press and release times, so that the text that has actually been typed in by the user is not recorded, and thus the privacy of the user is preserved. Once the data on the keystroke is collected, the system then extracts the features with the aim of establishing meaningful behavioral characteristics. Critical typing parameters such as dwell time, which describes the period by which a key is held down and flight time which describes the time interval between two successive key presses. The typing speed, the pause time and correction action frequency are also investigated. All these characteristics are the typing behavior of the user and are input data in machine learning models[7].

The features obtained are then subjected to supervised machine learning algorithm to classify stress levels. Random Forest and other ensembled-based algorithms can be useful to extract the complex patterns of behavior and offer reasonable predictive accuracy when the trained model is used to compare the patterns of typing with the learned patterns to decide whether the user is stressed or working under normal conditions. To offer useful usability, the system incorporates a real-time monitoring interface which shows stress indicators using visual dashboard enables users or administrators to perceive trend of stress, behavioral patterns and prediction of the system. The proposed system can be used to effectively monitor stress computer-based environments by integrating continuous data acquisition, machine learning processing with interactive visualization to offer an efficient and scalable solution to the current problem. In general, the suggested system provides a non-invasive and economic data analysis, the model enables constant monitoring without disrupting users and no extra sensory gadgets are needed [8].

IV. RESEARCH METHODOLOGY

The research methodology describes the systematic process used to design, implement, and evaluate the proposed stress detection system. The methodology includes several stages such as data collection, features extraction, model training, and performance evaluation. These stages help in transforming raw typing data into meaningful information that can be used for stress classification.

4.1 Data Collection

The initial phase of the methodology is gathering typing data of the users in the normal interactions with the computer. Background monitoring component records keyboard event e.g. key press and key release timestamps. Only timing information of keystroke is recorded by the system and the actual typing of the user is not, which contributes to privacy and security. Typing sessions are captured as users use the computer to accomplish daily chores like writing texts, browsing or coding. The data collected has various typing session that reflect various working conditions. The datasets are subsequently pre-processed to eliminate unfinished record, noises and abnormal typing occurrences [9].

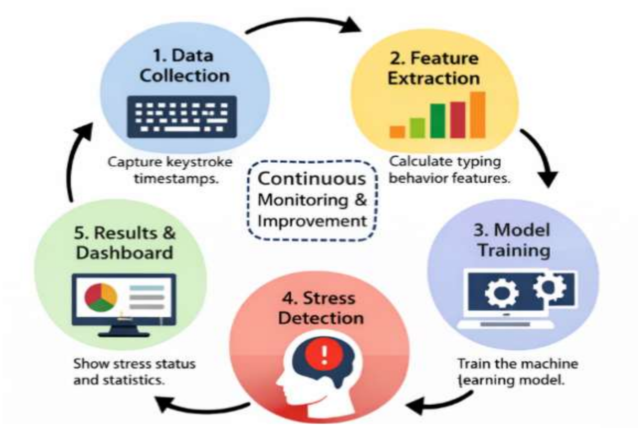

Figure 3 : workflow of proposed research work

4.2 Feature Extraction

A filter data collection, key behavioral characteristics are determined out of the raw keystroke logs. Such characteristics are typing patterns which might change during various stress conditions. A few of the features that are usually extracted are:

- **Dwell Time:** Time spent in holding a key.
- **Flight Time:** Time between releasing a key and pressing another key.
- **Typing Speed:** The nuber of characters typed per minute.
- **Pause Duration:** Idle time between typing activities.
- **Error Rate:** How often corrections are made e.g. use of backspace.

These are the features extracted of the input dataset that is used in the training of machine learning models.

4.3 Model Training

Once the features are prepared, machine learning algorithms are plied to classify stress level. Supervised learning techniques are used to train models using labelled that represented stress and non-stressed condition. Algorithm such as Random Forest, Decision Trees, or other classification models are suitable for analysing behavioural datasets. The training process enables the model to learn relationship between typing features and stress levels. After training, the model can predict stress conditions when new typing data is provided as input.

4.4 Model Evaluation

- To evaluate the performance of the trained model, the dataset is divided into training and testing subset. The model predictions are then compared with the actual stress labels.
- Performance metrices such as accuracy, precision, recall, and F1-cscore are used to measure the effectiveness of the system
- Cross-validation techniques are also applied to ensure the reliability and stability of the model across different datasets.
- Overall, the research methodology provides a structured framework for collecting behavioral data, processing typing features, training machine learning models, and evaluating the stress detection system.

