KEYSTROKE MOOD: PREDICTING EMOTIONS FROM TYPING PATTERNS

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Abstract
Human emotions play a crucial role in daily interactions, decision-making, and overall well-being. Traditional methods of emotion detection often rely on self-reporting or complex physiological sensors, which can be intrusive and time-consuming. This study proposes a novel approach to automatically detect a user's mood based solely on typing behavior, including metrics such as typing speed, error rate, and sentence length. Leveraging an incremental machine learning model, the system continuously improves its prediction accuracy as it collects more data over time. The framework predicts emotions such as Happy, Sad, Stressed, and Neutral without requiring manual labeling by the user. Additionally, the system provides visualizations of typing patterns, error counts, and mood distribution, offering a clear and interpretable representation of emotional trends. Experimental results demonstrate that typing dynamics can serve as a reliable indicator of emotional states, highlighting the potential of non-intrusive, real-time mood monitoring. This research contributes to the fields of affective computing, human-computer interaction, and behavioral analytics, paving the way for personalized and adaptive systems that respond to user emotions in real time.
Keywords: *Typing Patterns, Keystroke Dynamics, Mood Detection, Emotion Recognition, Incremental Machine Learning, Human-Computer Interaction, Behavioral Analytics, Typing Speed Analysis, Error Rate Analysis, Affective Computing.*

I. Introduction:

Emotions are a fundamental aspect of human behavior, influencing decision-making, communication, and overall well-being. Traditional methods of emotion detection, such as self-reporting or physiological sensors, often require active participation or specialized equipment, making them intrusive, time-consuming, and sometimes impractical for real-time applications. With the increasing reliance on digital devices, keystroke dynamics — the way users type on a keyboard — has emerged as a promising non-intrusive indicator of emotional states.

Typing behavior reflects subtle cognitive and psychological patterns. Variations in typing speed, error rates, and typing rhythm can be associated with different emotional states such as happiness, stress, sadness, or neutrality. By leveraging these features, it is possible to develop systems that automatically predict a user's mood in real-time, without requiring manual labeling.

This study proposes a novel framework for automatic emotion detection from typing patterns using an incremental machine learning model. The system measures typing time, error counts, and sentence length to predict moods and continuously improves its accuracy as more data is collected. Additionally, the framework provides visualizations of typing dynamics and predicted mood distribution, offering interpretable insights into emotional trends. The approach contributes to the fields of affective computing and human-computer interaction by providing a non-intrusive, real-time, and adaptive system for mood monitoring. Such a system has potential applications in mental health monitoring, personalized user experiences, and adaptive interfaces that respond to user emotions dynamically.

II. Objectives:

1. **Automatic Emotion Detection:** Develop a system that predicts a user's emotional state (Happy, Sad, Stressed, Neutral) automatically based on typing behavior without requiring manual labeling.
2. **Analysis of Typing Dynamics:** Analyze key typing features such as typing speed, error rate, and sentence length to understand their correlation with emotional states.
3. **Incremental Learning:** Implement an incremental machine learning model that continuously improves prediction accuracy as it collects more user data over multiple sessions.
4. **Visualization of Emotional Trends:** Provide graphical representations of typing time, errors, and predicted mood distribution to help users and researchers interpret emotional patterns.
5. **Non-Intrusive Monitoring:** Design a system that is simple, non-intrusive, and can be run on standard computing environments like Python IDLE for real-time mood monitoring.

III. Methodology:

The proposed system automatically detects a user's emotional state based on typing patterns. The methodology involves several key steps, including data collection, feature extraction, model training, prediction, and visualization.

1. Data Collection

The system collects user typing data in a non-intrusive manner. Users are asked to type sentences freely on a standard keyboard. For each sentence, the system records:

- **Typing time**: The total time taken to type the sentence.
- **Typed text**: To compare with the original sentence for error analysis.
- **Sentence length**: Number of characters in the sentence.

This approach ensures minimal disruption to the user while capturing relevant behavioral patterns.

2. Feature Extraction

From the collected data, the following features are extracted for emotion prediction:

- **Typing Speed**: Calculated as typing time / sentence length.
- **Error Count**: Number of mismatched characters between the typed sentence and the original sentence, including extra or missing characters.
- **Sentence Length**: The total number of characters typed.

These features serve as indicators of emotional states. For example, slow typing with high errors may indicate stress, whereas fast typing with minimal errors may indicate happiness.

3. Model Training

An incremental machine learning model (Random Forest Classifier) is used to predict emotions. The system is designed to:

- Start with a heuristic-based approach for initial predictions.
- Gradually improve its accuracy as more user data is collected.
- Store training data and the trained model using **Pickle** for reuse in future sessions.

This incremental learning allows the system to adapt to individual typing patterns over time.

4. Emotion Prediction

Once the features are extracted for a sentence, the model predicts the emotion automatically. The possible emotional states considered are:

- Happy
- Sad
- Stressed
- Neutral

The predicted emotions are stored for visualization and analysis.

