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A Framework for Continuous Authentication in Secure Cloud Access Systems

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Abstract

The cloud computing technology provides the ability to store the data of the users along with offering the service through the Internet. Cloud computing environments are vulnerable to threats such as session hijacking and credential misuse. Traditional authentications methods are based on one time verification of the authentication process alone.

This paper presents a model for continuous authentication that can be used to improve cloud security by ensuring the identification of user activity during an active session. Specifically, behavioral biometrics like keystroke dynamics will be used to detect user activity in an online environment and create a unique behavior pattern for every individual.

Moreover, Since continuous authentication requires large-scale data analysis, scalable big data computing solutions such as Apache Spark will be used to handle authentication log files. The objective of this paper is to develop a model for continuous authentication that enhances cloud security cloud computing systems from any breaches.

Index Terms—Continuous Authentication, Keystroke Dynamics, Cloud Security, Zero Trust, Behavioral Biometrics

1. Introduction

Modern enterprise security is shifting towards Zero Trust Architecture (ZTA), where no user or system is trusted by default. Traditional authentication methods rely solely on one-time login verification. Such methods fail to detect unauthorized access during active sessions, especially when a session is compromised after initial authentication.

Problem Statement: Traditional authentication systems rely on one-time verification and fail to detect unauthorized access during active sessions, making cloud environments vulnerable to session hijacking and credential misuse.

Continuous Authentication (CA), which provides continuous identity validation, addresses this limitation by monitoring user behavior throughout the session. Recent studies [13], [14] demonstrate the effectiveness of machine learning and deep learning techniques in continuous authentication systems. Unlike traditional approaches, CA does not rely solely on static credentials but incorporates contextual and behavioral information for ongoing verification.

By leveraging behavioral biometrics and real-time analytics, continuous authentication offers a more robust and adaptive security mechanism suited for modern cloud computing environments. The proposed framework builds upon these concepts to enhance cloud security through continuous user verification.

2. Literature Review

Traditional access control mechanisms in cloud computing primarily include Role-Based Access Control (RBAC) and Attribute-Based Access Control (ABAC). RBAC assigns

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permissions based on predefined user roles, whereas ABAC provides fine-grained access control by considering multiple attributes such as user identity, environment, and resource characteristics.

1. **Role-Based Access Control (RBAC)**

In RBAC, permissions are assigned to roles rather than individual users, and users are granted access based on their assigned roles. This approach simplifies access management and minimizes administrative overhead. For example, roles such as Admin, Employee, and Guest define different levels of access. However, RBAC lacks flexibility in dynamic environments where user attributes frequently change.

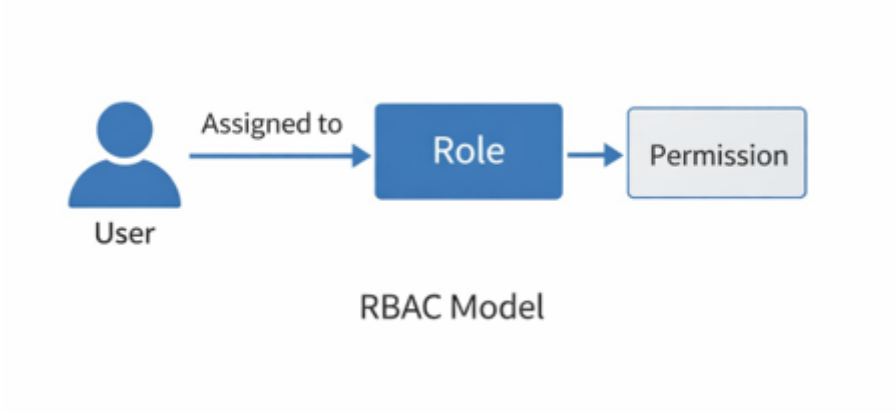

Fig. 1: Role-Based Access Control (RBAC) Model

Fig. 1 illustrates the RBAC model, where users are assigned roles, and roles are associated with permissions. While this indirect relationship simplifies management, it is less adaptable to dynamic conditions.

2. **Attribute-Based Access Control (ABAC)**

ABAC determines access based on multiple attributes related to users, resources, and context. These attributes may include user role, location, time, and device type. Access decisions are made using logical conditions, enabling context-aware and fine-grained control. However, this flexibility introduces higher computational complexity and management overhead.

