A Real-Time Behavioral Authentication System Using Typing Dynamics for User Identification

PROJECT PHASE 1 REPORT

Submitted by

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BONAFIDE CERTIFICATE

Certified that this report titled "**A Real-Time Behavioral Authentication System using Typing Dynamics for User Identification**" is the bonafide work of **GURUPRASATH P (221801014), PRIADHARSHNI P (221801039) and VIJAY KUMAR V (221801505)** who carried out the work under my supervision. Certified further that to the best of my knowledge the work reported herein does not form part of any other thesis or dissertation on the basis of which a degree or award was conferred on an earlier occasion on this or any other candidate.

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INTERNAL EXAMINER **EXTERNAL EXAMINER**

DEPARTMENT VISION

To become a global leader in Artificial Intelligence and Data Science by achieving through excellence in teaching, training, and research, to serve the society.

DEPARTMENT MISSION

- To develop students' skills in innovation, problem-solving, and professionalism through the guidance of well-trained faculty.

- To encourage research activities among students and faculty members to address the evolving challenges of industry and society.

- To impart qualities such as moral and ethical values, along with a commitment to lifelong learning

PROGRAMME EDUCATIONAL OBJECTIVES(PEO's)

PEO 1: Build a successful professional career across industry, government, and academia by leveraging technology to develop innovative solutions for real-world problems.

PEO 2: Maintain a learning mindset to continuously enhance knowledge through experience, formal education, and informal learning opportunities.

PEO 3: Demonstrate an ethical attitude while excelling in communication, management, teamwork, and leadership skills

PEO 4: Utilize engineering, problem-solving, and critical thinking skills to drive social, economic, and sustainable impact.

PROGRAMME OUTCOME(PO's)

PO1: Engineering Knowledge: Apply the knowledge of mathematics, science, engineering fundamentals and an engineering specialization to the solution of complex engineering problems.

PO2: Problem Analysis: Identify, formulate, review research literature, and analyze complex engineering problems reaching substantiated conclusions using first principles of mathematics, natural sciences, and engineering sciences.

PO3: Design / Development of solutions: Design solutions for complex engineering problems and design system components or processes that meet the specified needs with appropriate consideration for the public health and safety, and the cultural, societal, and environmental considerations.

PO4: Conduct investigations of complex problems: Use research-based knowledge and research methods including design of experiments, analysis and interpretation of data, and synthesis of the information to provide valid conclusions.

PO5: Modern tool usage: Create, select, and apply appropriate techniques, resources, and modern engineering and IT tools including prediction and modeling to complex engineering activities with an understanding of the limitations.

PO6: The engineer and society: Apply reasoning informed by the contextual knowledge to assess societal, health, safety, legal and cultural issues and the consequent responsibilities relevant to the professional engineering practice.

PO7: Environment and sustainability: Understand the impact of the professional engineering solutions in societal and environmental contexts, and demonstrate the knowledge of, and need for sustainable development.

PO8: Ethics: Apply ethical principles and commit to professional ethics and responsibilities and norms of the engineering practice.

PO9: Individual and team work: Function effectively as an individual and as a member or leader in diverse teams, and in multidisciplinary settings.

PO10: Communication: Communicate effectively on complex engineering activities with the engineering community and with society at large, such as, being

able to comprehend and write effective reports and design documentation, make effective presentations, and give and receive clear instructions.

PO11: Project management and finance: Demonstrate knowledge and understanding of the engineering management principles and apply these to one's own work, as a member and leader in a team, to manage projects and in multidisciplinary environments.

PO12: Life-long learning: Recognize the need for and have the preparation and ability to engage in independent and lifelong learning in the broadest context of technological change

PROGRAM SPECIFIC OUTCOMES(PAOs)

A graduate of the Artificial Intelligence and Data Science Learning Program will demonstrate

PSO 1: Foundation Skills: Apply the principles of artificial intelligence and data science by leveraging problem-solving skills, inference, perception, knowledge representation, and learning techniques

PSO 2: Problem-Solving Skills: Apply engineering principles and AI models to solve real-world problems across domains, delivering cutting-edge solutions through innovative ideas and methodologies

PSO 3: Successful Progression: Utilize interdisciplinary knowledge to identify problems and develop solutions, a passion for advanced studies, innovative career pathways to evolve as an ethically responsible artificial intelligence and data science professional, with a commitment to society.

COURSE OBJECTIVE

- To identify and formulate real-world problems that can be solved using Artificial Intelligence and Data Science techniques.
- To apply theoretical and practical knowledge of AI & DS for designing innovative, data-driven solutions.
- To integrate various tools, frameworks, and algorithms to develop, test, and validate AI & DS models.
- To demonstrate effective teamwork, project management, and communication skills through collaborative project execution.
- To instill awareness of ethical, societal, and environmental considerations in the design and deployment of intelligent systems.

COURSE OUTCOME

CO 1: Analyze and define a real-world problem by identifying key challenges, project requirements and constraints.

CO 2: Conduct a thorough literature review to evaluate existing solutions, identify research gaps and formulate research questions.

