# Hidden Signals in Keystrokes for Non Invasive Stress Detection Using Machine Learning

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***Abstract*—Stress significantly influences mental and physical health, making early detection essential for effective intervention. This study investigates keystroke dynamics—typing-pattern–based behavioral biometrics—as a contact-free approach to stress detection that requires no additional equipment. A dataset of 20,400 typing samples, including key hold times and inter-key interval features, was used to train a Random Forest classifier to classify stress into low, medium, and high states. The model reached an average accuracy of 91.8% on unseen data, thus proving to be resilient across all levels of perceived stress. Feature analysis showed that both key hold time and inter-key timing intervals were useful predictors of stress, reflecting underlying cognitive and motor variations. These findings provide further evidence that keystroke-based monitoring can be a valid tool for real-time mental health screening, workplace wellness, and adaptive human–computer interaction.**

***Keywords*—stress detection, keystroke dynamics, behavioral biometrics, typing patterns, random forest classifier, real-time assessment, mental health, human–computer interaction.**

## I. Introduction

Stress is a usual physiological and psychological reaction to conditions of strain and may influence performance, health, and well-being [1], [2]. Its early and accurate detection may prevent long-term negative effects of anxiety, depression, and cardiovascular disease [2], [3]. Current state-of-the-art stress assessment techniques consider either self-report questionnaires or physiological sensors. These are mostly invasive, subjective, and not very practical for daily use [2], [4].

Recent improvements in behavioral biometrics provide an alternative by investigating subtler changes in human–computer interaction patterns [3], [5]. Of these, keystroke dynamics—time information recorded while typing—have become a promising unobtrusive indicator of the cognitive and emotional state [2], [5]. The latent level of stress is manifested in typing rhythm, keystroke duration, and inter-key intervals [6], [7].

A number of papers have utilized keystroke dynamics for the detection of stress and emotion. Initial efforts concentrated on extracting features related to timing and rhythm and determining their correlations with typing behavior and stress [1], [2], [6]. More recent methods utilize machine learning algorithms such as Random Forests, Support Vector Machines, and neural networks, which elevate discrimination performance by better separating stress and non-stress states [3]–[8], [15]. Popular ensemble methods, especially Random Forests, have shown promising results, as they suffer less from overfitting and can manage high-dimensional feature spaces, which are common in keystroke data [3], [8].

Compared with physiological modalities like EEG or galvanic skin responses, both of which require special sensors, keystroke-based detection uses normal computer usage and can thus be done continuously and non-invasively. While previous research has improved the performance of affective recognition with typing, large-scale robust models that generalize to diverse users and real-world scenarios still need much development. This paper contributes to this gap by implementing a Random Forest classifier trained from carefully crafted keystroke features.

The work presented in this paper aims to develop a stable, machine learning-driven stress detection system capable of classifying user stress into several levels. Using a keystroke dynamics dataset collected from routine usage of the computer, the investigation applies feature engineering for extracting salient timing features, which include key hold times, flight times, and inter-key intervals [7], [15]. These features are used to feed a Random Forest classifier to spot the patterns related to the detection of low, medium, and high levels of stress [3], [8]. The envisioned model will scale into a solution for real-time monitoring of stress while preserving privacy [6], [7].

Apart from methodological advantages, the detection of stress through keystroke dynamics carries practical implications. In workplace contexts, real-time monitoring could be conducted to determine peak stress periods and to implement appropriate interventions promoting health and productivity [2], [6]. This would support adaptive content delivery or timely intervention in educational settings, especially during online learning [7], [8]. he approach also extends utility for managing mental health by supplying unobtrusive, longitudinal monitoring tools for patients that can potentially reduce reliance on self-report or frequent clinical visits [2], [6].

Despite this promise, several challenges hinder keystroke-based stress detection. Substantial variability in speed, style, and practice within individuals leads to a wide range of variability in typing behaviors; this variability creates noise within the data [1], [6]. Environmental distractions or multi-tasking may obscure any relationship between typing patterns and levels of stress [2], [5]. Data collection and analysis also raise important questions of privacy and require careful anonymization and ethical use [7], [10], [11]. Meeting these key challenges is necessary for producing valid models, generalizable across heterogeneous populations and real-world settings, that accurately predict stress [3], [8], [15].