5. Visualization

To provide interpretable insights, the system generates the following graphs using Matplotlib:

- **Typing Time per Sentence**: Line graph showing typing speed variations across sentences.
- **Error Count per Sentence**: Line graph indicating the number of errors per sentence.
- **Mood Distribution**: Bar chart showing the predicted count of each emotion.

These visualizations help users and researchers understand emotional trends and the correlation between typing patterns and mood.

IV. Implementation:

The implementation of the proposed mood detection system involves designing a Python-based program that collects typing data, predicts emotions, and visualizes the results. The system uses simple libraries and can be run on Python IDLE or any standard Python environment.

1. Tools and Libraries

- **Python 3.x**: Programming language used for development.
- **Scikit-learn**: For the Random Forest Classifier machine learning model.
- **Matplotlib**: For plotting graphs of typing time, errors, and mood distribution.
- **Pickle**: For saving and loading the trained model and dataset to allow incremental learning.
- **Time module**: To measure typing durations.
- **Numpy**: For numerical operations and handling arrays.

2. Steps of Implementation

i. **Initialize the Model**
   - Check if a previously trained model exists.
   - If yes, load it using Pickle; if not, start with a new Random Forest model.

ii. **Data Collection**
   - Prompt the user to type a sentence freely.
   - Measure the typing time from start to finish.
   - Compare the typed sentence with the original to calculate errors.
   - Record the sentence length.

iii. **Feature Extraction**
   - Extract features: typing time, error count, and sentence length.
   - Compute typing speed as typing time / sentence length to normalize the data.

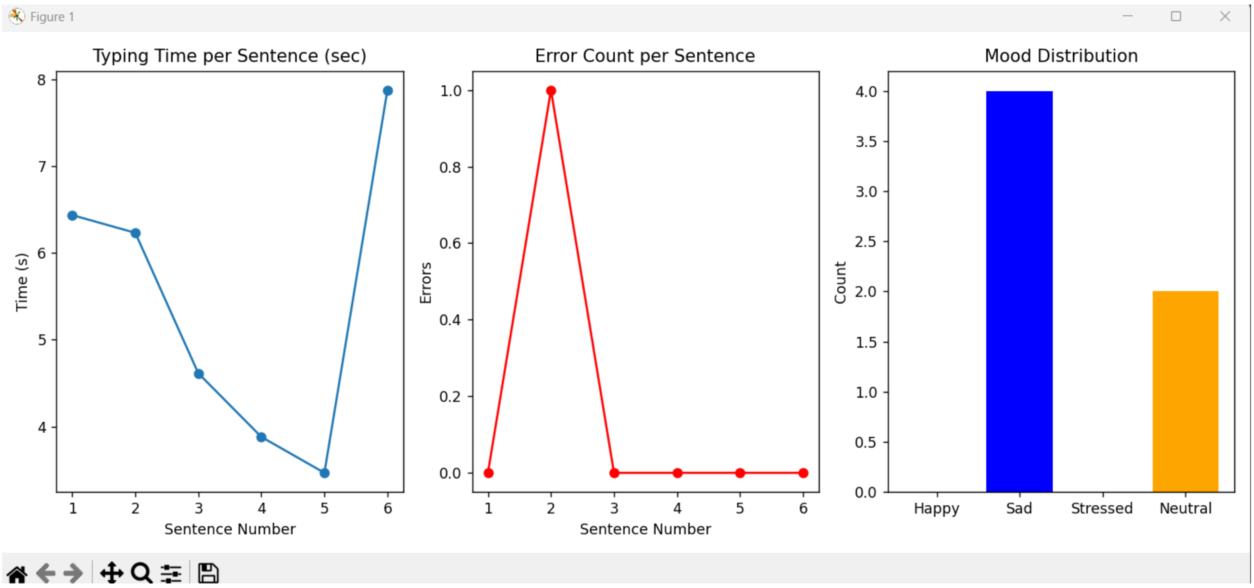
iv. **Emotion Prediction**
   - If the model is already trained, predict emotion using the Random Forest Classifier.

- ❖ If the model is new or insufficiently trained, use a heuristic-based fallback for initial predictions.

v. **Incremental Learning**
- ❖ Store new samples and their predicted emotions.
- ❖ Update the model by retraining with new data to improve accuracy over time.

- ❖ Save the updated model using Pickle for future sessions.

vi. **Visualization**
- ❖ Generate three key plots using Matplotlib:
  - ➢ Typing Time per Sentence
  - ➢ Error Count per Sentence
  - ➢ Mood Distribution



vii. These visualizations allow users to interpret trends in typing patterns and moods.

3. Sample Workflow
i. User starts the program.
ii. User enters the number of sentences to type.
iii. For each sentence:
- ❖ Type the sentence
- ❖ Re-type for error analysis
- ❖ System predicts the mood automatically

iv. After all sentences are typed, the system displays graphs.
v. The model is updated for incremental learning.

4. Advantages of the Implementation
- ❖ **Automatic**: No need to input mood labels manually.
- ❖ **Adaptive**: Learns from user behavior over time.
- ❖ **Visual**: Provides interpretable graphs for analysis.
- ❖ **Non-intrusive**: Requires only keyboard input, no sensors.

