



# International Journal of Multidisciplinary Research in Science, Engineering and Technology

*(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)*



**Impact Factor: 8.206**

**Volume 9, Issue 3, March 2026**



## International Journal of Multidisciplinary Research in Science, Engineering and Technology (IJMRSET)

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# Emotional Stability Assessment through Keyboard Typing: A Survey

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**ABSTRACT** Affective computing is an emerging paradigm that seeks to model human emotions and understand them in terms of behavioral signals, which has a useful area named emotional stability assessment. Detecting User Emotions Using Keystroke Dynamics: This a keystroke dynamics based project by finding out how a person types on keyboard. Many features will be extracted from our inputs, typing speed, dwell time (time taken before lifting off a designated area), latency (time between press/write of an input and release), interval (between two consecutive presses) will help us classify different emotions (Sad/Happy/calm/anxiety/anger).

**How It Works:** We trained and tested the system using a separate dataset of labeled keystroke (i.e., typing) data. But in reality cleaning, normalization and feature extraction techniques are deployed before the actual model to improve performance. We trained multiple machine learning models such as K-Nearest Neighbors (KNN), Multi-Layer Perceptron (MLP) and XGBoost, with the latter providing us with the best balance of accuracy due to its ability to capture complex entropy in the data.

An interface was also built to input typing data and display real-time emotion predictions.

Additionally, a user interface was built that allowed users to enter typing data and view real-time emotion predictions. In addition, it includes a weekly assessment so that you can pinpoint emotional patterns over time for an accurate analysis.

In summary, this project demonstrates an unobtrusive and effective method for determining emotional stability based on typing behavior, with potential applications in HCI (human-computer interaction) fields and mental health monitoring.

## I. INTRODUCTION

Emotion recognition in human-computer interaction has been progressively developed in the aim of affective computing. However, since the emotions have a significant impact on cognition and decision making along with productivity, emotion detection becomes important for enhancing user experience, detecting stress & anxiety as well as several mental health conditions. What they do is similar to traditional approaches for emotion detection, which usually depend on facial expressions, voice analysis or physiological sensors like heart rate monitors and EEG devices. But such methods are often intrusive, costly, and require additional hardware.

On the other hand, keystroke dynamics are less intrusive and cheap since they examine typing patterns on a keyboard. Its state-of-the-art design does not need users to wear any external devices, enabling more feasible use in realistic applications. In experiments, various keystroke characteristics like dwell time and latency have been shown to be different in emotional states. However, individual variability remains high, highlighting the potential need for personalized or adaptive models. Even better, characteristics such as time in key hold and flight time have recently been effective for even a most reduced composing period.

In prior work many different emotion recognition methods have been attempted. Facial expressions and vocal signals are the primary modalities of interest, but physiological signals (e.g., heart rate, skin conductance, EEG) are also



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frequently used. Recently, behavioral signals (e.g., keystroke dynamics and mouse movements) have arisen as effective non-intrusive measures. Yet, these methods are less explored than vision- and audio-based approaches.

It has been recently reviewed that keystroke dynamics is a potential new modality however, research of this modality is limited (e.g., Kołakowska et al.). Other recent approaches have also considered combining the keystroke features with text sentiment analysis [19] to improve detection accuracy of the emotion.

In this regards, the present work aims at introducing an emotional stability assessment using keystroke dynamics as a viable and non-invasive way to utilize these user profiles along with above mentioned findings.

### II. LITERATURE REVIEW

**Keystroke Dynamics:** The timing of keystrokes has been researched for user authentication for many years, but its application to infer affective states is more recent. One of the first proposals to use keystrokes for emotion detection was made in an early study (Zimmermann et al., 2003), although this was primarily theoretical. Epp et al. One of the earliest field studies was by system (2011): 29 participants labelled their own moods while typing and were able to achieve up to 88% accuracy for some emotions (confidence, nervousness, etc.) with keystroke rhythm classifiers. Their results are promising, especially for V2 when applied to two-level (binary) states such as anger/excitement (84% accuracy). More recent datasets, such as EmoSurv (Maalej & Kallel, 2020), collected typing data with a fixed phrase and covered five types of emotions in which 124 subjects participated. Later, Marrone and Sansone (2022) proposed a pipeline using a sliding-window approach for their dataset and concluded that even small segments (30 s) can work if the purpose is emotion recognition. Other research has applied keystroke analysis to detect stress: Kołakowska (2016) showed that when programming under stress, timing/frequency parameters change. Studies indicate that keystroke duration (dwell) or flight time (inter-key latency) varies with emotional valence, prolific error rates (backspaces), and typing speed.