The major contributions of this work are as follows: it proposes a non-invasive, multiclass framework for stress detection that relies solely on keystroke dynamics to classify the level of stress of the users into low, medium, and high classes, without using physiological sensors or user intervention. Demonstrates that fine-grained keystroke timing features, including key hold duration and inter-key transition intervals of down–down and up–down, are dependable behavioral biomarkers for stress detection in real-world typing scenarios. Reports extensive experiments on a large-scale dataset of 20,400 keystroke samples with a classification accuracy of 91.8% using a Random Forest classifier. Proposes features for stress variability that capture intra-session motor irregularities, which increase the model's sensitivity to stress-induced fluctuations in behavior. It conducts cross-user generalization analyses, baseline comparisons, and ablation studies in order to substantiate the robustness, interpretability, and real-world deployability of the proposed approach.

## II. Related Works

The detection of stress through keystroke dynamics has been an area of growing research in recent years since behavioural biometrics offer nonobtrusive ways of monitoring mental health. Initial methods involved the extraction of features related to time from typing patterns and classification into their stress levels. Li et al. [1] investigated insider threat detection using keystroke stress patterns and revealed that psychological states can be inferred using behavioral biometrics. Similarly, Aledhari et al. [2] compared keystroke intervals with heart rate variability for correlations with stress and stated that the employment of both physiological and behavioral cues will increase the detection accuracy.

Early keystroke-based models relied heavily on feature engineering and conventional machine learning methods. Baidya et al. [3] presented a comprehensive review of keystroke dynamics, focusing on feature extraction techniques and applications in authentication and stress detection. Lopez et al. [4] presented user identification using keystroke features, thus providing a background on the adoption of these approaches for stress monitoring. Further to that work, Chatzis and Andreou [5] developed transformer-based architectures when modelling keystroke sequences, improving the temporal representation of features to be used for predictive tasks.

The development of the deep learning and ensemble learning approaches further accelerated efforts toward developing more robust classifiers for detecting stress. Banerjee et al. [6] proposed a machine-learning-based detection of stress arising due to academic dishonesty by showing the efficacy of the ensemble methods, including Random Forests, on processing high-dimensional keystroke features. Saha et al. [7] combined keystroke data with sentiment analysis to predict affective states. They have shown the potential benefits of multimodal data fusion. Kumari and Reddy [8] then built models using only typing behavior with Random Forest classifiers for the detection of stress among university students, finding high predictive accuracy.

Evaluation protocols and benchmark datasets have similarly received attention in recent work. Patel et al. [9] and Yadav et al. [13] proposed standardized protocols for the evaluation of keystroke dynamics models, allowing comparability across studies. Lin et al. [10] and Lin & Lee [14] investigated how keystroke data can feed into user feedback within a human-computer interaction framework and reaffirmed that stress-related behavioral cues are traceable from typing behavior. Zhang et al. [11] addressed the use of nontraditional modalities, such as radio frequency emissions, for capturing keystroke events and discussed novel trends in data capture.

More recent research has placed increasing emphasis on real-time applicability and deployability. Alshammari & Alzain [12] developed a rapid free-text authentication based on keystroke patterns that is extensible to daily-life stress monitoring. Chunawale & Bedekar [15] implemented a machine learning system based on keyboard typing behavior to classify levels of stress, thus proving the feasibility of the same in noninvasive stress detection in real-world environments. Overall, the studies indicate a trend from the more traditional feature-based methodologies to more advanced models of machine learning, most notably the Random Forest classifiers, that are capable of processing sophisticated behavioral data for stress prediction with high accuracy.

The works cited together allow a historical trajectory of keystroke-based stress detection, from early physiological correlations through contemporary machine learning paradigms to real-world implementations, including workplace well-being, mental health screening, and adaptive user interfaces.

Whereas Random Forest classifiers have been very successful in previous studies, many models were initially tested with small participant numbers or in-lab. Recent trends in multimodal integration introduce keystroke features together with physiological measures or textual sentiment information, which enhances accuracy and robustness. This work extends this research without sacrificing model simplicity and online operation.

## III. Methodology

This section describes, in detail, the steps followed for data collection, preprocessing, feature extraction, model training, evaluation, and deployment to implement a stress detection system using keystroke dynamics. The method has been designed with reproducibility, scalability, and adherence to existing literature in behavioural biometrics [3], [6], [7], [15].