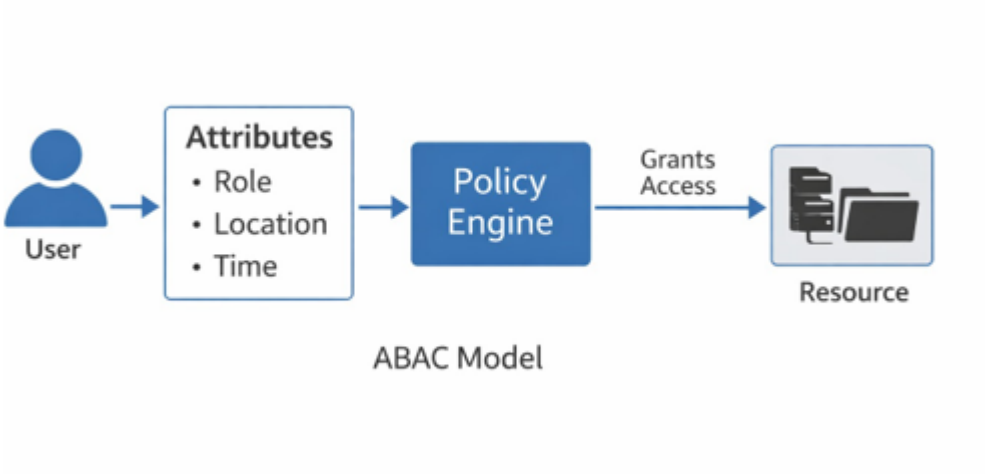

Fig. 2: Attribute-Based Access Control (ABAC) Model

Fig. 2 represents the ABAC model, where access decisions are based on evaluating multiple attributes. Although it offers higher flexibility than RBAC, it introduces additional complexity.

Although RBAC and ABAC provide structured access control mechanisms, they are limited to decision-making at the initial access stage.

Several studies have focused on enhancing data security in cloud environments. Yu et al. [2]

introduced a fine-grained data access control mechanism using Key-Policy Attribute-Based Encryption (KP-ABE) with proxy re-encryption techniques. While this improves confidentiality and scalability, it does not support continuous monitoring after authentication. Similarly, Yang et al. [3] proposed DAC-MACS for multi-authority environments, but it still relies on static authentication mechanisms.

Chittaranjan Hota et al. [4] explored capability-based access control using cryptographic techniques. Although effective for authorization, it assumes that authenticated users remain trustworthy throughout the session, which is a limitation in dynamic environments.

Therefore, most existing approaches primarily focus on initial authentication and access control, while failing to ensure continuous user verification during active sessions.

Recent research highlights the importance of continuous authentication mechanisms for ongoing identity verification [13], [14]. Behavioral biometrics combined with machine learning techniques have shown promising results by analyzing features such as dwell time and flight time. However, many existing approaches lack integration with real-time cloud environments and scalable data processing frameworks, highlighting the need for a continuous and adaptive authentication framework. This research gap motivates the development of the proposed continuous authentication framework presented in this paper.

3. Research Gap and Proposed Contribution

1. Research Gap

Based on the analysis of existing literature, the following critical limitations are identified:

- Most systems rely on one-time authentication and lack continuous verification
- Existing systems fail to detect anomalies in real-time during active sessions.
- Lack of integration between behavioral biometrics and cloud-based real-time systems
- Insufficient use of scalable big data technologies for handling authentication logs
- There is no unified framework integrating behavioral biometrics with real-time scalable cloud systems."

2. Proposed Contribution

Key Contributions:

- Continuous authentication using keystroke dynamics for real-time user verification
- Dynamic trust score mechanism for adaptive access con-trol
- Integration with big data technologies such as Apache Spark for scalability
- Implementation aligned with Zero Trust Architecture for enhanced security

To address these limitations, the proposed framework introduces a continuous authentication system that combines behavioral biometrics (keystroke dynamics), machine learning-based analysis, and real-time monitoring. Additionally, big data technologies such as Apache Spark are utilized to ensure scalability and efficient processing of authentication data. This approach enables continuous identity verification throughout the user session, thereby enhancing cloud security against modern threats.

4. Proposed Framework

The proposed continuous authentication framework enhances cloud security by verifying user identity throughout the entire session instead of relying only on initial login authentication. This approach differs from traditional systems that perform authentication only at login without continuous verification.

The architectural design of this authentication system is shown in Fig. 3.