**Emotion Recognition Methods:** Emotion recognition — the keystroke is only one of the many signals. Standard modalities include facial expression and voice analysis (prosody), but wearables with physiological signals (heart rate, skin conductance, EEG) are also widely used. Social leads have also been recently used, but typing or mouse movements and other behavioral signals are emerging as less-intrusive alternatives. Reviews of emotion detection highlight that other modalities, such as keystroke and mouse dynamics, remain relatively lackluster compared to vision/audio. Kołakowska et al.[23] performed a systematic review of the literature. (2013) highlighted that keystroke dynamics can be integrated with other modalities, but studies on this topic are scarce. Recent methods have combined text sentiment analysis and keystroke patterns to improve accuracy.

**Related Behavior Research:** Mood and cognition are connected to typing behavior. For instance, Chen et al. (2023) detected depressive tendencies (hold- and flight-time) using smartphone typing data 23k+ (24 subjects) typing sessions fed as features to ML models (decision trees, boosting, etc.) reached  $AUC \approx 0.98$  for depression screening. Bi Affect; mo Se: a wearable app to correlate mood and typing habits using keystroke dynamics The Bi Affect project combines data from smartphone keystrokes and moSe: A wearable which better correlates a user's mood and typing behavior. accelerometer data to track mood over time, like a "Fitbit for the brain." These studies underscore that typing data collected passively can indicate mental health. However, they often rely on custom applications or smartphones. In contrast, this study approached standard PC keyboards to achieve wider contexts (academic helixing, desk work, etc.).

**Hurdles and Challenges:** Although some good results have been obtained, gaps exist. First, a generalization problem: Lee et al. (2014) found that the emotional effect on keystrokes exists but is smaller than individual differences, implying that models need personalization. Second, a lot of research involves fixed text or controlled stimuli; free-text contexts (like chats or blogging) are not as well studied. Third, LSTM, CNN, or transformers have never been applied to keystroke emotion data top our knowledge even if they are very good in sequential tasks. A third area that isn't often discussed is privacy and ethics: typing logs are sensitive (they leak personal content), and emotional inference raises consent issues. We will do this by making the data anonymized and gathering prior consent.

**Proposed/Implemented:** All of free and fixed typing exercises were run based on an agreed dataset. It employs features like keystroke timing, error statistics, typing speed and latency. Several models were applied, including some machine learning such as KNN, MLP, XGBoost. The output expected is the multi-class emotion classification



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accuracy, and for this task best performing algorithm was then XGBoost. The hold time, flight time and error rate are example features driving the prediction.

Study (Year)	Data & Task	Features	Models	Performance Findings
Lee et al. (2014)	17 subjects; typing under IAPS stimuli	Keystroke durations, latencies	ANOVA (statistical analysis)	Emotions affect the timing of typing behavior ( $p < 0.001$ ), and the effect size is small compared to individual differences.
Epp et al. (2011)	29 users; free and fixed text (15 emotions self-annotated)	Keystroke timing features	SVM and other classifiers	Multiple emotions correct classification 77–88% correct; anger/excitement ~84%.
Marrone & Sansone (2022)	124 subjects; fixed text (EmoSurv dataset, 5 emotions)	Sliding-window keystroke features	MIL-SVM, CNN	~76% accuracy; short 30 sec windows are enough
Kořakowska (2016)	Students programming; stress vs non-stress	Key hold, typing frequency, rate	Statistical analysis	Timing and frequency features indicate stress
This Work (Implemented)	Predefined dataset; emotion classification	Dwell time, latency, typing speed, error rate	KNN, MLP, XGBoost	Highest accuracy with XGBoost; keystroke features classify emotions accurately

**Table 1: Comparison of Key Keystroke Emotion Detection Studies**

### III. METHODOLOGY OF PROPOSED SURVEY

However, in this project, rather than gathering real-time typing data from participants, we relied on an already defined dataset. It contains keystroke dynamics from multiple users, including features such as key press timings and dwell time, latency, typing speed, pause frequency, and backspace usage with emotional labels happy, sad calm anxious angry.

#### A. Data Preprocessing

What is the data of this project? The dataset was preprocessed for data quality, consistency, and normalization prior to applying machine learning models. Step 1: To avoid inconsistencies during training, we first detect any missing or duplicate values in the dataset and then handle them.

We normalized the keystroke features, specifically dwell time, latency, typing speed, and error rate, to obtain a common scale. This is a necessary step to squeeze forth the functioning of machine learning algorithms by ensuring that no respective feature overweighs any other based on its scale.



