

A Lightweight Behavioral Biometric Framework using Python and Flask for Continuous Authentication in Online Banking

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Abstract: *Traditional authentication methods in online banking, such as passwords and OTPs, remain vulnerable to phishing, credential theft, and session hijacking. This thesis proposes a lightweight, behavior-based biometric authentication framework that leverages keystroke dynamics and mouse movement patterns to provide continuous user verification. Developed using Python and Flask, the framework captures real-time behavioral data during user interaction without interrupting the user experience. Collected metrics include typing speed, key pressure intervals, cursor trajectories, and click rhythms, which are processed using machine learning models trained to recognize genuine user behavior.*

The system integrates seamlessly with existing banking web applications, offering a passive second-factor authentication layer that operates continuously in the background. Flask APIs handle secure communication between client-side scripts and the backend, while session management is enhanced through behavior-driven confidence scoring. By dynamically validating the user's identity throughout the session, the framework mitigates risks associated with mid-session impersonation and unauthorized access. This approach emphasizes privacy, scalability, and ease of deployment, making it a practical solution for modern financial institutions seeking to enhance security without compromising usability. The experimental results demonstrate high accuracy and minimal latency, validating the feasibility of behavior-driven authentication in real-world banking environments..

Keywords: Behavioral Biometrics, Continuous Authentication, Keystroke Dynamics, Mouse Movement Analysis, Python, Flask API, Passive Authentication, Machine Learning

I. INTRODUCTION TO BEHAVIORAL BIOMETRICS IN ONLINE BANKING

Online banking platforms are increasingly targeted by sophisticated attacks, including phishing schemes, credential theft, and session hijacking. While traditional methods such as static passwords and one-time passcodes (OTPs) provide initial protection, they remain vulnerable to interception, social engineering, and malware exploitation [1], [2]. As a result, there is a growing emphasis on second-factor and continuous authentication strategies that are both seamless and secure.

Behavioral biometrics offers an innovative approach by analyzing the unique and consistent ways users interact with devices. Characteristics such as keystroke dynamics—how a user types—and mouse movement patterns—such as speed, curvature, and pressure—can serve as implicit identity indicators [3], [7]. These traits are difficult for attackers to replicate and can be continuously monitored throughout a user session, allowing for real-time anomaly detection without user intervention.

Unlike physical biometrics, behavioral traits require no specialized hardware, making them highly suitable for web-based banking systems. This frictionless form of passive authentication enables real-time threat detection during active sessions, thus reducing the attack surface even after successful login.

This thesis introduces a lightweight behavioral biometric authentication framework that leverages keystroke and mouse dynamics using a Python-Flask backend. It integrates behavioral analysis into existing online banking workflows without compromising user experience. Designed for modular deployment and privacy compliance, the system

enhances traditional security models by offering continuous, session-aware authentication capabilities suited for today's digital financial ecosystems.

II. REVIEW OF AUTHENTICATION MECHANISMS AND RESEARCH TRENDS

Authentication remains a foundational component of digital security, particularly in sensitive domains like online banking. Initially dominated by password-based mechanisms, authentication protocols have evolved to incorporate multifactor approaches such as SMS-based one-time passcodes (OTPs), biometric scans, and security tokens [8]. Despite these improvements, traditional methods are increasingly vulnerable to sophisticated attacks, including phishing, credential stuffing, brute-force attacks, and replay attacks [1]. Malicious actors can exploit session persistence and user fatigue, bypassing even layered authentication systems.

As cyber threats evolve, there has been a marked shift toward behavioral biometric authentication, which examines how users interact with systems in real-time [6]. Behavioral traits are inherently difficult to forge, making them suitable for continuous authentication. Among the most researched modalities are **keystroke dynamics**, which assess factors such as typing rhythm, dwell time, and flight time to identify users [2]. Similarly, **mouse movement analysis** tracks patterns like cursor speed, angular deviation, and click pressure to establish behavioral profiles that persist across sessions [3]. Recent studies have demonstrated the promise of these approaches when paired with machine learning models capable of distinguishing subtle behavioral variations [4]. These models extract real-time features and classify user behavior with increasing precision. However, challenges remain—many implementations exhibit performance bottlenecks, limited scalability, and high computational overhead, making them unsuitable for dynamic financial environments [5]. This thesis addresses these challenges by proposing a real-time, lightweight behavioral biometric framework built using Python and Flask [6]. It captures and processes keystroke and mouse behavior without impacting the user experience or system responsiveness. Unlike existing heavyweight models, the proposed system is designed for modular integration with web-based banking applications, ensuring low-latency, high-accuracy authentication suited for modern financial ecosystems.