V. IMPLEMENTATION

The implementation phase focuses on developing the stress monitoring system using software tolls and machine learning techniques. The system is implemented using the Python programming language due to its flexibility and strong support for data analysis and machine learning libraries. The main objective of the implementation is to capture typing behavior, process the collected data, and provide real-time stress monitoring through a user-friendly interface.

5.1 Development Environment

The system is developed using Python along with several supporting libraries. Libraries such as Pandas and NumPy are user for data processing and feature extraction, while Scikit-learn. It used to implement machine learning algorithms for stress classification. The graphical user interface is developed using Streamlit, which allows easy visualization of typing patterns and stress prediction results. The application is executed within a virtual environment to, manage dependencies effectively. The development process is carried out using tools such as Visual Studio Code or similar integrated development environments

5.2 Keystroke Data Capture

A keyboard monitoring module is implemented to capture typing events during user interaction with the system. The module records the timestamp of key press and key release events in real time. These events are stored temporarily and later converted into structured datasets. The system ensures that only timing information related to keystrokes is captured. The actual text typed by the user is not recorded, which protects user privacy and ensures ethical data collection practices.

5.3 Feature Processing

The collected keystroke data is processed to calculate behavioral typing features. Algorithms are implemented to compute dwell time, flight time, typing speed, and pause durations from the raw keystroke logs. These features are then organized into a structured dataset that can be used for machine learning analysis. Data preprocessing techniques such as normalization and removal and removal of incomplete records are applied to improve data and model performance.

5.4 Machine Learning Integration

A machine learning model is integrated into the system to classify stress levels based on extracted typing features. The model is trained using historical typing datasets that represent different stored and used to predict stress levels when new typing data is received. The prediction results are generated in real time and used to identify whether the user is experiencing normal or stressed typing behavior.

5.5 Dashboard Visualization

To make the system interactive and easy to understand, a web-based dashboard is implemented using Streamlit. The dashboard displays stress prediction results, typing statistics, and graphical representations of typing patterns. Users can observe stress levels dynamically while typing. This visualization component helps users understand behavioral patterns and provides an intuitive interface for monitoring stress levels. Overall, the implementation combines real-time data collection, machine learning analysis, and interactive visualization to create a practical stress monitoring system for computer users.

VI. Results and Analysis

The results and analysis section evaluates the performance of the proposed stress monitoring system. The system was tested using typing datasets collected from users during normal computer interactions. The dataset was divided into training and testing sets to measure the performance of the machine learning model in predicting stress levels.

6.1 Model Performance

After training the machine learning model with the extracted typing features, the system was evaluated using standard performance metrics such as accuracy, precision, recall, and F1-score. These metrics help in measuring how effectively the model can identify stressed and non-stressed typing behavior. The experimental results show that the proposed system can successfully classify stress levels based on typing dynamics. The Random Forest classification model demonstrated better performance compared to other traditional models due to is ability to handle complex behavioral data patterns.

6.2 Performance Metric Value

The results indicate that the model can reliably detect stress conditions with high accuracy. The combination of keystroke dynamics and machine learning techniques improves the prediction capability of the system.

6.3 Behavioral Pattern Analysis

Typing behavior changes significantly when users experience stress. The analysis show that stressed users often exhibit irregular typing patterns, including increased pause durations, inconsistent typing speed, and higher error rates. These variations are effectively captured through extracted features such as dwell time and flight time. The machine learning model learns behavioral differences and uses them to classify the stress state of users. The results confirm that typing dynamics can serve as a useful behavioral indicator for stress detection[10].

6.4 System Efficient

Another important factor evaluated in the system is real-time performance. The proposed system processes typing data quickly and provides stress predictions without noticeable delay. The integration of a lightweight data processing module and efficient machine learning algorithms ensures smooth system performance. The Streamlit-based dashboard provides real-time visualization of typing patterns and stress predictions. This allows users to monitor stress levels continuously while interactions with the system. Overall, the experimental results demonstrate that proposed stress monitoring system is capable of identifying stress conditions accurately and efficiently using typing behavior analysis.