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The dataset was improved by eliminating noisy or inconsistent data samples, and the following basic data cleaning steps were performed to ensure valid and meaningful records for further analysis.

The prepared dataset can be utilized for feature extraction and model training after preprocessing.

### B. Feature Extraction

Keystroke dataset was analyzed and the features relevant to typing behaviour were extracted for emotional state analysis. The selected features included:

The time between key press and release is known as Key Hold Time (Dwell Time): This shows how long a key is pressed, which varies with emotions.

**Flight Time (latency):** Timing between two consecutive presses of the same key which is a value that tends to record typing cadence and hesitation.

**Typing speed:** Number of characters typed in a fixed time period, expressed with the given time interval Impediments in typing speed signify emotional states

**Error/Backspace:** No of backspaces or deletions to correct the errors. More errors could be a sign of stress or distraction.

**Pause Patterns:** How long between typing actions Longer pauses can be a sign of hesitation or mental load.

Instead, they directly use the features generated from the dataset as inputs of machine learning models. The selected features mirror the behavioral habits across different emotional states.

### C. Signal Processing and Feature Engineering

The keystroke features were filtered and transformed to improve the data quality and performance of the model before being used in training.

**Cleaning Data:** Values which are identified as outliers (extremely large hold times or unusual typing patterns, for instance) are detected and removed. Only sequences involving valid keypresses and releases were kept for further analysis.

**Handling Missing and Noisy Data:** The system does away with incomplete or inconsistent data. This guarantees a better accuracy of the models.

**Feature Normalization:** The features, like dwell time and latency are normalized to a common scale. This ensures that features with large values do not dominate the model.

**Outlier Removal:** This helps in keeping the right data and will help it for both noise and bad keyboard typing behavior which means they have to create consistent data instead of abnormal values.

**Feature Selection:** This step helps us select only the most relevant features to our prediction model(e.g. hold time, flight time, typing speed, pause duration and error rate) while eliminating/reducing the number of unnecessary or redundant features.

In conclusion, these procedures yield a clean and significant dataset for emotion classification using ML models.

### D. Machine Learning Models

This project utilizes machine learning methods to classify Emotional States based on keystroke dynamics features. We implemented and evaluated three models:

#### K-Nearest Neighbors (KNN):

KNN or k-nearest neighbors is the most basic form of instance-based learning algorithm where a new data point is classified based on the majority class among its nearest neighbors. The data served as a reference point for how the dataset would behave. But its effectiveness is limited due to its sensitivity to noise and high dimensional data.

#### Multi-Layer Perceptron (MLP):

An MLP is a type of artificial neural network capable to model complex and nonlinear connections among input features and output classes We have an input layer, hidden layer and output layer. MLP outperforms KNN in characterizing keystroke data.



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### XGBoost (Extreme Gradient Boosting):

XGBoost (Extreme Gradient Boosting) is a gradient boosting algorithm on base learners. It builds multiple decision trees in a sequential way where each new tree minimizes the errors of its predecessor. Due to its high power on feature interactions and overfitting reduction it achieves the best performance of all models we trained especially on structured data.

Split: Thus we can split our dataset into train and test. Using the training data, models were trained and testing data were evaluated using evaluation metrics such as accuracy, precision, recall, f1-score. XGBoost proved to be the best of the three models as it had attained the best accuracy on this data.

**Model Evaluation:** The efficiency of the implemented ML models was assessed using standard classification metrics. The dataset was then split into training and testing sets, so the models were trained on one part of the data set, while another remained unseen to complete their evaluation.

Mainly, accuracy is used as the evaluation metric which indicates the overall correctness of models predicted emotional state. In addition to accuracy, the classification performance of each emotion class is represented in precision, recall and F1-score.

A \* **confusion matrix** \* is also employed to examine model performance by displaying correct and incorrect predictions for all types of emotions. This way you can tell which emotions are being accurately classified and where misclassifications happen.

We compare the outputs from various models (KNN, MLP and XGBoost) based on those metrics. XGBoost outperforms others in accuracy, indicating that it offers better performance with this dataset in emotion classification.

Thus, this selection process serves to validate the model chosen as being suitable and practical for predicting emotional states based on keystroke dynamics.

Model	Type	Important Settings	Notes
KNN	Classical	Number of neighbors, how distance is measured	Simple model; depends on nearby data points
MLP (NN)	Neural Network	Number of layers, number of neurons, learning speed	Learns complex patterns
XGBoost	Ensemble	Learning rate, number of trees, tree depth	Best performance for structured data

**Table 2: Implemented Machine Learning Models and Configuration**

### F. Experimental Design

This project will focus on the experimental design to evaluate the machine learning models using a predefined dataset in the context of keystroke sounds.

