Analysing and Predicting Acute Stress in Smartphone-based Online Activities using Keystroke Dynamics and Advanced Sensory Features

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ABSTRACT
Acute stress is a short-term cognitive burden. It impacts user engagement and performance during online activities such as meetings, classes, competitive exams, and more. This mental state can be predicted and analysed using Keystroke Dynamics (KD) attributes and the combination of advanced sensory features and Machine Learning (ML) techniques. The purpose of this study is to develop a benchmark dataset incorporating KD and sensory features through a web-based application to analyse acute stress in online settings. The dataset was collected from 103 participants across different demographic groups (e.g., age, gender, and qualification) in two sessions, each involving a minimum of three repetitions in a real-world environment. It includes timing and sensory features, such as gyroscope, accelerometer, and rotational information in various directions, recorded at 2 Hz. In the first session, participants were asked to complete four simple mental math tasks without any induced mental pressure. These samples were labelled as "Calm". In the second session, the same participants were asked to perform three complex mental math tasks, designed to induce mental pressure, and these samples were labelled as "Stress". This dataset provides KD patterns in both non-stress and stress conditions, enabling the design of a classification model to detect acute stress in real-time environments. The findings could be applied to implement more advanced online platforms for meetings, learning, and competitive exams.

General Terms
Biometrics, Online learning platform, Cognitive load, Mental Health, Stress Management Strategies.

Keywords
Acute Stress, Benchmark Dataset, Keystroke Dynamics, Smartphone Sensors, Web-based Applications.

1. INTRODUCTION
With advancements in embedded sensors, smartphones now provide sophisticated sensory features, making them a primary tool for biometric systems across various applications [1, 7, 10]. This is an opportunity to explore user behaviour and activities on smartphones. User modelling in the context of human-computer interaction focuses on describing user attributes, such as fine motor skills and cognitive responses, to recognize specific behavioural patterns [8]. One important application of this modelling is in identifying acute stress, a significant condition that requires detection for effective meeting, online class and to determine cognitive deficiency. Earlier findings in research in Keystroke Dynamics (KD) field has found links between mental stress and typing patterns [2]. Stress, particularly from tasks performed under pressure, affects users' typing performance by impairing cognitive processes [12]. Therefore, monitoring typing behaviour on conventional keyboards or touchscreens becomes crucial in stress detection.

Stress is an integral part of life, with acute stress sometimes proving productive and motivating. However, chronic stress can lead to serious mental disorders, such as anxiety and depression, which require proper diagnosis and treatment. According to the Center for Disease Control and Prevention (CDC), 8.1% of Americans aged 20 and older experienced depression over any two-week period from 2013 to 2016 [4]. This condition manifests in different ways, including reduced cognitive function and impaired productivity. Recognizing acute stress is challenging, as there is no standard system for effective diagnosis. Researchers in KD have found that typing patterns can indicate changes in cognitive load, potentially leading to accurate detection of mood disorders [13].

Detection of acute stress is crucial for optimizing online activities such as meetings and learning environments. Although previous studies [11] have utilized social media content and physiological indicators like Heart Rate Variability (HRV) and skin conductance to predict stress, these methods require additional hardware, making them impractical for seamless integration into web-based systems. KD, by contrast, has the potential to offer a non-intrusive solution by analysing typing behaviour. Studies have shown that KD attributes can be effective in stress prediction [6, 9]. Additionally, integrating KD features with Mouse Dynamics (MD) has proven useful in identifying acute stress [5]. With the growing use of smartphones and computers, there is a significant opportunity to develop stress detection systems for online and offline activities.

Stress can alter typing patterns, as highlighted by Vizer et al. [12], while physiological measures such as typing movement may provide clues to cognitive load [3]. Cognitive load refers to the mental effort required for a task and varies across individuals, depending on factors like age and task complexity. It has been shown that increased cognitive load can slow down typing speed and cause more errors. KD can capture these changes by measuring features like key Hold Time (HT) and Flight Time (FT), which reflect cognitive load during tasks. This dataset can be used to develop accurate stress detection models in smartphone, particularly for online environments like meetings or competitive exams. The primary objective of this paper is to introduce a new benchmark dataset that includes both timing and sensory features for analysing and detection of acute stress. This dataset, gathered through smartphones, offers insights into user behaviour during stressful online activities, with potential applications in education, meetings, and health monitoring.

The scientific understanding of stress involves the intricate coordination of mechanisms within the brain and body, primarily regulated by the hypothalamus. Located beneath the thalamus, the hypothalamus plays a crucial role in responding to stress stimuli by activating two main systems: the Sympathetic Nervous System (SNS) and the Hypothalamus-Pituitary-Adrenal (HPA) axis. The SNS triggers the "fight-or-flight" response, influencing physiological changes such as increased heart rate, blood pressure, and pupil dilation. The HPA axis, on the other hand, mediates hormone production to help counteract stress. In situations of stress reduction, the Parasympathetic Nervous System (PNS) takes precedence, promoting relaxation and inhibiting stress hormone production.