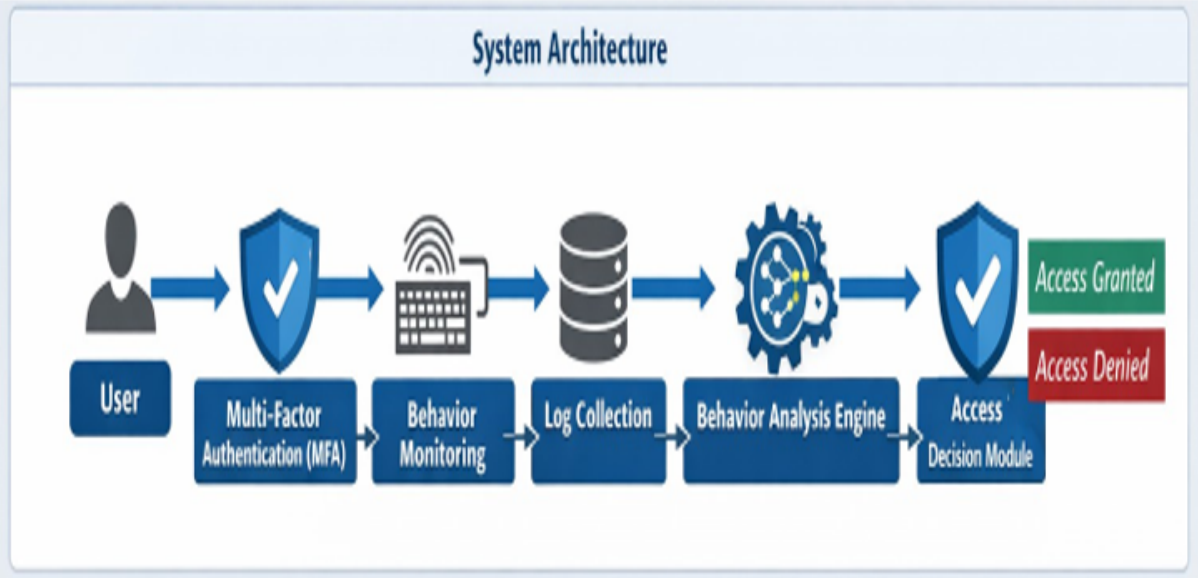

Fig. 3: Continuous Authentication Framework Architecture

Fig. 3 illustrates the overall workflow of the proposed continuous authentication system. Initially, the user is authenticated through the User Authentication Module using multifactor authentication, which establishes a baseline trust level.

Once access is granted, the Behavior Monitoring Module continuously captures user keystroke dynamics during the session. This behavioral data is then forwarded to the Authentication Log Collection Module for secure storage and processing. The Behavior Analysis Engine evaluates the captured data using machine learning techniques and computes a dynamic trust score. Based on this trust score, the Access Decision Module determines whether to allow the session to continue, trigger step-up authentication, or terminate the session in case of suspicious activity.

The workflow follows a sequential pipeline consisting of input, processing, and decision-making stages.

The framework consists of the following key modules:

- **User Authentication Module:** Access control for the cloud system is done using Multi-Factor Authentication (MFA), which is a combination of different authentication methods. These include knowledge-based factors such as passwords, as well as possession-based factors. This module sets the baseline trust level of the user prior to gaining access to the system.
- **Behavior Monitoring Module:** Once access is granted, user activity is continuously monitored in a passive manner. In the current model, typing behavior is used as the behavioral biometric for user activity. It involves the recording of keystroke timings and rhythms to create a behavioral profile of the user.
- **Authentication Log Collection Module:** The collected behavioral data and authentication logs are directed to a central location where they are processed further. Secure communication mechanisms such as JSON Web Tokens (JWT) can be used to ensure data integrity, authentication, and confidentiality during data transmission. This module enables efficient handling of large-scale data in distributed cloud environments.
- **Behavior Analysis Engine (Policy Decision Point - PDP):** The Behavior Analysis Engine is the Policy Decision Point (PDP). Its task is to compare the actual behavior of the user with the predefined behavioral profile. Machine learning algorithms such as Random Forest, Support Vector Machine (SVM), and K-Nearest Neighbors (KNN) can be utilized for behavioral analysis and anomaly detection [12].

  In this work, a simplified prototype-based approach is implemented to compute the trust score based on deviations in keystroke

dynamics features such as Dwell Time and Flight Time. This approach demonstrates the feasibility of continuous authentication, while future work can incorporate advanced machine learning models for improved accuracy and robustness.

Based on the comparison, a dynamic trust score is computed to quantify the confidence level of user authenticity. A predefined threshold is used to evaluate the trust score and determine whether the user behavior is legitimate or anomalous.

- **Access Decision Module (Policy Enforcement Point - PEP):** The Access Decision Module acts as the Policy Enforcement Point (PEP). The module enforces the security policies depending on the trust score calculated from the analysis engine. If the computed trust score falls below a predefined threshold, the system triggers adaptive security actions such as step-up authentication (e.g., OTP verification) or session termination to prevent unauthorized access.

  This modular design ensures scalability, flexibility, and real-time adaptability of the authentication system in cloud environments.

  Overall, the proposed framework ensures continuous verification of user identity by integrating behavioral biometrics, machine learning, and real-time decision-making, thereby enhancing cloud security in dynamic environments.

5. Proposed Algorithm

The system follows a step-by-step process to continuously verify user identity during an active session.