Table 1 : Performance analysis of detection methods

Measures	RF	NB	SVM
Accuracy	92.14	93.58	94.65
precision	90.94	91.58	94.10
Recall	91.12	93.78	93.28
F1-Score	90.17	90.57	94.87

VII. CONCLUSION

This study reports the use of software-based stress monitoring system which measures the level of stress among users of computers through typing behavior. The solution proposed in the paper applies the concept of keystroke dynamics and machine learning in recognizing typing pattern variations which can be used to detect psychological stress. The system is able to model behavioral changes with respect to stress by capturing timing data (dwell time, flight time, typing speed, and pause duration) which can be utilized.

The experimental outcomes show that the suggested system will be able to classify stress conditions with high level of accuracy. The machine learning model could learn the behavioral patterns based on the typing data collected and give an accurate prediction. Moreover, the system does not need any extra hardware devices and therefore, it is a non-invasive and cost-effective solution to stress monitoring. Introducing a real-time dashboard with the help of Streamlit allows constantly visualizing typing statistics and stress predictions. It is an interactive interface which enables users to track their stress levels while using the computer and use it to track the behavioral patterns over time.

Comprehensively, the suggested system shows that typing dynamics can be applied as a viable measure of stress identification in computer-based settings. The strategy offers an effective architecture to combine behvioral data analysis with machine learning to aid stress applications.

To improve the system in future work, it is possible to gather larger and more varied datasets that can contribute to the better precision of the model. Other behaviofal characteristics like patterns of mouse movement and typing rhythm analysis can also be added to enhance stress detection rhythm analysis can also be added to enhance stress detection performance. Additionally, more sophisticated deep learning algorithms can be considered to learn more intricate behavioral patterns and make more accurate predictions.

REFERENCES

[1] M. Paniagua-Gómez and M. Fernandez-Carmona, "Trends and challenges in real-time stress detection and modulation: The role of the iot and artificial intelligence," *Electronics,* vol. 14, no. 13, p. 2581, 2025.

[2] R. Asekneye and A. Agatha, "Adaptive User Interface Design Based on Keystroke Dynamics for Enhanced Digital Well-being," *Big. D,* vol. 2, no. 3, pp. 23-31, 2025.

[3] L. Yang and S.-F. Qin, "A review of emotion recognition methods from keystroke, mouse, and touchscreen dynamics," *Ieee Access,* vol. 9, pp. 162197-162213, 2021.

[4] A. Sultanov and K. Kogos, "Insider threat detection based on stress recognition using keystroke dynamics," *arXiv preprint arXiv:2005.02862,* 2020.

[5] R. Shadman, A. A. Wahab, M. Manno, M. Lukaszewski, D. Hou, and F. Hussain, "Keystroke dynamics: Concepts, techniques, and applications," *ACM Computing Surveys,* vol. 57, no. 11, pp. 1-35, 2025.

[6] E. A. Sağbaş, S. Korukoglu, and S. Balli, "Stress detection via keyboard typing behaviors by using smartphone sensors and machine learning techniques," *Journal of medical systems,* vol. 44, no. 4, p. 68, 2020.

[7] A. Martins, T. Dias, A. Dias, J. Vitorino, E. Maia, and I. Praça, "Keystroke dynamics for intelligent biometric authentication with machine learning," *Discover Applied Sciences,* vol. 7, no. 9, p. 992, 2025.

[8] A. Darabseh and D. Pal, "Performance analysis of keystroke dynamics using classification algorithms," in *2020 3rd International Conference on Information and Computer Technologies (ICICT)*, 2020: IEEE, pp. 124-130.

[9] L. de-Marcos, J.-J. Martínez-Herráiz, J. Junquera-Sánchez, C. Cilleruelo, and C. Pages-Arevalo, "Comparing machine learning classifiers for continuous authentication on mobile devices by keystroke dynamics," *Electronics,* vol. 10, no. 14, p. 1622, 2021.

[10] S. Roy, U. Roy, D. Sinha, and R. K. Pal, "A novel approach to identify parkinson's disease and other similar neural stress by analysing keystrokes on modern active devices with ensemble classification," *Multimedia Tools and Applications,* vol. 84, no. 29, pp. 36163-36202, 2025.