Historically, stress has been measured through devices like polygraphs, which monitor physiological responses such as heart rate, skin conductivity, and blood pressure. The scientific measurement of psychological stress was significantly advanced in 1983 with the development of the Perceived Stress Scale (PSS), a widely used questionnaire that quantifies perceived stress levels. With advances in technology, wearable devices are now capable of automatically measuring stress, further enhancing our understanding of its physiological and psychological effects.

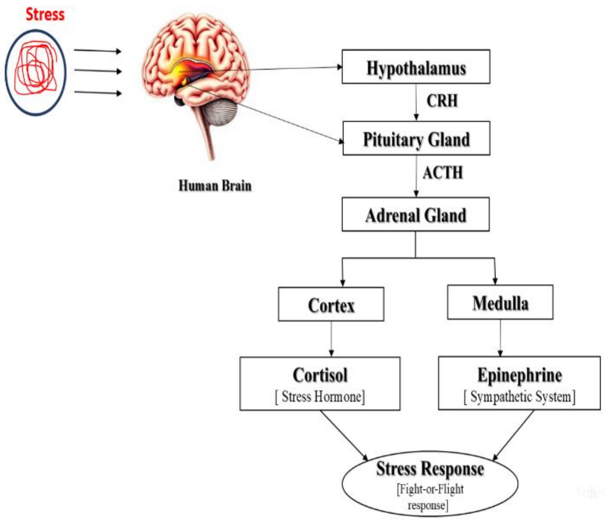

Fig. 1: Stress response: Role of the hypothalamus

2. LITERATURE REVIEW

Stress has become a pivotal factor in both individual well-being and broader health paradigms in modern society. Since at least 2002, stress has been referred to as a "hidden epidemic" of contemporary times [14]. The economic ramifications of stress are profound, particularly in the context of workplace stress, where an estimated $300 billion is spent annually in the United States [15]. The World Health Organization emphasizes the significant returns on investment in mental health, estimating that every dollar spent on combating depression and anxiety yields a fourfold return [16]. Walter Cannon, the distinguished American psychologist (October 19, 1871 – October 1, 1945), defined stress as any deviation from homeostasis, a concept he also introduced. Homeostasis represents the steady physiological state of the human body, characterized by parameters such as temperature, heartbeat, and blood pressure, which can be quantitatively monitored using biological sensors [17].

Recent advancements have introduced diverse sensor-based solutions for stress detection, leveraging both single-sensor and multimodal approaches [18-20]. Traditionally, Heart Rate Variability (HRV), measured using electrocardiography (ECG), has been the cornerstone for stress detection [21]. In addition to HRV, biomarkers such as Galvanic Skin Response (GSR), Electro-Dermal Activity (EDA), respiration, and electromyography (EMG) are increasingly employed for assessing affective states and stress levels [22–24]. The term "stress", first introduced into medical terminology in 1936, was initially described as a syndrome caused by diverse nocuous agents that severely disrupt homeostasis [25]. However, conventional stress detection approaches often lack compatibility with modern lifestyles and real-time monitoring requirements. These methods are invasive, prone to subjective biases, costly, and necessitate time-consuming visits to clinical settings. Over the past two decades, technological advancements have driven the development of more efficient, cost-effective, and non-invasive stress measurement techniques aligned with contemporary lifestyles. Wearable devices, mobile applications, and Machine Learning (ML) algorithms have revolutionized stress detection methodologies, enabling continuous, long-term monitoring through HRV-based measurements using smart watches, fitness trackers, and chest straps [26-30]. Given the nonlinear nature of HRV, ML algorithms and statistical models such as the Modified Varying Index Coefficient Auto Regression model (MVICAR) [31] have been instrumental in enhancing the accuracy and efficiency of stress detection systems [32-36].

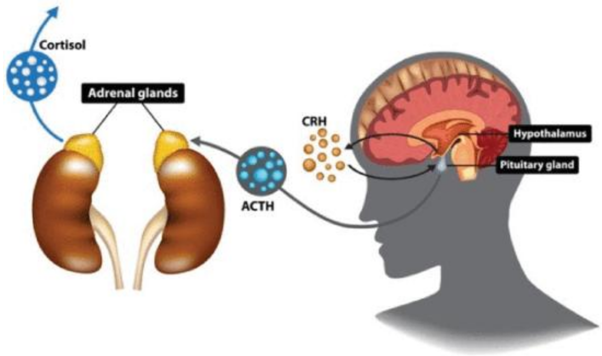

Fig. 2: The hypothalamus releases corticotropin hormone (CRH) and triggers the release of adrenocorticotropic hormone (ACTH) from the anterior pituitary into the circulation. Finally, the adrenal cortex releases stress hormones (such as cortisol) [63].