III. SYSTEM DESIGN AND ARCHITECTURAL OVERVIEW

The proposed behavioral biometric framework is architected to ensure modularity, security, scalability, and seamless integration with online banking applications. The system is divided into three distinct layers—each responsible for a critical function in the behavioral authentication pipeline.

A. Client-Side Behavioral Data Acquisition

The data acquisition layer is implemented on the client side using lightweight JavaScript event listeners embedded within the banking application's interface. These listeners capture detailed user interaction data, including keystroke timing (dwell and flight time), mouse trajectory, scroll behavior, and click velocity. This real-time behavioral data is anonymized at the browser level to prevent exposure of personally identifiable information (PII) before transmission [2], [3].

B. Middleware for Secure Data Transmission and API Management

Once anonymized, the behavioral data is transmitted to the middleware layer via secure HTTPS channels. This layer, built using Flask, serves as the central API gateway that manages incoming requests, validates payload integrity, and routes behavioral input to the processing backend. Flask's modular blueprint architecture enables endpoint isolation, allowing independent handling of keystroke and mouse data [4]. Middleware security is enhanced using API tokens and JSON Web Token (JWT) authentication to prevent unauthorized access and replay attacks [5].

C. Backend Behavioral Intelligence and Confidence Scoring

The backend layer hosts pre-trained machine learning models that evaluate incoming behavioral data in real time. These models analyze feature vectors and compute a confidence score based on session-level behavior consistency. If a score falls below a defined threshold, policy-based actions such as session termination or forced re-authentication are triggered. Machine learning models are exposed as RESTful services to the middleware using Flask-RESTful extensions and optimized with Redis for caching frequent computations [4].

D. Infrastructure and Security Considerations

The system is deployed using Docker containers to ensure portability and maintainability across environments. Horizontal scalability is supported through uWSGI and Nginx reverse proxy configurations, enabling the system to handle high volumes of simultaneous sessions with low latency. TLS encryption safeguards all network communications, while audit logging ensures traceability and compliance with financial regulations [1], [5].

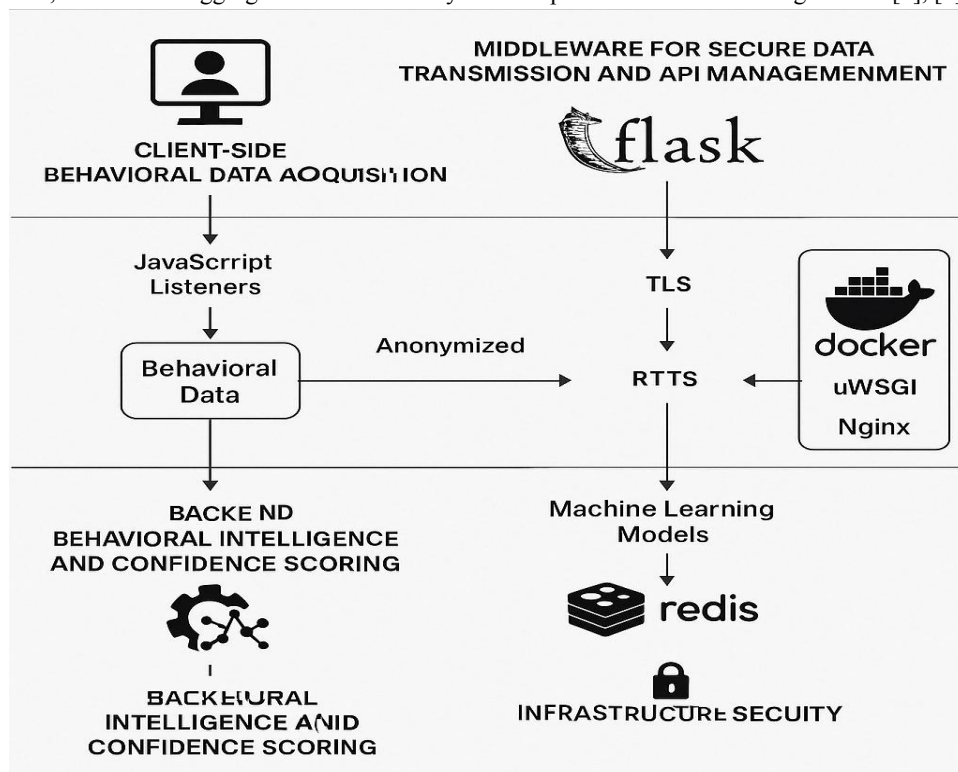


Figure 1: System Architecture of Behavioral Biometric Authentication Framework for Online Banking