**Data Splitting:** The dataset is separated to training and testing sets. These are trained on training data and tested on separate unseen testing data to check their performance and generalization capability.

**Model Training:** KNN, MLP, and XGBoost are three trained machine learning models on the extracted keystroke features. Each model learns the association between typing behaviour and emotional states.

**Model Comparison:** Evaluation metrics such as accuracy, precision, recall and F1 scores are used to compare the performance of the models. This is useful in hopping on the best model for emotion recognition.

**Result Analysis:** In this way, predictions are made and a confusion matrix is built to evaluate the behavior of the models by displaying accurate and inaccurate predictions in various emotional classes. This aids in comprehending which emotions are accurately classified and where misclassifications take place.

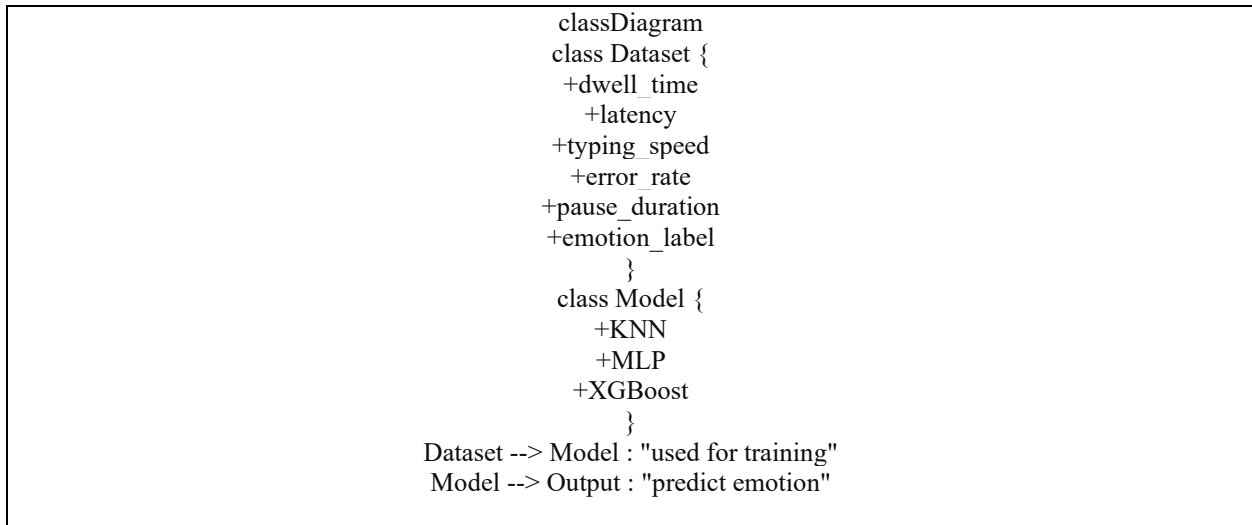


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**Implementation Environment:** Experiments are performed using Python and applicable machine learning libraries. It implements a structured and reproducible workflow for the full pipeline from preprocessing to model training and evaluation.

Thus, the experimental design is simple and an effective way to validate the proposed system on existing data without adopting complex experimental procedures



**Figure 1:** Simplified data flow showing how keystroke features from the dataset are used for training machine learning models and predicting emotional states.

#### IV. RESULTS AND ANALYSIS

To test the effectiveness of the proposed system, it is evaluated on a pre-existed keystroke dataset. The models for KNN, MLP and XGBoost are all trained and tested both to classify the emotional states according to the typing behavior.

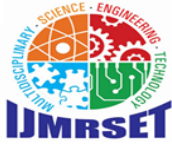
**Classification Performance:** The models perform well in multi-class emotion classification. From the models being implemented, the most precision with best accuracy is XGBoost model, followed by MLP and KNN. It then describes some evaluation metrics of machine learning algorithms, like accuracy, precision, recall and F1-score.

**Confusion Matrix Analysis:** The models are analyzed based on the confusion matrix. Which tells us some emotions like calm and happy are classified well, whereas anxious & angry may overlap due to similarities in typing patterns.

**Feature Importance:** It shows that features derived from keystroke like dwell time, latency and typing speed as well as error rate constitute important elements of the emotion classification process. Of these, time hold and time of flight are the factors that most influence the prediction.

**Model Comparison:** Even though KNN is a basic model, the drawback in this algorithm is that it suffers from noise and generally does not provide accurate predictions. MLP is used for better performance which captures non-linear relationships. And that is precisely why XGBoost delivers the best performance, as it can effectively handle complex feature interactions.