KD has emerged as a promising method for detecting stress in users, leveraging the analysis of typing patterns to identify physiological and psychological changes associated with stress. Research indicates that stress can significantly alter typing behaviors, such as increased speed and error rates, which can be quantified to establish markers for stress detection [37]. Various ML techniques, including Dynamic Cat-Boost and Random Forest classifiers, have been employed to analyse keystroke data, achieving accuracies of up to 76% in distinguishing stress levels [38, 39]. Additionally, studies emphasize the importance of personalized approaches, as stress responses can vary widely among individuals, necessitating tailored models for effective detection [37, 40]. This non-invasive method is particularly relevant in modern work environments, where remote work has become prevalent, highlighting the need for unobtrusive stress monitoring systems [39].

Stress exerts a profound impact on well-being and health, with triggers ranging from workplace pressures to social interactions and economic challenges, leading to decreased productivity and an array of health issues [41, 42]. Effective stress detection is critical for mitigating these adverse effects. Recent technological advancements, particularly in wearable sensors and deep learning methodologies, have significantly improved stress monitoring capabilities [43]. These technologies utilize physiological signals and behavioral indicators, such as body movement and speech patterns, to assess stress levels [41, 43]. Moreover, workplace stress management strategies play an essential role in fostering supportive environments that enhance employee mental health and productivity [44]. By integrating advanced data analysis techniques and recognizing the multifaceted nature of stress, these approaches hold promise for significantly improving psychosomatic health outcomes [42, 43].

Research into acute stress detection through KD has shown that analysing timing, keystroke, and linguistic features can achieve accuracy levels comparable to other affective computing methodologies. This non-intrusive method enables effective stress monitoring in real-time [45]. Furthermore, integrating conventional keystroke features with pressure sensor data has been shown to enhance classification performance by 6%, allowing for seamless stress detection using commonplace workplace devices like keyboards and mice [46]. Studies have also demonstrated the efficacy of KD in detecting cognitive stress during mental arithmetic tasks, where increased task demand and time pressure significantly influence typing behaviours. These findings highlight the potential of KD for adaptive e-learning systems and stress evaluation [47].

2.1 Stress management in the workplace

Several studies have highlighted the significant role of stress management in improving employee well-being and productivity at the workplace.

Tran et al. [48] focused on stress management during the COVID-19 era, emphasizing the critical role of HR managers in safeguarding employees' physical and psychological health. Their research identified three main types of workplace stress—acute, episodic acute, and chronic stress—and proposed physiological, psychological, and autonomic methods for measuring stress. The study concluded that HR managers play a key role in managing stress by implementing primary, secondary, and tertiary strategies to address workplace stressors.

Katic et al. [49] analysed the impact of managerial and personal lifestyles on stress levels. They found that modifications in managerial styles could help employees better balance work and personal life, thereby reducing stress. The study advocated for a supportive managerial style to help mitigate stress. Rawal and Mhatre [50] examined stress among lecturers, identifying workload as a major stressor, leading to frequent absences. The study suggested techniques to cope with stress, including behavioral and attitudinal adjustments towards productivity.

Bhui et al. [51] conducted a qualitative study and found that poor management practices, unrealistic job demands, and lack of support were significant contributors to stress. They proposed organizational and individual interventions such as better planning, improved management styles, and support systems to alleviate stress. Vandana [52] argued that stress, if properly managed, could lead to positive outcomes (Eustress). She suggested several coping strategies, including job redesign, physical activities, and relaxation programs to manage stress effectively.

Sahoo [53] identified a gap between job demands and employee capabilities as a key source of stress, recommending closing this gap to reduce uncertainties and stress. Kumari and Devi [54] focused on stress among working women, identifying workplace culture, job insecurity, and higher job demands as the primary causes of stress. They suggested that family support and organizational initiatives to balance work and personal life could mitigate stress.

Ismail et al. [55] found a significant positive relationship between physiological and psychological stress and job performance. The study suggested competency mapping as a method to reduce stress and improve performance. Kushwaha [56] emphasized the organization's role in identifying stress-inducing aspects of the work environment. He proposed stress management techniques, such as awareness, time management, and developing a healthy lifestyle.

Nekzada and Tekesta [57] found that heavy workload, workplace conflicts, and poor working environments were the major stressors at Volvo trucks AB. They recommended time management, relaxation activities, and positive peer relationships as effective stress management strategies.

2.2 Stress management among students

Stress management among students during the Covid-19 era has been a critical area of focus due to the significant impact of the pandemic on mental health and education. The pandemic introduced unprecedented challenges, leading to increased psychological distress and anxiety among students, as evidenced by a longitudinal study that tracked mental health over two years, showing that distress levels spiked during the pandemic and remained higher than pre-pandemic norms even after two years [58]. The shift to online learning and social restrictions further exacerbated stress, affecting students' daily activities and mental health, necessitating effective stress management strategies [59]. Various coping strategies have been identified, including problem-focused coping through painful problem solving and seeking social support, as well as emotion-focused coping like positive reappraisal and self-control [60]. Additionally, religious coping strategies such as tawakal and qanaah have been noted among students [60]. Counseling approaches, particularly group counseling and cognitive behavioral therapy, have been effective in managing academic stress by providing mutual support and modifying irrational thoughts and behaviors [61]. Health education initiatives have also proven beneficial, increasing students' knowledge and attitudes towards stress management through diverse methods such as lectures and discussions [59]. Overall, a combination of counseling, education, and personalized coping strategies is essential to support students in managing stress during and beyond the Covid-19 pandemic [61, 62, 59].