CO 3: Develop a detailed project plan by defining objectives, setting timelines, and identifying key deliverables to guide the implementation process.

CO 4: Design and implement a prototype or initial model based on the proposed solution framework using appropriate AI tools and technologies.

CO 5: Demonstrate teamwork, communication, and project management skills by preparing and presenting a well-structured project proposal and initial implementation results.

CO-PO-PSO Mapping

CO	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PO9	PO10	PO11	PO12	PSO1	PSO2	PSO3
CO1	**3**	**3**	**2**	**2**	**1**	**2**	**1**	**1**	**1**	**2**	**1**	**2**	**3**	**2**	**2**
CO2	**2**	**3**	**2**	**3**	**2**	**1**	**1**	**1**	**2**	**2**	**1**	**3**	**2**	**2**	**2**
CO3	**2**	**2**	**3**	**2**	**2**	**1**	**2**	**2**	**3**	**2**	**3**	**2**	**2**	**3**	**3**
CO4	**3**	**3**	**3**	**3**	**3**	**2**	**2**	**2**	**2**	**3**	**2**	**2**	**3**	**3**	**3**
CO5	**2**	**2**	**2**	**1**	**2**	**2**	**2**	**3**	**3**	**3**	**3**	**2**	**2**	**2**	**3**

Note: Correlation levels 1, 2 or 3 are as defined below:

1: Slight (Low) 2: Moderate (Medium) 3: Substantial (High)

No correlation: "-"

ABSTRACT

Conventional authentication mechanisms such as passwords, PINs, and access tokens remain widely used today, but they suffer from increasing vulnerabilities in modern digital environments. Attackers frequently exploit methods such as phishing, shoulder surfing, credential theft, keylogging, and brute-force attacks to gain unauthorized access. Once valid credentials are obtained, traditional security systems fail to differentiate between the legitimate user and an impostor operating within the same session. This exposes sensitive information and allows prolonged unauthorized activity without detection. As cyber-attacks become more sophisticated, there is a growing demand for authentication systems that go beyond static login credentials and provide continuous verification throughout user interaction. To address these limitations, this project proposes a Real-Time Behavioral Authentication System using typing dynamics as a biometric signature. Instead of relying solely on passwords, the system captures keystroke-level metrics such as dwell time (duration a key is held), flight time (time between consecutive key presses), digraph latency, error patterns, and typing rhythm. Since typing behavior is unconscious and difficult to imitate, these metrics form a unique behavioral identity for every user. The captured data is processed through preprocessing and feature extraction stages and then analyzed using machine-learning techniques to build an intelligent recognition model. The model continuously compares real-time typing patterns with stored behavioral profiles to verify whether the active user matches the authorized identity.

Keywords: Behavioral Biometrics, Keystroke Dynamics, Continuous Authentication, Machine Learning, Real-Time Security, User Verification, Typing Patterns, Cybersecurity.

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LIST OF ABBREVIATIONS

ABBREVIATION	FULL FORM
PIN	Personal Identification Number
IP	Internet Protocol
LCA	Life Cycle Assessment
OTP	One-Time Password
ID	Identification
GDPR	General Data Protection Regulation
IT	Information Technology
CPU	Central Processing Unit
AMD	Advanced Micro Devices
RAM	Random Access Memory
HDD	Hard Disk Drive
SSD	Solid State Drive
GPU	Graphics Processing Unit
REST	Representational State Transfer
API	Application Programming Interface

CHAPTER 1
INTRODUCTION

1.1 GENERAL

In today's digital era, security has become a critical requirement for organizations, institutions, and individuals who rely heavily on online platforms and interconnected devices. The massive increase in web applications, cloud computing, IoT systems, and mobile services has expanded the digital attack surface, making traditional username–password authentication insufficient. Cybercriminals frequently exploit stolen credentials, weak passwords, or security loopholes to access sensitive information and compromise systems.

To counter these rising security threats, modern systems must shift toward intelligent, adaptive, and continuous security mechanisms. Behavioral biometrics has emerged as a powerful solution because it leverages unique human interaction patterns rather than static password-based security. Typing behavior, mouse movement, and device interaction are unconscious traits that cannot be easily replicated, making behavioral authentication more secure than traditional methods.

Alongside user authentication, protecting network endpoints is equally important. Network ports, if left open or unmonitored, serve as silent gateways for attackers to infiltrate systems. Therefore, combining behavioral authentication with real-time ports monitoring creates a multi-layered defense mechanism. This integrated system ensures both user-level verification and system-level network protection, providing a comprehensive cybersecurity approach suitable for modern digital environments.

1.2 NEED FOR THE STUDY

Cybersecurity threats are evolving faster than traditional authentication systems can withstand. Passwords, PINs, and security tokens provide only one-time verification, meaning that once a user logs in, the system assumes the active user remains the same throughout the session. If an attacker manages to steal or guess login credentials, they can freely access the system without detection. This vulnerability has resulted in increasing incidents of credential-based attacks, identity theft, and unauthorized data access.