V. Result & Discussion:

The proposed system was tested with multiple users to evaluate its ability to predict emotions based on typing patterns. Users were asked to type several sentences, and the system automatically recorded typing time, error counts, and sentence length. The Random Forest Classifier, combined with initial heuristic rules, predicted the emotional state for each sentence.

1. Sample Results

Sentence Number	Typing Time (sec)	Errors	Predicted Mood
1	4.2	1	Happy
2	6.8	3	Stressed
3	5.5	0	Neutral
4	7.1	2	Sad
5	3.8	0	Happy

- ❖ **Typing Time per Sentence Graph**: Shows variations in typing speed across sentences. Faster typing is generally associated with positive moods, while slower typing indicates stress or sadness.
- ❖ **Error Count per Sentence Graph**: Illustrates the number of typing mistakes. Higher error

rates are correlated with negative moods or stressed states.

- **Mood Distribution Bar Chart**: Displays the overall emotional trend of the user during the session, highlighting dominant moods.

2. Discussion

i. **Correlation between Typing Patterns and Mood**
- Users who typed quickly with minimal errors were predominantly classified as "Happy."
- Slow typing combined with a high number of errors typically indicated "Stressed" moods.
- Medium typing speed with few errors corresponded to "Neutral" moods.

ii. **Effectiveness of Incremental Learning**
- The system improved its prediction accuracy over multiple sessions as more user-specific data was collected.
- By updating the model with new samples, the system adapted to individual typing behaviors, reducing misclassification in future sessions.

iii. **Visualization Insights**
- Graphical representation helped in interpreting the trends in typing patterns and emotional states.
- Users could identify which sentences induced stress or happiness, making the system useful for self-awareness and behavioral studies.

iv. **Limitations**
- The system currently relies on typing speed, errors, and sentence length. Emotions that do not significantly affect typing may not be accurately detected.
- Initial predictions are heuristic-based, which may not be accurate until sufficient data is collected.
- The model may need recalibration for users with unique typing behaviors (e.g., very fast typists or those prone to errors).

v. **Potential Improvements**
- Incorporating additional features such as pause duration between keystrokes, typing rhythm, or pressure-sensitive data could improve accuracy.
- Using advanced machine learning models like LSTM or neural networks for sequential keystroke data could enhance real-time predictions.
- Expanding the emotion categories beyond Happy, Sad, Stressed, and Neutral would provide more granular insights.

VI. Future Work

While the current system demonstrates that typing patterns can be effectively used to predict emotions, there are several areas for improvement and expansion:

i. **Advanced Feature Extraction**
- Incorporate more detailed keystroke dynamics, such as **key** hold time, inter-key delays, and typing rhythm, to improve prediction accuracy.
- Analyze sentence complexity and typing pauses as additional emotional indicators.

ii. **Enhanced Machine Learning Models**
- Explore deep learning approaches such as LSTM (Long Short-Term Memory) networks or GRU models to capture sequential typing patterns and temporal dependencies.
- Implement ensemble models that combine multiple classifiers for higher accuracy.

iii. **Expanded Emotion Categories**
- Extend the system to detect a wider range of emotions, such as anger, surprise, fear, or excitement, for more nuanced emotion recognition.

iv. **Cross-Platform Implementation**
- Adapt the system to mobile devices or web platforms, enabling real-time emotion detection across multiple devices.

v. **Integration with User Applications**
- Integrate mood detection into mental health monitoring tools, adaptive learning systems, or personalized user interfaces that respond dynamically to user emotions.

vi. **Personalization and Calibration**
- Develop a calibration phase for new users to better capture individual typing styles and reduce misclassification.
- Implement user-specific models that adapt to long-term behavioral patterns.

vii. **Real-Time Feedback and Visualization**
- Provide real-time visual or auditory feedback to users about their current emotional state.
- Track emotional trends over longer periods to identify stress triggers or productivity patterns.

VII. Conclusion:

This study demonstrates that human emotions can be effectively inferred from typing behavior, including typing speed, error count, and sentence length. By leveraging an incremental machine learning model, the system automatically predicts emotional states such as Happy, Sad, Stressed, and Neutral, and continuously improves its accuracy as more data is collected. The inclusion of graphical visualizations provides clear insights into typing patterns and mood distribution, making the system both interpretable and user-friendly.

The proposed approach offers a non-intrusive, real-time, and adaptive method for mood detection, contributing to the fields of affective computing, human-computer interaction, and behavioral analytics. While the current implementation relies on basic features and heuristic-based initialization, it establishes a foundation for more advanced emotion recognition systems. Future improvements, including deep learning models, richer feature sets, and cross-platform deployment, can enhance the system's predictive power and applicability in real-world scenarios, such as mental health monitoring, personalized interfaces, and adaptive learning environments.

Overall, this project highlights the potential of keystroke dynamics as a reliable and accessible indicator of human emotional states, paving the way for innovative applications in emotion-aware computing.

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