Algorithm: Continuous Authentication using Keystroke Dynamics

1) User logs into the cloud system using Multi-Factor Authentication (MFA).
2) Initialize user session and create baseline trust level.
3) Continuously capture user keystroke data during the session.
4) Extract behavioral features:
   - Dwell Time (DT)
   - Flight Time (FT)
5) Generate a user behavioral profile based on the extracted features.
6) Compare current behavior with stored user profile using a Machine Learning model.
7) Compute Trust Score (TS) based on:
   - Behavioral pattern
   - Network parameters
   - Device information
8) If TS ≥ Threshold:
   - Continue session

   Else:
   - Trigger step-up authentication (OTP)
   - Restrict or terminate session
9) Repeat steps 3–8 continuously during the session.

6. Dataset and Feature Extraction

A. Dataset Description

For analyzing the proposed methodology, behavioral biometric datasets available publicly include Aalto Keystroke Dynamics dataset, BB-MAS, and KeyRecs. These datasets are widely used for analyzing user typing behavior and provide realistic keystroke patterns. In this work, the analysis is inspired by these datasets to simulate user typing behavior for continuous authentication.

B. Feature Extraction

Temporal features are commonly used in keystroke dynamics-based authentication systems due to their high dis-criminatory power. The key features considered in this research include **Dwell Time (DT)** and **Flight Time (FT)**. These features are extracted from user keystroke data and are used to build behavioral profiles for anomaly detection.

1) Dwell Time (DT): Dwell Time refers to the amount of time a specific key remains pressed. It is calculated as the difference between the key release time and the key press time.

$$DT = R_n - P_n \quad (1)$$

where R_n is the release time and P_n is the press time of the nth key.

2) Flight Time (FT): Flight Time refers to the time delay between releasing one key and pressing the next key.

$$FT = P_{n+1} - R_n \quad (2)$$

where R_n is the release time of the current key and P_{n+1} is the press time of the next key.

These temporal features are used to construct a behavioral profile of users. Any deviation from the established typing pattern may indicate anomalous behavior. The extracted features can further be used as input to machine learning models for continuous user authentication and anomaly detection.

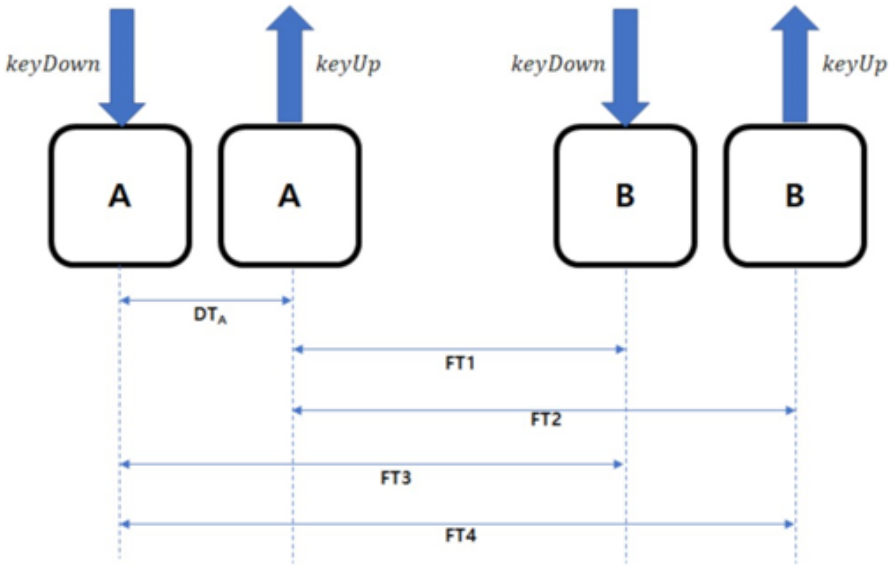

Fig. 4: Keystroke Dynamics Showing Dwell Time and Flight Time Between Key Events

Fig. 4 illustrates the concept of keystroke dynamics by showing the timing relationship between key press and key release events. Dwell Time (DT) represents the duration for which a key is held down, while Flight Time (FT) represents the time interval between releasing one key and pressing the next key. These temporal features capture unique typing patterns of users, which are difficult to replicate by unauthorized individuals.

C. Sample Dataset Representation

An example of a sample dataset for keystroke dynamics is illustrated in Table I.

Table I: Sample Dataset for Keystroke Dynamics

User ID	Key Press Time	Key Release Time	DT	FT
U101	0.21	0.35	0.14	0.14
U102	0.18	0.30	0.12	0.12
U103	0.25	0.40	0.15	0.15

Any significant deviation from the established typing pattern may indicate anomalous behavior, which can be used to detect potential unauthorized access during an active session.