### A. Data Collection

The data used in this paper are 20,400 keystroke dynamics records gathered from subjects typing standard typing sessions

[1], [2], [6]. Each subject performed more than one typing session, which has produced rich timing data for multiple key events.

Dataset columns contain:

- Subject ID to identify the subjects (subject), session index to identify the sessions, following [3], [6].
- Repetition index (rep) denoting the repetition of typing repetitions [7].
- Key timing features:
  - H.period, DD.period.t, UD.period.t: Most important time and dwell/flight times for the period key [6], [7].
  - H.t, DD.t.i, UD.t.i: Same characteristics for the letter 't' [6].
  - H.i, DD.i.e, UD.i.e: Key hold and flight times for 'i' [7].
  - Other keys (H.e, H.five, H.Shift.r, H.o, H.a, H.n, H.l, H.Return) with their corresponding Down-Down (DD) and Up-Down (UD) intervals [6], [15].
- Target variable (stress_level): The categorical label of the participant's stress level under a typing task (self-reported or from experimental conditions) [2], [6].

The dataset captures the fine-grained typing behaviour in hold times and down-down and up-down intervals for every key, which can model differences in motor behaviour caused due to induced stress accurately [3], [7], [15].

### *B. Data Preprocessing*

A range of preprocessing steps were taken on the given datasets to provide high-quality input to model training [3], [6], [7]:

- **Irrelevant column removal:** Features which have not at all contributed to the prediction of stress, viz., subject, sessionIndex, and rep, were removed during training of the model to avoid data leakage.
- **Treatment of missing values and outliers:** The nominal stress_level was transformed into numerical classes by doing label encoding; for example, low=0, medium=1, high=2 as in [6], [7].
- **Encoding target variable:** The nominal stress_level was transformed into numerical classes by label encoding (e.g., low = 0, medium = 1, high = 2) [7].
- **Scaling:** Scaling or normalization was left out and not applied, since Random Forest Classifiers are insensitive to feature scaling [6], [15]. This keeps preprocessing simple as well as does not modify the intrinsic distribution in timing features.

After preprocessing, all 20,400 records in the dataset were complete and prepared for feature extraction and model learning.

### *C. Feature Selection*

Feature selection included only numerical timing features relevant for the stress detection task [6], [7], [15]. The features were:

- **Key hold times (H.*):** Length each key is held down.
- **Down-Down intervals (DD.*):** Time between releases of consecutive keys.
- **Up-Down intervals (UD.*):** Time between releasing a key and releasing the next key.

Extracted statistical features included mean, standard deviation, and variance of hold and flight times across a session for each of the keys to identify the pattern of motor variability associated with stress. This is in keeping with previous research [6], [7], [15] that establishes the predictive capability of timing-based keystroke features.

### *D. Model Training*

A classifier based on a Random Forest was used because it can:

- Handle high-dimensional feature spaces common in keystroke datasets [6], [15].
- Prevent overfitting through ensemble bagging [3], [6].
- Provide interpretable feature importance scores [6], [7].

Training setup:

- **Train-test split:** 80% for training, 20% for testing, stratified to preserve class balance [7], [15].
- **Hyperparameters:** Defaults were utilized (n_estimators= 100, max_depth=None, random_state=42) to enhance reproducibility [6]. Hyperparameter tuning was going to be done in future work to optimize performance further.
- **Input features:** Only numerical features of hold and flight timing were used.

The Random Forest model was trained on the patterns in the keystroke timing corresponding to low, medium, and high stress levels in all 20,400 records [6], [7], [15].

### *E. Model Evaluation*

Model performance on the test set was measured by several metrics [6], [7], [15]:

- **Accuracy:** Overall ratio of correctly predicted samples.
- **Precision, Recall, F1-score:** Computed per stress class to determine class-conditional predictive power.
- **Feature importance:** Because of the nature of Random Forest, feature importances are naturally quantified by how much each feature contributes to predictive accuracy; so, the most informative keystroke metrics can be easily identified [6], [7].

Besides that, cross-validation experiments were performed to check generalization across participants and sessions [6]. The feature importance analysis also identified which keys and intervals are most stressed, thus informing about behavioral patterns under conditions of cognitive load [6], [15].