3. METHODOLOGY

To collect the data for acute stress analysis, a web-based application has been developed using HTML, JavaScript, and various sensor APIs. This application is currently available online as depicted in Fig. 1, allowing researchers worldwide to utilize it for their individual studies on acute or chronic stress. The data was collected at a sampling rate of 2 Hz to ensure compatibility with all major web browsers, which also minimizes battery consumption—a critical consideration for smartphone-based data collection, where power efficiency is a priority.

Data collection was conducted under two conditions: Calm (under non-stressful job) and acute stress (under stressful job). Fig. 2 presents the tasks for non-stressful and stressful jobs. To capture typing and gait features in a calm state, participants were asked to solve simple mental arithmetic problems, such as four straightforward calculations (typing forward and backwards series). For the acute stress condition, participants were tasked with solving more complex mathematical problems, including serial seven subtraction, N-back arithmetic, and skip counting. KD and gait patterns were recorded under both conditions, enabling the identification of variations in these patterns associated with acute stress.

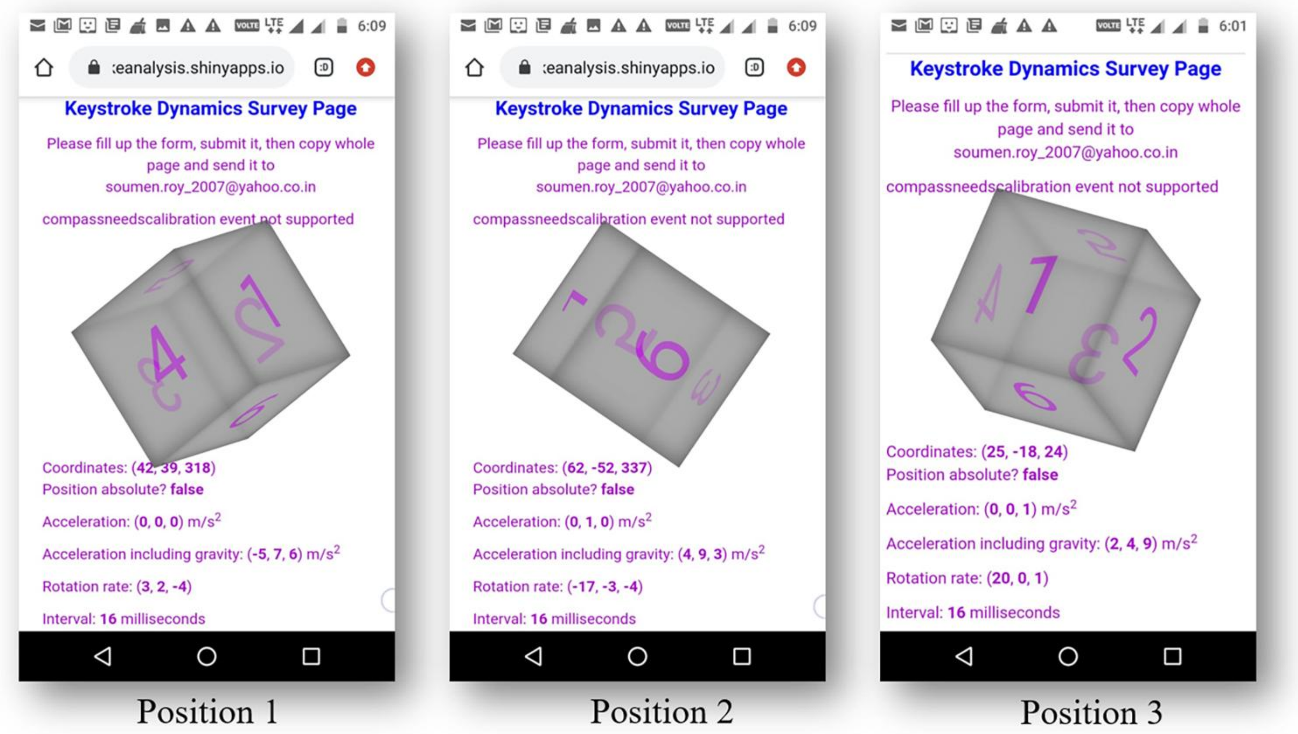

Fig 3: Web application for data acquisition can be found in the following link: https://computerscience.shinyapps.io/datacollect/