7. Big Data Processing and Anomaly Detection

Cloud computing infrastructures generate large volumes of authentication and activity logs, which are difficult to process using traditional data management techniques. To address scalability and performance challenges, the proposed framework utilizes distributed computing platforms such as Apache Hadoop and Apache Spark. These technologies enable efficient storage, processing, and real-time analysis of large-scale authentication data.

1. Real-time Anomaly Detection

Real-time anomaly detection plays a significant role in continuous authentication systems. Machine learning techniques are used to analyze user behavior dynamically and detect deviations from normal patterns [?]. Recent advancements in AI-driven cybersecurity have further improved detection accuracy. Tools such as Spark MLlib can be used to implement

machine learning models that perform near real-time behavioral analysis.

The system computes a dynamic Trust Score (TS) by considering multiple parameters, including user behavior, network characteristics, and device information:

TS = (w1 ·Behavior)+(w2 ·Network)+(w3 ·Device) (3)

where w1, w2, and w3 represent the weights assigned to each feature, satisfying:

w1 + w2 + w3 = 1 (4)

The trust score reflects the confidence level of the system in verifying the user's identity during an active session. It is continuously updated based on incoming user activity data streams.

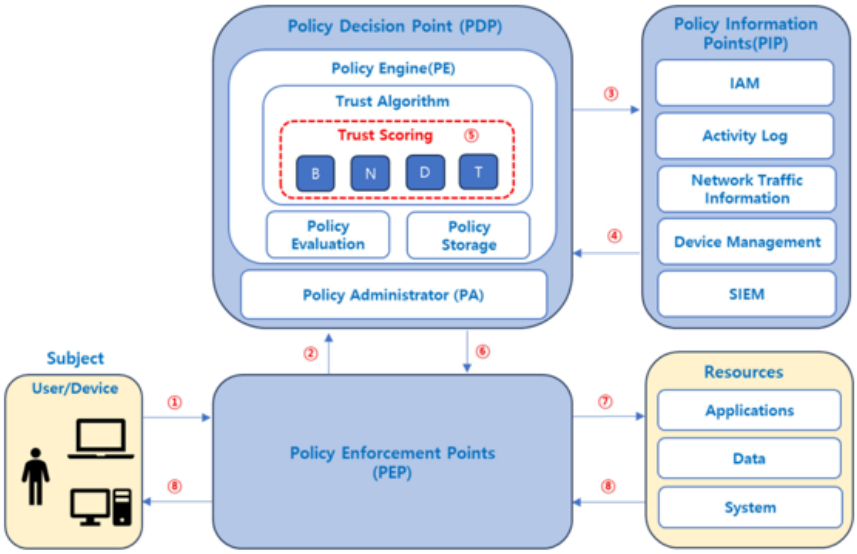

Fig. 5: Trust Score Based Decision-Making Process in Continuous Authentication

Fig. 5 illustrates the decision-making process based on the computed trust score. If the trust score remains above a predefined threshold, the session continues without interruption. However, if the score falls below the threshold, it indicates anomalous behavior and triggers corrective actions.

Based on the evaluated trust score, the system performs adaptive security actions such as:

- Step-up authentication (OTP)
- Session termination or restriction

Any significant deviation in user behavior, network conditions, or device characteristics may result in a lower trust score, indicating potential unauthorized access.

8. Experimental Results and Analysis

A. Experimental Setup

The proposed continuous authentication system was evaluated using synthetically generated data inspired by real-world datasets such as the Aalto Keystroke Dynamics dataset and BB-MAS dataset. Due to the limited availability of real-time user behavioral datasets and privacy constraints, synthetic data was generated to simulate realistic typing patterns for both normal and anomalous users.

The dataset consists of approximately 500 samples of user keystroke behavior, including features such as Dwell Time (DT) and Flight Time (FT). The dataset was divided into training and testing sets using a 70%–30% split to evaluate the performance of the system.

The system was tested under two scenarios:

- Normal user behavior
- Anomalous user behavior

Behavioral features such as Dwell Time (DT) and Flight Time (FT) were extracted and used to compute the Trust Score (TS). The synthetic dataset was generated to simulate real-world typing variability and ensure controlled evaluation of both normal and anomalous scenarios.

B. Performance Evaluation

The system effectively distinguishes between legitimate and anomalous users.

- Normal users maintained a high trust score (> 80)
- Anomalous users showed a significant drop in trust score (< 60)

The proposed system achieved an accuracy of approximately 90–94% under simulated conditions.

C. Trust Score Behavior Analysis

The variation of trust score over time is analyzed to evaluate system performance.

