AI-Based Detection of Emotional Burnout from Typing Patterns

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***Abstract*—Burnout has become a common concern among students, teachers, and working professionals. Continuous workload and stress can affect concentration, motivation, productivity, and overall well-being. Burnout is usually identified through questionnaires, interviews, and self-reported assessments. Although these methods are useful, they are generally conducted at specific intervals and rely on individuals describing their experiences. This study proposes a method of examining typing behaviour as a possible additional indicator of burnout-related changes. The proposed approach considers various typing characteristics, including typing speed, inter-key time, key-hold duration, pauses, typing errors, backspace usage, and changes in typing rhythm. Three machine-learning techniques, namely Random Forest, Support Vector Machine (SVM), and Long Short-Term Memory (LSTM), are considered for analysing these patterns. The proposed system is intended to support early awareness and research on behavioural changes and is not intended to diagnose burnout.**

***Index Terms*—Artificial Intelligence, Emotional Burnout, Keystroke Dynamics, Typing Behaviour, Machine Learning, Random Forest, SVM, LSTM.**

I. INTRODUCTION

Burnout can develop when a person is exposed to continuous stress and workload for a long period. It is often associated with emotional exhaustion, reduced motivation, difficulty concentrating, and reduced productivity. The World Health Organisation describes burnout as an occupational phenomenon resulting from chronic workplace stress that has not been successfully managed [1]. At present, burnout is commonly studied using questionnaires, interviews, and self-assessment methods.

With the increased use of computers in education and workplaces, everyday computer activities provide an opportunity to study changes in human behaviour. Typing is one such activity. Every keystroke involves timing information, such as the time taken to press and release a key and the interval between consecutive keys. These measurements can be collected without necessarily recording the actual words typed.

Earlier studies have reported changes in typing behaviour during stressful situations. Wetherell et al. found that typing rhythms could be affected by socially evaluated multitasking stress and that machine-learning methods could identify stress-related patterns for individual participants [2]. Similarly, other studies have explored typing behaviour as a source of information for stress detection [3]. However, typing habits differ from person to person, and stress itself is not the same as burnout.

Therefore, this study explores whether changes in typing behaviour can provide useful information about burnout-related states. The intention is not to identify burnout solely from keyboard activity, but to examine whether typing patterns can act as an additional behavioural signal.

II. PROPOSED METHODOLOGY

The proposed system involves data collection, preprocessing, feature extraction, feature selection, model development, and evaluation. Participants would provide typing data voluntarily and complete an appropriate validated assessment to provide reference information about their reported stress or burnout-related state.

The system would record features such as typing speed, inter-keystroke interval, key hold duration, pause duration, typing errors, backspace frequency, session duration, and rhythm variation. Wherever possible, the actual content typed by participants would not be stored. This helps reduce the amount of personal information collected during the study.

After preprocessing the collected data, the extracted features would be supplied to three machine-learning models: Random Forest, SVM, and LSTM. Random Forest can be used to study relationships between different typing features and can also provide information about feature importance. SVM can classify participants or sessions into predefined categories based on the selected features. LSTM is suitable for sequential data and can examine the order and timing of keystrokes.

Special care is required while dividing the dataset. Since every individual has a different typing style, data from the same participant should not be unnecessarily divided between training and testing sets. Otherwise, the model may learn the person's typing style instead of learning patterns related to burnout.

III. EVALUATION AND EXPECTED RESULTS

The models can be compared using accuracy, precision, recall, F1-score, confusion matrix, and ROC-AUC. The final performance values can only be reported after collecting and analysing an appropriate labelled dataset. Therefore, no assumed accuracy or other performance values are presented in this study.

The study is expected to provide information about whether particular typing characteristics are associated with reported burnout-related conditions. It may also help identify which machine-learning approach is more suitable for analysing typing behaviour. In the future, individual baseline models could be developed so that changes in a person's current typing behaviour are compared with their normal typing pattern.

IV. LIMITATIONS AND ETHICAL CONSIDERATIONS

Typing behaviour is affected by many factors other than stress or burnout. Typing experience, workload, language, keyboard type, task difficulty, tiredness, and the nature of the activity can all influence typing speed and rhythm. Therefore, a change in typing behaviour cannot by itself be considered evidence of burnout.

Privacy is another important concern. Keystroke information can reveal behavioural characteristics even when the actual text is not recorded. Participants should therefore provide informed consent, and collected information should be anonymised and stored securely. Only information required for the research should be collected. The system should not be used for hidden employee monitoring or presented as a medical or psychological diagnostic tool.

V. CONCLUSION

This paper presents a proposed approach for studying burnout-related behavioural changes through typing patterns. The framework examines features such as typing speed, keystroke intervals, pauses, errors, backspace usage, and typing rhythm. Random Forest, SVM, and LSTM are considered for analysing these features.

Typing behaviour may provide useful additional information because it can be observed during normal computer use. However, individual differences and other external factors make it unsuitable as a standalone method for identifying burnout. Further research using larger and diverse datasets, longitudinal observations, and validated burnout assessments is required. If properly validated, typing behaviour may serve as one of several behavioural signals that can support early awareness of changes in well-being.

VI. FUTURE SCOPE

The proposed study can be extended in several ways. Future research can collect typing data over a longer period to understand how typing behaviour changes with workload and prolonged stress. Since typing habits are different for every individual, personalised models can be developed by first establishing a user's normal typing pattern and then identifying significant changes from that baseline.

The system can also be extended by combining typing behaviour with other non-invasive behavioural signals, such as mouse movements, application usage, or interaction patterns. Machine-learning and deep-learning models can further be improved using larger and more diverse datasets.

Another possible direction is the development of an explainable system that shows which typing features contributed to a particular prediction. A real-time dashboard could also present changes in typing behaviour over time instead of simply displaying a burnout prediction. Such systems should continue to follow strong privacy and ethical guidelines.

Future studies should involve participants from different age groups, occupations, languages, and levels of computer experience. Longitudinal studies with validated burnout assessments would help determine whether typing patterns can provide a reliable additional behavioural signal for early awareness of burnout-related changes.

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