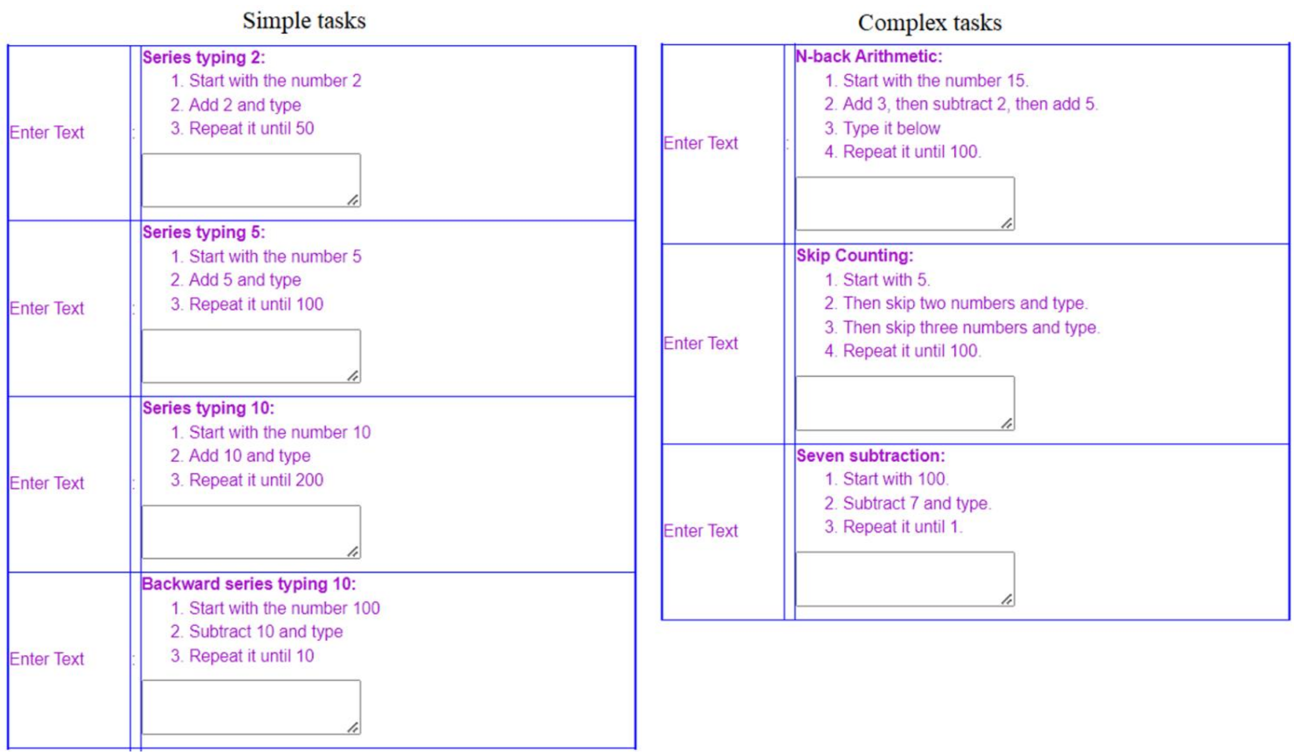

Fig. 4: Two different tasks (simple and complex) were given while typing

The study involved 103 participants, ranging from school students to university students and teachers, to ensure a diverse sample representative of different demographics. Fig. 3 presents the subject distribution that indicates the diversity of the subjects. This diversity is crucial for enhancing the reliability and generalizability of the stress detection models developed using this dataset. Each participant was asked to complete four simple and three complex mathematical problems to provide data under both calm and stress-inducing conditions. Several Schools, Colleges, and University were visited to collect the data from different groups as depicted in Fig. 4.