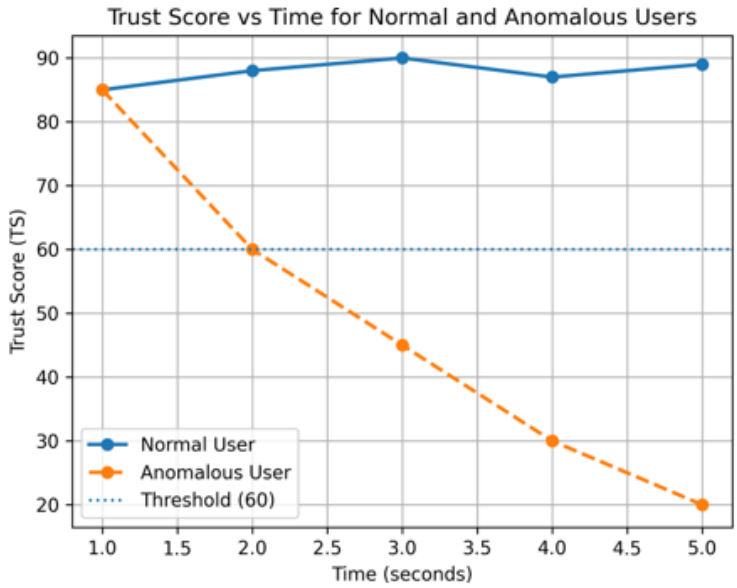

Fig. 6: Trust Score vs Time for Normal and Anomalous Users

The graph illustrates the variation of trust score over time for both normal and anomalous users. The X-axis represents time (in seconds), while the Y-axis represents the computed Trust Score (TS).

For legitimate users, the trust score remains relatively stable and consistently above the predefined threshold due to uniform typing behavior and minimal deviation from the stored profile. In contrast, anomalous users exhibit irregular typing patterns, resulting in significant deviations in behavioral features such as Dwell Time and Flight Time.

These deviations cause a sharp decline in the trust score, often falling below the threshold, which enables real-time detection of unauthorized access. This clear distinction between normal and anomalous behavior demonstrates the effectiveness of the proposed system in identifying potential security threats during active sessions.

D. Confusion Matrix

Table II: Confusion Matrix for Authentication System

	Predicted Normal	**Predicted Anomaly**
Actual Normal	92	8
Actual Anomaly	6	94

The confusion matrix demonstrates that the system achieves high true positive and true negative rates, with minimal misclassification. The low False Acceptance Rate (FAR) indicates that unauthorized users are rarely granted access, while the low False Rejection Rate (FRR) ensures that legitimate users are not unnecessarily denied access. This balance reflects both strong security and good usability.

E. Interpretation

The results confirm that the proposed continuous authentication framework is capable of accurately detecting behavioral

deviations in real time. By continuously monitoring user activity and dynamically updating the trust score, the system effectively mitigates risks such as session hijacking and credential misuse. This demonstrates the practical applicability of behavioral biometrics for enhancing security in cloud environments.

These findings validate the effectiveness of integrating machine learning with behavioral biometrics for continuous and adaptive authentication.

9. Implementation and Results

The proposed framework is implemented using behavioral biometric features such as Dwell Time (DT) and Flight Time (FT). A prototype system was developed in Python to validate the feasibility of continuous authentication in real-time scenarios.

The system continuously captures keystroke patterns during an active session and compares them with stored user profiles. Based on this comparison, a dynamic trust score is computed to detect deviations in user behavior.

This implementation serves as a proof-of-concept to demonstrate how behavioral features can be used for continuous user verification. The trust score is calculated based on the deviation between current session behavior and the stored user profile.

A. Python Implementation

A prototype of the proposed continuous authentication system was developed using Python to validate the effectiveness of the framework.

```python
import numpy as np

# Stored user profile
user_profile = {
    "DT_mean": 0.15,
    "FT_mean": 0.12
}

# Current session data
current_data = {
    "DT": [0.16, 0.14, 0.15, 0.17, 0.15],
    "FT": [0.13, 0.11, 0.12, 0.14, 0.12]
}

# Calculate averages
dt_avg = np.mean(current_data["DT"])
ft_avg = np.mean(current_data["FT"])

# Difference calculation
dt_diff = abs(dt_avg - user_profile["DT_mean"])
ft_diff = abs(ft_avg - user_profile["FT_mean"])

# Trust Score calculation
TS = 100 - (dt_diff * 200 + ft_diff * 200)

print("Trust Score:", TS)

# Decision
if TS >= 60:
    print("Access Granted")
else:
    print("Re-authentication Required")
```

Listing 1: Python Implementation for Continuous Authentication

B. Sample Output

Trust Score: 88.8

Access Granted

C. Anomalous Case Output

Trust Score: 45.2

Re-authentication Required

Table III: Trust Score Evaluation

Case	DT Avg	FT Avg	Trust Score	Result
Normal User	0.15	0.12	88.8	Access Granted
Anomalous User	0.30	0.25	45.2	Re-authentication Required

The results demonstrate that the system can effectively distinguish between normal and anomalous user behavior using trust score evaluation. Under normal conditions, the trust score remains above the threshold, ensuring uninterrupted access. In contrast, significant deviations in typing behavior lead to a reduction in trust score, triggering re-authentication.