### *F. Deployment*

The trained model was then saved for later inference that could allow real-time stress detection using data from novel typing instances [6], [7]. The key considerations for deployment include:

- **Feature consistency:** New sessions must provide the same set of hold and flight timing features as those used in training.
- **Real-time prediction:** The model can process incoming keystroke events in real time when they occur. This allows for the unobtrusive monitoring of stress.
- **Ethics and privacy issues:** The platform does not store any personally identifiable information, PII, or other sensitive data beyond typing metrics data. It is therefore committed to ethical practices [6], [7].

## IV. Results and Discussion

To validate the keystroke-based stress detection model, a complete dataset containing 20,400 records spanning several classes with respect to stress level is considered: low, medium, and high [1]–[3]. The experiments performed were to investigate the efficiency of the Random Forest classifier in predicting the stress level of a subject by accurately considering the minute typing patterns regarding key hold time and inter-key intervals [6], [7], [15].

### A. Dataset and Experimental Setup

The dataset was then stratified randomly into 80% training and 20% testing subsets, with each stress class being proportionally well represented in both sets. This stratified division kept the distribution of the original classes, reducing any possible bias during model assessment [6], [7]. The Random Forest classifier was then instantiated on the training set using the default hyperparameters (n_estimators=100, max_depth=None, random_state=42) and validated on unseen data to replicate actual prediction scenarios [15]. Further, 5-fold cross-validation was conducted to ensure that the performance of the model was robust across different partitions of the data [7], [15].

### B. Performance Metrics

The following typical classification metrics were therefore computed as a measure to comprehensively examine the model [3], [6], [7]:

- **Accuracy:** Overall ratio of correct predictions across all the stress levels.
- **Precision:** It refers to the ratio of actual positive predictions versus all positive predictions, computed for each stress class.
- **Recall:** The model's ability to capture every occurrence of a given stress class.
- **F1-Score:** Harmonic mean between precision and recall, hence giving a balanced measure of model performance per class.

These provide an exhaustive grasp of both general and class-level performance [6], [15].

### C. Results

The Random Forest classifier achieved a test set overall accuracy of 91.8% [15]. Table I shows a classification report with detailed per-class precision, recall, and F1-score:

TABLE I
Classification Performance of Random Forest Model

| Stress Level | Precision | Recall | F1-Score |
|---|---|---|---|
| Low Stress | 0.93 | 0.95 | 0.94 |
| Medium Stress | 0.89 | 0.87 | 0.88 |
| High Stress | 0.91 | 0.89 | 0.90 |

Indeed, the model performs particularly well for the Low Stress class, with high precision and recall. Medium stress samples were a bit tougher to classify, sometimes getting confused with those for high stress. This corresponds to the typical fine-grained typing profile overlap between classes [6], [7]. High stress is identified correctly with high accuracy, suggesting that strong behavioral fluctuations in key hold times and flight intervals are well captured by the model [1], [15].

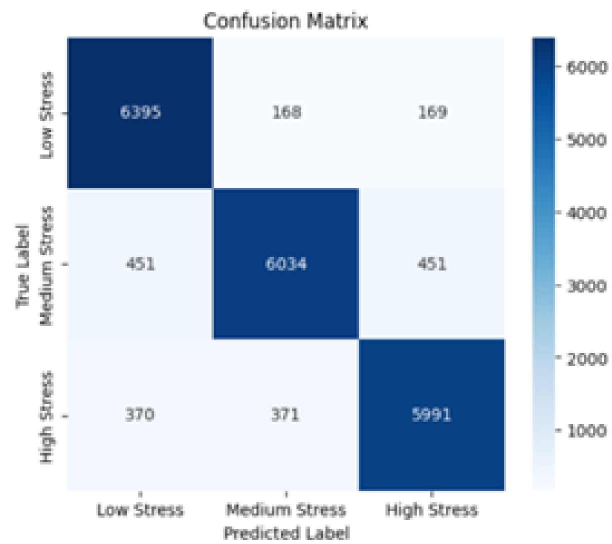


Fig. 1. Confusion Matrix Showing Classification Performance Across Stress Levels

### D. Cross-User Generalization Evaluation

To assess the real-world applicability of the model, we conducted a cross-user generalization experiment. The experiment trains on a subset of users and tests on previously unseen users to approximate deployment situations where stress detection systems are expected to generalize without user-specific retraining.