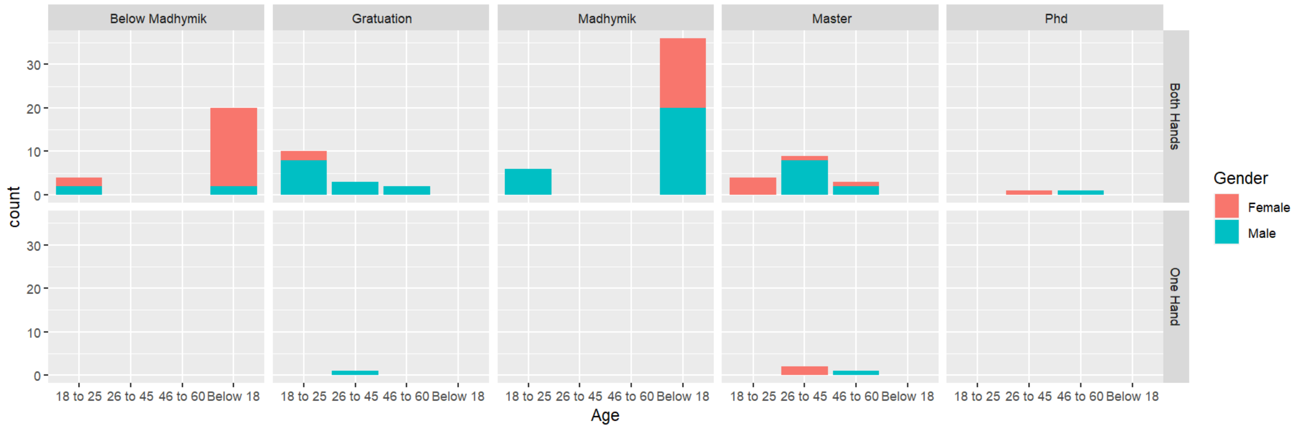

Fig. 5: Distribution of the subjects considered for preparing dataset

Fig. 6: Dataset preparation from different groups

A comprehensive set of features was considered for the analysis, including gyroscope data, accelerometer readings, rotational information, and KD (timing features such as key press and release times measured in milliseconds) as mentioned in Fig. 5. These features were chosen to capture a wide range of physiological and behavioural responses to stress, facilitating the development of robust models for acute stress detection.

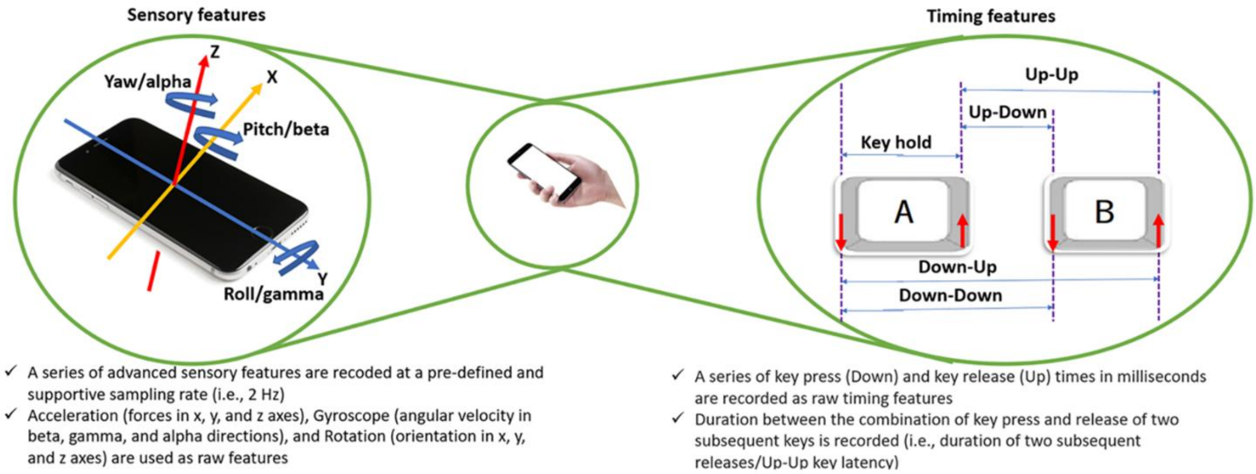

Fig. 7: Feature sets for stress determination (source: authors)

The following are the timing features were recorded:

(1) Key Hold Time: The time a key is held down before release.

(2) Press-Press Latency: The delay between consecutive key-presses.

(3) Release-Release Latency: The time between releasing consecutive keys.

(4) Release-Press Latency: The time from releasing one key to pressing the next.

(5) Digraph Latency: The total latency between pressing a key and releasing a next key.

The following are the advanced sensory features were collected at 2 Hz:

(1) **Gyroscope Information:**

(a) Alpha (Rotation around Z-axis)
(b) Beta (Rotation around X-axis)
(c) Gamma (Rotation around Y-axis)

(2) **Acceleration Information (From Accelerometer):**
(a) Alpha Direction (Along the Z-axis)
(b) Beta Direction (Along the X-axis)
(c) Gamma Direction (Along the Y-axis)

(3) **Rotational Information:**
(a) Roll (Rotation around X-axis)
(b) Pitch (Rotation around Y-axis)
(c) Yaw (Rotation around Z-axis)

4. MODEL IMPLEMENTATION

Three state-of-the-art classifiers were employed to train and evaluate the model: Support Vector Machine (SVM), Random Forest (RF), and XGBoost. These classifiers were chosen due to their robust performance in handling complex datasets and their widespread application in various machine-learning tasks. To develop the model, a custom dataset has been constructed that includes both timing and sensory features extracted from smartphones. This dataset was collected from 103 participants, representing diverse age groups and genders, to ensure a comprehensive representation of user behaviour. Feature selection was performed using XGBoost, which allowed us to identify the most relevant features for model training. From this, the top ten features were selected, enhancing the model's predictive accuracy and reducing computational complexity.

Fig. 6 presents the performances of three state-of-the-art classifiers in realistic evaluation. It is observed that the performance of XGBoost outperforms others. Therefore, we present the ROC curve of XGBoost in Fig. 7. The AUC of the curve is 83.92%. For the comparison purpose significantly, we used TukeyHSD. The comparing performance is depicted in Figure 8. Figure indicates the performance of XGBoost and SVM is 5.57% where it is 6.85% for SVM and RF. It is also observed that XGBoost and RF are quite similar; only the difference is 1.28%.