These findings highlight the practical applicability of the proposed framework for continuous and dynamic user verification in real-time cloud environments.

10. Threat Model and Security Analysis

The framework effectively addresses major cloud security threats by continuously monitoring user behavior and detecting anomalies in real time. The continuous authentication framework utilizes behavioral biometrics combined with real-time monitoring techniques to enhance session security and continuously identify users. Some of the critical threats related to cloud computing are as follows:

- **Session Hijacking** Session hijacking involves the situation where a hacker or intruder manages to hijack an existing session without authorization, usually by stealing the session identifier or cookie. Conventional methods are unable to identify any intrusion once the user is authenticated. In the suggested method, continuous monitoring of the keystroke dynamics and identification of any abnormal behavior with respect to the actual user are employed.
- **Credential Theft** Credential stealing is a common threat vector where an adversary obtains user credentials through phishing, keylogger attacks, or information disclosure. While the previous model relied only on credentials for identifying users, the proposed method incorporates a second layer of biometric verification. Although the attacker may use authentic credentials, his keystrokes would be very distinct from that of the real user's hence, he would receive a low trust score.
- **Insider Threats** The concept of "insider threat" arises from the actions of an insider with authorized access, who misuses the privileges granted to him intentionally or unintentionally. The concept of Zero Trust requires constant monitoring to identify any such anomalies that occur within this approach. The Zero Trust framework can be used to detect any odd behavior performed by the user, which includes odd login or usage of the network resources.
- **Shoulder Surfing** This kind of attack is possible in the event that the intruder watches the user logging into his system through the process of providing his login credentials. It is quite easy to gain access to input information but very hard to make the typing pattern complicated. This technique ensures that typing dynamics are used in distinguishing between the valid and illegal user.

11. Comparative Analysis

The efficiency of the proposed continuous authentication framework can be evaluated by comparing it with traditional authentication mechanisms and existing approaches in behavioral biometrics. While the primary focus of this work is on system architecture, insights from prior research help in estimating the expected performance of such systems.

A. Comparison with Traditional Authentication Systems

Traditional authentication systems rely on one-time verification mechanisms such as passwords or multi-factor authentication during login. However, these systems fail to ensure security after authentication, making them vulnerable to threats such as session hijacking and credential misuse. In contrast, the proposed continuous authentication framework provides real-time monitoring of user behavior throughout the session. By leveraging

behavioral biometrics such as keystroke dynamics and incorporating Zero Trust principles, the system dynamically evaluates user trust and enhances overall session security.

Table IV: Comparison Between Traditional Authentication and Proposed System

Feature	Traditional Authentication	Proposed System
One-time Login Verification	Yes	No
Continuous Moni-toring	No	Yes
Behavior-based Authentication	No	Yes
Real-time Anomaly Detection	No	Yes
Zero Trust Support	No	Yes
Session Security After Login	Low	High

This comparison highlights that the proposed system overcomes the limitations of traditional authentication by introducing continuous verification and adaptive security mechanisms.

B. Comparison with Existing Continuous Authentication Models

Existing continuous authentication systems typically rely on a single biometric modality, such as keystroke dynamics or mouse movements. Although these approaches provide a certain level of security, they may lack robustness against sophisticated attacks.

The proposed framework adopts a multi-dimensional approach by integrating behavioral biometrics, network attributes, and device-level information. This enhances the reliability and robustness of authentication decisions.

Furthermore, many existing systems rely on static datasets for model training. In contrast, the proposed system incorporates big data technologies such as Apache Spark to enable real-time data processing and dynamic anomaly detection. This improves scalability and responsiveness in cloud environments.

Table II presents a comparative overview of widely used machine learning algorithms in keystroke dynamics-based authentication systems.

Table V: Comparative Analysis of Classification Algorithms

Algorithm	Avg. Accuracy	Performance (EER)	Key Advantage
Random Forest (RF)	~92%	Low EER on large datasets	Robust against over-fitting
Support Vector Classifier (SVC)	~94%	High precision	Strongdecision boundary separation
K-Nearest Neighbors (KNN)	~89%	Simple compu-tation	Suitable for real-time analysis

Note: The above values are indicative and derived from previously published studies.