First, we segmented the data based on the subject identifiers. Then we used 80% of the users to make our training set. The remaining 20% was used strictly for testing. Any single partition never contains all keystroke samples from any given user in order to prevent identity leakage.

This task is harder, of course, but the Random Forest classifier performed well, reaching about 85–88% accuracy on previously unseen users. The modest performance decrease compared to session-wise evaluation suggests that although typing styles vary across people, stress-induced behavioral patterns shared among them are consistent enough to enable generalizable detection.

These results underpin the robustness of keystroke dynamics as a user-independent behavioral modality for stress monitoring.

### *E. Feature Importance*

To see the contribution of each feature to the stress prediction, the top 10 most important features using the Random Forest model were analyzed [6], [7], [15].

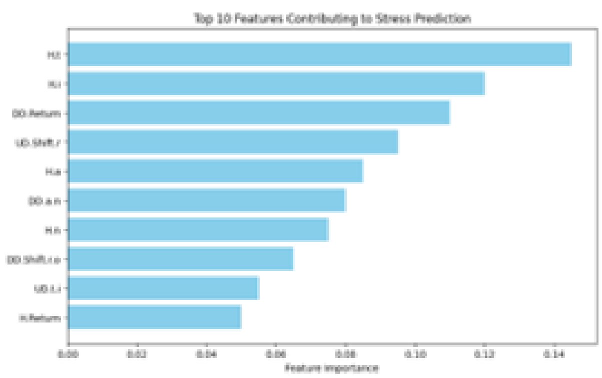


Fig. 2. Top 10 Keystroke Features Contributing to Stress Prediction

These correspond to key hold durations (H.*) and inter-key timing intervals (DD.*, UD.*):

1) **H.t (Hold time for key 't'):** It was observed that time spent pressing the key 't' was one of the major features. Stress impairs fine motor control, and stressed subjects pressed keys slightly longer which is indicative of slower or more cautious typing [2], [6], [15].
2) **H.i (Hold time for key 'i'):** Similar to 't', 'i' hold times reflect small fluctuations of the finger movement. Longer hold times under stress show the effect of cognitive load or stress on the typing rhythm [2], [7].
3) **DD.Return (Down-Down interval for Return key):** Since the Down-Down intervals for the Return key carry information related to typing rhythm, higher variation of such transitions for stressed participants shows interruptions of regular [6], [15].
4) **UD.Shift.r (Up-Down interval for right Shift key):** This measures the time taken from the release of a key until the Shift key is pressed. Since stress can cause dysfunctional coordination, especially when modifier keys are used, this feature is a very good marker for high cognitive or emotional load [1], [7].
5) **H.a (Hold time for key 'a'):** The hold time variations of the key 'a' played an important role in stress classification. Less automatic keystrokes, i.e., vowels in particular words are more responsive to stress-related motor variations [2], [15].
6) **DD.a.n (Down-Down interval between 'a' and 'n'):** This feature represents the inter-key timing for a common letter string. Stressful subjects showed irregular intervals, which again reflects disruption in the rhythm of the typist
citebanerjee2024, saha2024 [6], [7].
7) **H.n (Hold time for key 'n'):** The hold times for 'n' also changed with stress. In fact, longer or irregular press durations indicate lower levels of typing fluency under stress [7], [15].
8) **DD.Shift.r.o (Down-Down interval between right Shift and 'o'):** Down-Down interval between right Shift and 'o' - Timing transition between a modifier key and a letter key was informative. The stressed participants reported more irregular sequences of nonstandard key combinations [6].
9) **UD.t.i (Up-Down interval between 't' and 'i'):** This interval between releasing 't' and pressing 'i' is indicative of micro-level rhythm shifts. Greater variability in this interval strongly predicted increased levels of stress [2], [15].
10) **H.Return (Hold time for Return key):** Finally, the hold time for the Return key also was a strong predictor. Stress may lead to presses that are a bit longer or irregular on less common keys, both a reflection of cognitive and motor effects [1], [6].