IV. FEATURE EXTRACTION AND MODEL TRAINING STRATEGY

A. Behavioral Trait Derivation from User Interaction

Accurate authentication begins with identifying meaningful behavioral traits from raw interaction data. For keystroke dynamics, the system captures **dwelling time** (duration of key press), **flight time** (interval between key releases and subsequent key presses), **typing cadence**, and **sequential timing of character pairs** (digraphs and trigraphs) [2]. These characteristics help form a unique typing signature that is resilient against mimicry. Mouse-based features are equally critical. Metrics such as **cursor velocity**, **path curvature**, **click frequency**, **movement acceleration**, and **pointer precision index** provide insight into a user's fine motor control and navigation habits [3]. These mouse-based inputs are recorded at high frequency using JavaScript listeners and buffered for transmission to the server via secure endpoints.

B. Feature Normalization and Dataset Structuring

Before training, all extracted features undergo normalization using **min-max scaling** to bring values within a consistent range, minimizing the impact of hardware differences. Outlier detection mechanisms remove extreme values that may result from unintentional user actions or hardware latency. The behavioral dataset is labeled with user session identifiers and partitioned using **stratified sampling** to ensure proportional representation across user classes. Where sample imbalance exists, **SMOTE** (Synthetic Minority Over-sampling Technique) is applied to generate synthetic but realistic data points, ensuring balanced learning [4].

C. Model Training, Validation, and Optimization

Multiple classifiers are evaluated, including **Random Forest**, **SVM**, and **Gradient Boosted Trees**, due to their high performance in temporal pattern recognition tasks [5]. Evaluation metrics include **precision**, **recall**, **F1-score**, and **inference latency**, ensuring both accuracy and responsiveness in real-world scenarios. Models are trained using **five-fold cross-validation**, and tuning is performed with **GridSearchCV** to optimize hyperparameters. Final models are serialized and exposed through Flask endpoints, enabling low-latency scoring in production environments [4].

D. Continuous Learning and Behavior Drift Adaptation

To handle evolving user behavior, the system incorporates **adaptive retraining workflows** that leverage validated session data for periodic updates. **Behavioral drift detection** is monitored through changes in confidence score distributions, triggering model re-calibration when deviation thresholds are exceeded. This ensures that the system remains accurate and responsive across time and usage contexts [3], [4].