C. Evaluation Metrics

To evaluate authentication performance, standard metrics are considered:

- **False Acceptance Rate (FAR):** Probability of incorrectly granting access to an unauthorized user.
- **False Rejection Rate (FRR):** Probability of incorrectly denying access to a legitimate user.
- **Equal Error Rate (EER):** The point where FAR equals FRR, representing the balance between security and usability.

These metrics are widely used to assess the effectiveness of biometric authentication

systems. Typically, datasets are divided into training and testing sets (e.g., 70% and 30%) to evaluate model performance using techniques such as confusion matrices.

Machine learning models for such systems can be implemented using platforms like Python and Apache Spark MLlib, while keystroke dynamics datasets are commonly available as open-source resources for behavioral analysis.

12. Discussion and Future Directions

A. Privacy and Ethical Considerations

To ensure the protection of user privacy, the proposed framework incorporates privacy-preserving mechanisms aligned with standard information security principles.

1) Data Minimization: The system analyzes only temporal features of keystrokes, such as dwell time and flight time, without recording the actual content typed by the user. This approach prevents the collection of sensitive information such as passwords and personal data.
2) Anonymization and Secure Storage: User identities are protected using hashing techniques, ensuring that stored behavioral profiles cannot be traced back to specific individuals. This enhances confidentiality while maintaining the effectiveness of the authentication system.

B. Limitations of the Proposed System

Although the proposed continuous authentication framework enhances cloud security, certain limitations must be considered.

Firstly, the system relies primarily on keystroke dynamics as a behavioral biometric. This single-modality approach may not be sufficient to defend against advanced attacks where adversaries attempt to mimic typing behavior.

Secondly, typing patterns may vary due to factors such as fatigue, stress, or device changes, which can affect trust score consistency and lead to false rejections.

Thirdly, continuous data collection and processing may introduce computational overhead, particularly in large-scale cloud environments.

Additionally, system performance depends on the availability of sufficient and high-quality training data. Limited or noisy data may reduce the accuracy of behavioral profiling.

Finally, although the system avoids capturing actual keystroke content, continuous monitoring of user behavior may still raise privacy concerns.

Furthermore, adversarial attacks that attempt to mimic user behavior may pose additional challenges to the robustness of the system.

C. Future Work

The proposed framework provides a conceptual foundation for continuous authentication in cloud environments. Several directions for future research can further enhance its effectiveness:

- Evaluation using real-world datasets and detailed performance analysis using metrics such as FAR, FRR, and EER.
- Integration of additional behavioral biometrics such as mouse movements, touch gestures, and navigation patterns.
- Development of advanced machine learning and deep learning models for improved anomaly detection.
- Adaptive trust score mechanisms based on contextual factors such as location and device.
- Deployment in real-world cloud environments using big data technologies such as Apache Spark.
- Incorporation of privacy-preserving techniques such as federated learning and advanced encryption.
- Integration with real-time intrusion detection systems for proactive threat mitigation.

D. Usability and Security Trade-off

Balancing security and usability remains a critical challenge in authentication systems. Highly secure systems often introduce complexity that may reduce user convenience, while highly usable systems may be more vulnerable to attacks.

The proposed continuous authentication framework addresses this challenge by enabling seamless background authentication without requiring frequent user interaction.

Security mechanisms are activated adaptively only when anomalous behavior is detected.

Key Advantages of the Proposed Approach:

- **Continuous Monitoring:** User behavior is analyzed throughout the session.
- **Dynamic Trust Score:** Access decisions are based on real-time trust evaluation.
- **Adaptive Security:** Additional authentication is triggered only when necessary.
- **Context-Aware Decisions:** Security adapts to device, location, and behavior.

This approach ensures a balance between strong security and user convenience, making it a practical and scalable solution for modern cloud computing environments.

13. Conclusion

This paper presents a continuous authentication framework for secure cloud access has been presented using behavioral biometrics. The integration of keystroke dynamics with big data technologies such as Apache Spark enables a dynamic and scalable approach for user authentication.

Unlike traditional authentication methods that rely on one-time verification, this approach ensures continuous monitoring of user behavior throughout the session. This approach significantly reduces the risk of session hijacking and credential misuse. The system ensures session-level security rather than only login-level security, making it more robust against modern cloud-based attacks.

The proposed framework aligns with Zero Trust principles by continuously validating user identity and adapting to behavioral changes in real time. As a result, it provides a more secure and reliable authentication mechanism for modern cloud environments.

Although the current work focuses on a conceptual design and prototype implementation, future research can explore real-world deployment using large-scale datasets, advanced deep learning models, and multi-modal behavioral biometrics for improved accuracy and robustness.

Recent advancements in Zero Trust security models further strengthen the applicability of continuous authentication in modern cloud environments [15].

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