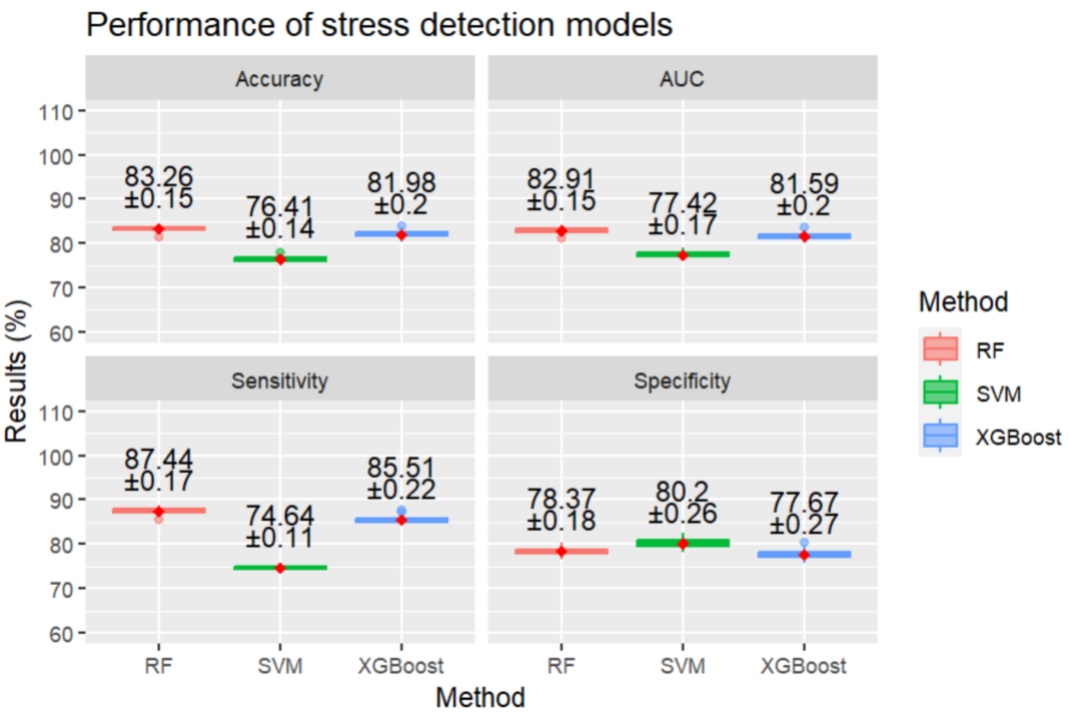

Fig. 8: Performances of the applied state-of-the-art classifiers in realistic evaluation

The model training and evaluation were conducted using the Leave-One-User-Out Cross-Validation (LOUOCV) method. This approach involved 103 iterations, wherein each iteration, the data from a single participant was treated as the test set, while the data from the remaining 102 participants constituted the training set. This method enabled a rigorous evaluation of the model's generalizability across different users. The average performance metrics were recorded across all iterations to provide a comprehensive assessment of the model's robustness. The inclusion of state-of-the-art classifiers in the evaluation process enabled a thorough analysis of model performance, offering a strong foundation for future enhancements. The results from this study will guide further optimization and refinement of the model, contributing to advancements in the field of user behavior modeling based on smartphone data.

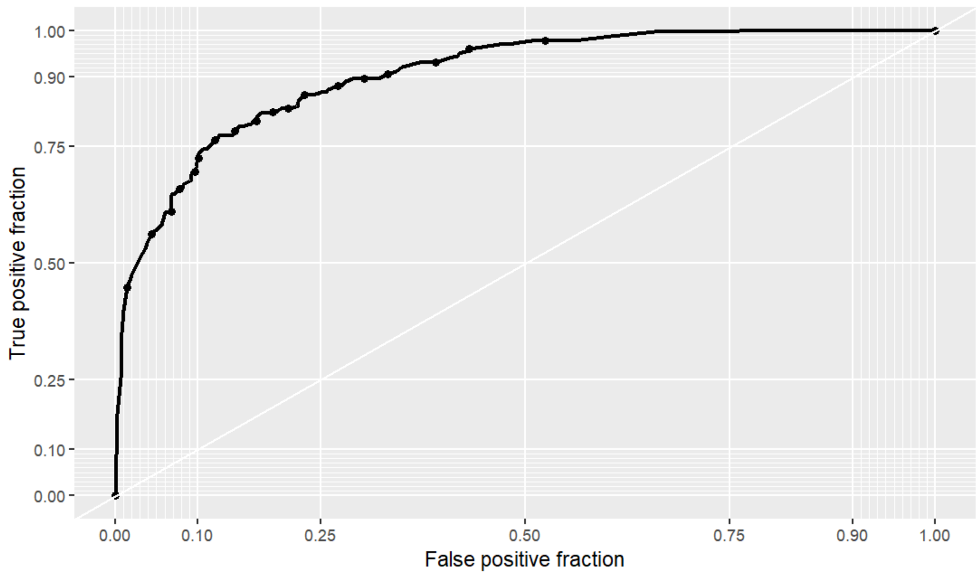

Fig. 9: ROC of the top performer (XGBoost)