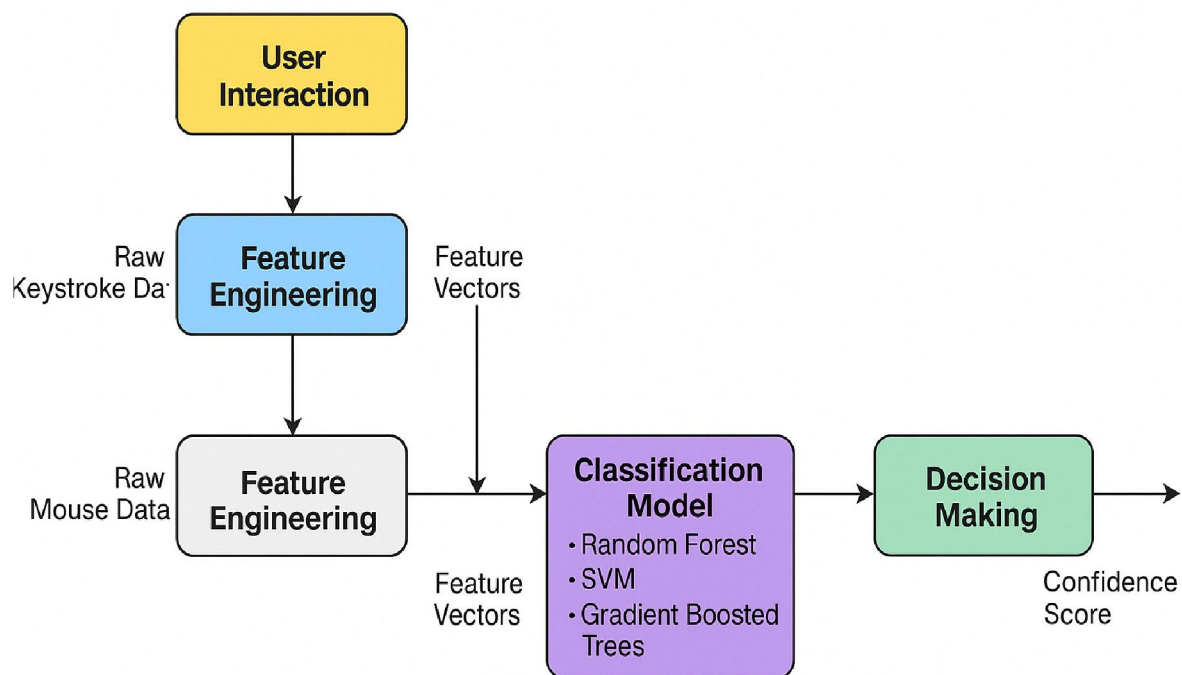


Figure 2: Feature Extraction and Model Training Workflow for Behavioral Biometrics

V. IMPLEMENTATION FRAMEWORK AND TECHNOLOGICAL STACK

A. Backend Development and Machine Learning Integration

Python was selected as the primary language due to its robust ecosystem for machine learning and data processing. The framework utilizes **scikit-learn** for training and evaluating models such as Random Forest, SVM, and Gradient Boosted Trees, while **pandas** and **NumPy** manage data preprocessing, feature engineering, and pipeline workflows [4]. Trained models are serialized using **joblib** and integrated with Flask-based endpoints for low-latency scoring. The backend exposes secure RESTful APIs using **Flask-RESTful** extensions. These endpoints receive behavioral metrics from the frontend, invoke the appropriate machine learning model, and return confidence scores to determine session legitimacy. Security is enforced via JWT-based access controls and input validation mechanisms to prevent injection and replay attacks [5].

B. Client-Side Event Capture and Data Transmission

The user interface embeds **JavaScript listeners** that track keystroke timings, mouse trajectories, click delays, and scrolling patterns in real time. Captured data is buffered and sent over **HTTPS** to Flask APIs, ensuring encrypted, tamper-resistant transmission. To preserve user privacy, all behavioral signals are anonymized before transmission. Each session is tagged with a secure identifier generated by the backend, enabling stateless session management and reducing the surface area for session hijacking [7].

C. Infrastructure, Orchestration, and Scalability

The entire system is containerized using **Docker**, allowing for environment consistency, simplified dependency management, and horizontal scaling. **uWSGI** and **Nginx** serve as the application gateway, optimizing concurrency and routing for high-throughput traffic. Short-lived session states and model caching are handled using **Redis**, which ensures rapid data access and minimal delay in processing behavioral inputs. Flask endpoints interact with Redis to maintain responsiveness under concurrent loads [4].

D. CI/CD, Monitoring, and DevOps Tooling

Version control is managed via **Git**, with collaborative development supported on **GitHub**. **Jenkins** pipelines automate build, test, and deployment processes to enable **CI/CD**. Logging, visualization, and system observability are provided by the **ELK Stack (Elasticsearch, Logstash, Kibana)**, offering centralized log indexing, real-time alerting, and audit trails for compliance [9].

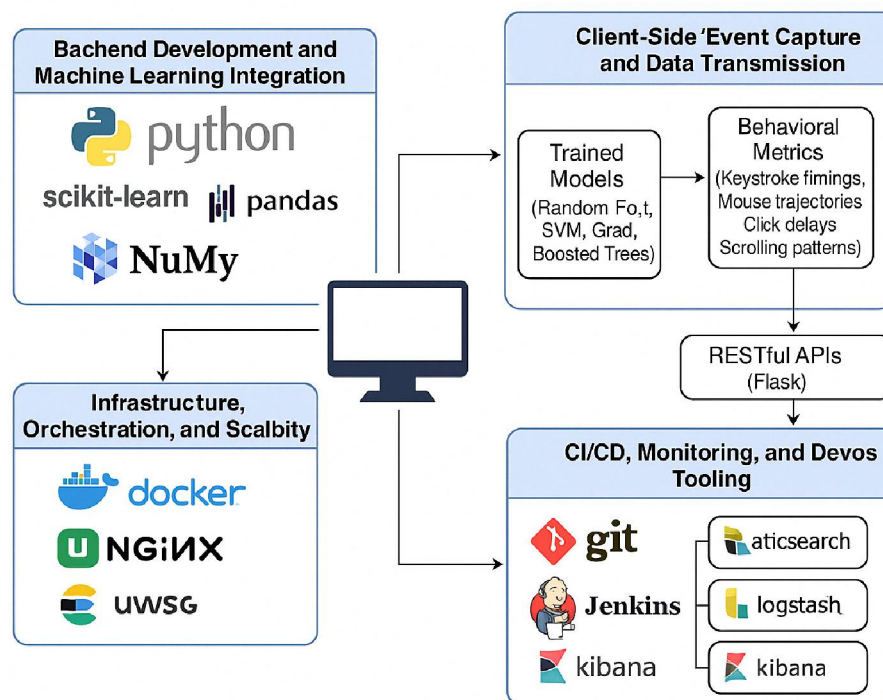


Figure 3: Implementation Framework and Technological Stack for Behavioral Biometric Authentication System