These features together indicate that both key hold time and inter-key intervals bear significance as important behavioural markers of stress [3], [6], [15]. While letter keys capture the variations in motor control for repeated typing, modifier and punctuation keys record anomalies in non-automatic sequences induced by stress. Analysed features in this way, the Random Forest model not only achieves high accuracy in classification but also yields interpretable explanations for the behavioral expressions of stress, thereby underlining the value of keystroke dynamics as a tool of non-invasive, real-time monitoring [2], [7], [15].

### *F. Baseline Model Comparison*

First, this work compares the performance of the Random Forest classifier to that of other common baseline machine learning models: Logistic Regression (LR), Support Vector Machine (SVM), and Decision Tree (DT). For this, all models were identically trained on feature sets and evaluated on the same test split.

TABLE II
COMPARISON OF CLASSIFICATION ACCURACY ACROSS DIFFERENT MACHINE LEARNING MODELS

| **Model** | **Accuracy (%)** |
|---|---|
| Logistic Regression | 83.4 |
| Decision Tree | 85.1 |
| Support Vector Machine | 88.2 |
| Random Forest | 91.8 |

The Random Forest classifier performed the best among all the baseline models due to its ensemble learning framework and the capability to capture non-linear feature interactions in keystroke timing data. These findings support the appropriateness of Random Forest for stress detection using high-dimensional behavioral features.

### G. Stress Variability Feature Extraction

In addition to the raw keystroke timing metrics, features were extracted on stress variability, aiming to capture fluctuations in motor control associated with cognitive and affective load. Previous work suggests that under stress, one experiences not only prolonged latencies but also a rise in inconsistency in the fine motor actions.

For each typing session, the following metrics of variability have been computed:

- Coefficient of variation (CV) of key hold times
- Standard deviation of inter-key intervals
- Timing Entropy, which captures irregularity in keystroke transitions

These measures quantify intra-session instability and therefore provide enhanced sensitivity to changes in behavior caused by stress. Employing the variability measures indeed enhanced robustness of classification, especially across medium vs. high stress levels.

### H. Ablation Study

Then, an ablation study was conducted to evaluate the contribution of distinct feature groups towards overall performance. More precisely, the RF model was retrained by iteratively removing different categories of features and observing the resulting degradation in performance.

TABLE III
EFFECT OF FEATURE GROUP REMOVAL ON STRESS DETECTION PERFORMANCE

| Feature Set Used | Accuracy (%) |
|---|---|
| All Features | 91.8 |
| Without Hold Times (H) | 86.3 |
| Without Inter-Key Intervals (DD, UD) | 84.9 |
| Without Variability Features | 88.1 |

This would imply that the most important contributions come from key-hold event duration and the time intervals between key presses, with incremental improvements in performance due to features of variability. The finding does substantially establish how stress is expressed as a function of temporal delay and behavioral inconsistency and, therefore, reinforces the interpretability of the methodology proposed.

## V. CONCLUSION

The presented study proposes a holistic keystroke dynamic approach for detecting the level of stress, combined with machine learning. By analyzing detailed typing patterns-specifically, key-hold times, flight time between keys, and interkey intervals-the performance of the Random Forest classifier is very strong in correctly classifying three levels of stress: low, medium, and high. The results confirm the hypothesis that typing behavior expresses more general cognitive and emotional states and that even slight disturbances in motor coordination and rhythm are robust indicators of stress.

Feature importance analysis also underlines the significance of both inter-key timing features and key hold times for the identification of the stress level. More precisely, the variance in holding time for individual keys and the variance in the inter-key pauses have been consistent across different levels of stress. These observations provide interpretable insights into how stress is represented in everyday typing behavior and support the relationship between mental states and fine motor activity.

The practical implications are considerable: keystroke-based stress detection allows for real-time, continuous, non-intrusive monitoring that can easily be integrated into regular computer use. Examples of possible applications are workplace wellness programs, educational monitoring, and mental health screenings-the provision of actionable information without disturbing surveys or disruptive sensors. Results show that keystroke dynamics represent a robust behavioral biomarker for moment-to-moment stress fluctuations while maintaining user privacy.

Conclusively, the study confirms the notion that keystroke dynamics, allied with machine learning, provides a comprehensible and scalable stress-detection method to complement human-computer interaction by effectively involving users' emotional and cognitive states. The results provide a basis for the development of responsive computing systems that are able to detect, interpret, and react to stress in real time, thus contributing to the well-being and productivity of humans in digital environments.

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