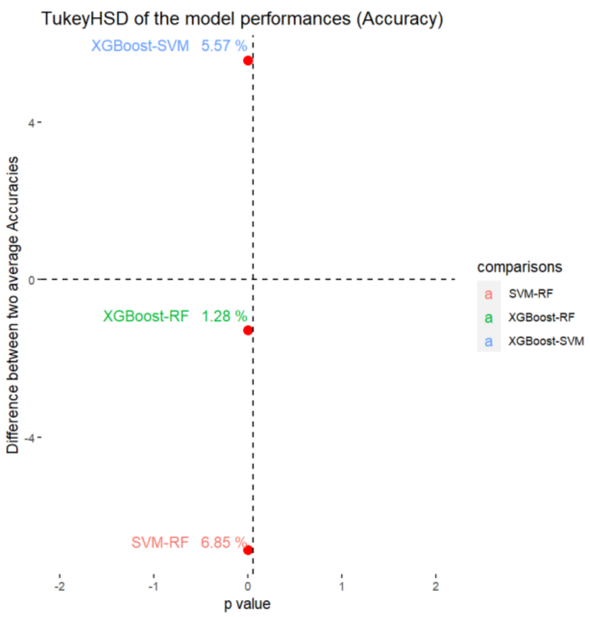

Fig. 10: TukeyHSD results (Accuracy): Comparing the performance of the adopted classifiers

5. IMPLICATIONS

The development of our dataset for acute stress determination offers significant implications for various real-world applications. In online teaching and learning environments, the dataset can be utilized to monitor and assess stress levels among students during live sessions. By analysing keystroke patterns and gait data, educators can gain insights into how specific topics or teaching methods may contribute to heightened stress levels. This information can help educators tailor their approaches to reduce stress and improve learning outcomes, thereby enhancing the overall educational experience.

Online competitive examinations are another promising application of this dataset. Educators and examiners can identify questions that may be causing students undue stress or confusion by analysing the stress associated with answering each question. This insight could be used to refine exam questions, making them fairer and more balanced, or to provide additional support to students who may be experiencing significant anxiety. Furthermore, understanding how students respond under stress could also offer valuable information for psychological studies related to performance anxiety and stress management.

The dataset also has potential applications in the analysis of social interactions on networking platforms. By examining KD and gait patterns during social networking chats, it is possible to determine the collective stress levels of users during various interactions. This could be particularly useful for detecting stressful or potentially harmful interactions, such as cyberbullying or heated debates. Social platforms could use this data to implement real-time interventions, providing users with tools to manage stress or offering support when high stress levels are detected.

However, challenges remain in fully leveraging KD and gait analysis for stress detection. One significant limitation is that typing patterns may not always be available or consistent across all scenarios. To address this, our dataset also incorporates sensory rotational features from smartphones to create a more accurate model. Nonetheless, continuously operating all sensors can drain battery power rapidly, posing a practical constraint for long-term stress monitoring. Future research should focus on optimizing sensor usage to balance power consumption with the need for accurate stress detection. Developing algorithms that intelligently activate sensors only when necessary, could mitigate this issue, enabling more sustainable and effective use of smartphone-based stress analysis tools.

6. CONCLUSIONS

To determine acute stress using ML algorithms needs dataset. This paper presents a benchmark dataset for the determination of acute stress in online setting. This dataset can be analysis to understand the acute stress while typing as part of human-computer interaction using recent smartphones. State-of-the-art ML models have been applied and observed 83.29% of accuracy considering only the typing pattern of consecutive ten characters. This performance can be enhanced in the near future with more novel methods and advanced features. Furthermore, the aim of this study is to enhance the performance of this predictive design with increasing the duration of typing and design novel ML model for practical use.

The current application demonstrates robust predictive capabilities in distinguishing between stressed and non-stressed individuals, enabling the detection of stress levels in specific environments. From a futuristic perspective, there is potential to develop an advanced application aimed at optimizing various online activities, including teaching and learning processes, competitive examinations, meetings, and discussions. Such an application could be designed for multiple platforms, incorporating tailored features and attributes to enhance its functionality. These software solutions are increasingly relevant in contemporary online system monitoring. An online marker could be established to measure the stress levels of participating individuals, allowing the program to adapt and respond dynamically based on the nature and intensity of the detected stress. This approach holds significant promise for improving the efficacy and responsiveness of online systems in real-time stress management.

Declarations

Ethical approval All procedures performed in studies involving human participants were in accordance with the ethical standards.

Conflict of interest Informed consent was obtained from all individual participants.

Data availability The dataset is available from the corresponding author on reasonable request.

Informed consent The authors declare that they have no conflict of interest.

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