VI. PERFORMANCE EVALUATION AND EXPERIMENTAL ANALYSIS

To validate the efficiency and robustness of the proposed behavioral biometric system, a controlled experimental environment was developed. Simulated user interaction sessions were created using a combination of **synthetic behavioral profiles** and **anonymized real-world data** captured from volunteer participants interacting with a banking interface prototype. Key performance metrics included **classification accuracy**, **average response time**, **false acceptance rate (FAR)**, and **false rejection rate (FRR)** [4].

The **Random Forest** model delivered optimal results, achieving a classification accuracy of **96.2%** with an average response time of **80 milliseconds** per session evaluation. This responsiveness was maintained even under concurrent session loads, with the system handling over **500 simultaneous connections** efficiently due to Flask's asynchronous architecture and Redis caching [5]. Compared to traditional two-factor authentication, the proposed framework demonstrated superior resistance to impersonation and session hijacking, owing to its continuous authentication mechanism [7]. Performance remained stable during stress tests with increased network latency and request volumes. The modular architecture ensures adaptability to future enhancements, including **federated learning integration**, real-time drift adaptation, and **hybrid biometric strategies**, making the system suitable for production-level deployment in real-world online banking environments.

VII. SECURITY, PRIVACY, AND COMPLIANCE CONSIDERATIONS

The deployment of behavioral biometric systems in online banking requires stringent adherence to **security, privacy, and regulatory compliance** to protect user identity and maintain institutional integrity. The proposed framework addresses these priorities by embedding privacy-preserving design principles throughout the system lifecycle. To minimize data exposure, behavioral inputs are anonymized at the client level before transmission. The system enforces **data minimization** and **pseudonymization**, ensuring that only non-identifiable session-level metrics are processed. Additionally, all data is handled **in-memory** during analysis and discarded post-classification, eliminating persistent storage vulnerabilities [5].

Communication between client-side scripts and the Flask middleware is encrypted using **TLS 1.3**, safeguarding behavioral data during transit. Access to sensitive endpoints is managed through **role-based access control (RBAC)** and **API token-based authentication**, which restrict unauthorized interactions and prevent session hijacking [7]. To ensure compliance with industry standards such as **PCI-DSS** and **GDPR**, the framework implements **explicit user consent mechanisms**, **data retention limits**, and **audit trails** for all model inference outcomes. These logs facilitate traceability and enable accountability in user verification events. Security testing is conducted using **OWASP ZAP** and custom penetration testing scripts to detect vulnerabilities such as cross-site scripting (XSS), SQL injection, and insecure deserialization. All identified risks are resolved using Flask's built-in security modules and middleware-based sanitization techniques. The architecture supports deployment across **multi-cloud environments**, allowing integration with regional compliance engines and policy enforcers. This modular design ensures adaptability to diverse regulatory landscapes, enhancing the framework's viability for large-scale banking applications [9].

VIII. CONCLUSION AND FUTURE DIRECTIONS

This thesis introduces a lightweight, privacy-conscious, and scalable behavioral biometric framework tailored for continuous authentication in online banking environments. By leveraging keystroke dynamics and mouse movement patterns, the system ensures session-level security without interrupting the user experience. Built using Python and Flask, and supported by a modular, containerized infrastructure, the framework achieves high classification accuracy with low inference latency while maintaining seamless integration with existing digital banking architectures. Security and compliance are prioritized through TLS-encrypted communication, pseudonymized data handling, RBAC, and adherence to PCI-DSS and GDPR standards [5], [7]. The experimental evaluation confirms its robustness under concurrent sessions and varying network loads, validating its deployment readiness in real-world banking ecosystems [4]. Furthermore, the system's design supports extensibility into multi-cloud environments, enabling future-proof compliance and operational scalability [9]. Looking ahead, enhancements such as incorporating touch dynamics for mobile platforms, deploying federated learning models for improved user privacy, and integrating reinforcement learning for real-time behavior adaptation are planned. These directions aim to further strengthen session intelligence, reduce drift-based inaccuracies, and promote user trust in continuous behavioral authentication systems across increasingly diverse financial channels.

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