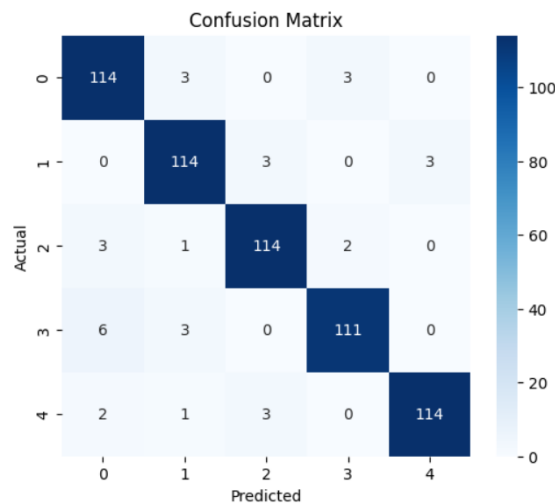
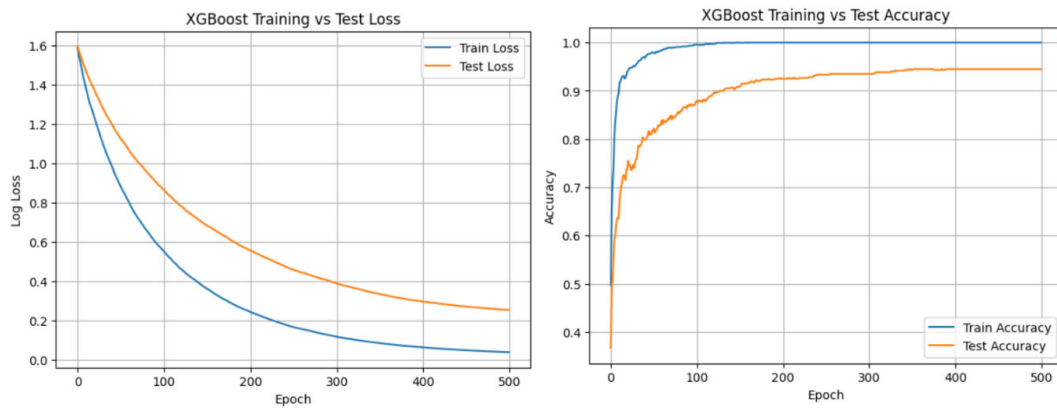
**System Validation:** Finally, by integrating the trained model with the UI (user interface), we can implement a system where live user text inputs are passed through to predict emotion in real-time. Weekly assessment feature also helps to monitor emotional patterns through time.



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The experimental results prove the efficiency of keystroke dynamics for emotion recognition, and that our proposed system works as a practical and accurate solution.



### V. DISCUSSION

Keystroke dynamics can provide a non-intrusive and low-cost approach to detect emotional states, as suggested by the proposed system. Since humans are highly expressive even through typing, analyzing these factors [dwell time, latency, typing speed and error rate] within the dataset can help discover differences in user emotion without the need of other sensors to detect where the human is at.

**Interpretation of Results:** The results indicate that the way people type is affected by their emotional state. For instance, more typing errors or slower speed at typing can signal stress or anxiety. Machine learning models are then trained on this data which enables the system to accurately capture these behavior changes as well as predicts meaningful emotion.

**Comparison with Existing Work:** The results obtained are in conformity with previous findings which show that keystroke dynamics is an effective method of emotion identification. As in previous work, characteristics such as hold time and flight time are key features for classification. Of the implemented models, XGBoost performs better, consistent with research that notes its performance on tabular data.

**Limitations:** The system has certain limitations. This is tested only on a pre-defined set of data, which may not cover real world typing scenarios. However, distinct typing styles may exist across individuals which could impact model



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performance, leading to challenges in generalization. Some emotions can be mistaken for others that have similar typing styles.

**Ethical and Privacy Considerations:** We train the system on data that was anonymized so we do not ever capture your personal or sensitive information. Due to its non-intrusive nature and the lack of textual content capture, this method helps safeguard user privacy. In a production environment however user consent and data protection needs to be in place.

**Practical Implications:** The possibilities for the system include mental health tracking and even human-computer interaction. But, it can also be plugged into your apps to track how emotions vary over time within a user and is able to offer insights into the well-being of users. It is extremely useful and the weekly assessment feature adds even more feature to it.

This paper, in summary, has shown that keystroke dynamics can be a viable solution for emotion detection while spotlighting the potential pitfalls surrounding overfitting on datasets and lack of generalizability to account for variability in crowded environments.

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