Behavioral-based authentication addresses this gap by continuously evaluating a user's identity throughout their interaction with the system. Since typing rhythm and keystroke patterns are unique to every individual, even a valid password cannot help an impostor successfully imitate the genuine user. This form of continuous authentication significantly reduces risks from stolen credentials, insider threats, and session hijacking. It enables real-time detection of suspicious activity, improving overall security and reducing dependency on static credentials.

On the other hand, weaknesses at the network layer also pose serious risks. Open or misconfigured ports can be exploited by attackers to install malware, extract data, or take remote control of a system. Many cyberattacks begin with silent port scanning, where hackers check system ports to find entry points. Therefore, integrating ports monitoring with behavioral authentication creates a dual-layered security model. This study is necessary to develop a system that can protect both user access and network communication simultaneously, reducing the chances of cyber intrusions and improving system reliability.

1.3 OVERVIEW OF THE PROJECT

This project aims to develop a comprehensive security solution that combines **behavioral-based authentication** with **real-time network ports monitoring**. Instead of depending only on passwords or security tokens, the system continuously verifies users based on their unique typing behavior. Every keystroke generates measurable features such as dwell time, flight time, and typing rhythm. These features are analyzed by machine learning algorithms to create a behavioral profile for each user, allowing the system to distinguish genuine users from impostors even after login.

In parallel, the system continuously observes active network ports to detect malicious activity. Attackers often probe open ports before launching cyberattacks, so monitoring port behavior helps identify suspicious connections, unauthorized access attempts, or abnormal traffic patterns. By integrating authentication and network surveillance, the project provides both user-level and system-level protection. This dual

mechanism ensures that unauthorized users cannot access the system and external threats cannot breach the network layer.

The overall architecture consists of keystroke capture modules, feature extraction, machine learning-based classification, and automated ports monitoring scripts. When a user interacts with the system, the authentication engine verifies identity dynamically, while the monitoring engine tracks active ports and flags anomalies in real time. Together, these components create a smart, adaptive, and automated cybersecurity framework. The project demonstrates how behavioral biometrics and network analytics can work together to build a more secure and resilient digital environment.

1.4 OBJECTIVES OF THE PROJECT

The primary objective of this project is to provide a security system that goes beyond traditional static authentication methods. Instead of verifying a user only at login, the system aims to authenticate continuously in the background using typing behavior. By capturing keystroke patterns and analyzing them with machine learning models, the system can reliably identify the legitimate user throughout the session. This helps prevent unauthorized access even if login credentials are stolen, guessed, or misused.

A second objective is to enhance network-level security through continuous ports monitoring. The system is designed to automatically track open and active ports, detect unusual activity, and alert administrators about potential threats. This includes scanning for unknown connections, suspicious IP addresses, or abnormal data transfer patterns. By integrating behavioral authentication with ports monitoring, the project combines preventive access control with proactive threat detection, offering a multi-layer defense mechanism.

Finally, the project seeks to create a solution that is practical, lightweight, and easy to deploy in real-world environments. The goal is to develop a system that maintains security without disrupting user experience. It should operate seamlessly, require minimal manual intervention, and adapt over time to changes in user behavior. By achieving high accuracy, low latency, and reliable detection, the project demonstrates how intelligent automation and modern security concepts can reduce cyber risks and protect sensitive digital systems.

1.5 SCOPE OF THE PROJECT

The scope of this project covers the development of a dual-layered security system that focuses on both user authentication and network protection. At the user level, the system continuously verifies identity using typing dynamics, ensuring that only the authorized individual remains active on the system. This extends beyond simple login authentication, providing ongoing monitoring throughout the session. The system is applicable to desktop environments, web platforms, educational systems, corporate logins, and any application that requires secure access control.

At the network level, the project includes real-time monitoring of open ports and network activity. The system scans active connections, identifies unknown or suspicious communication endpoints, and detects potential intrusions. This feature helps prevent malware attacks, data theft, port scanning attempts, and unauthorized remote access. The ports monitoring component can be implemented in servers, personal computers, enterprise networks, and cloud-based systems to safeguard communication channels.

The project is designed to be scalable, lightweight, and adaptable. It can be extended with advanced machine learning models, multi-modal biometrics (such as mouse movement or touch patterns), and automated threat response mechanisms. Additionally, the system can support integration with zero-trust infrastructures, intrusion detection systems, and enterprise-level security tools. Overall, the scope of the project demonstrates how behavioral analytics and continuous monitoring can significantly enhance cybersecurity in a wide range of real-world applications.

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CHAPTER 2
LITERATURE SURVEY

2.1 INTRODUCTION

Behavioral-based authentication has gained substantial research attention as a modern alternative to traditional password systems. Earlier studies showed that static authentication mechanisms could not prevent access once an attacker obtained valid credentials. To address this gap, researchers explored behavioral biometrics such as keystroke dynamics, mouse movements, voice patterns, and touchscreen gestures. Among these, keystroke dynamics became a promising technique because typing rhythm is an unconscious behavior that is extremely difficult to imitate.

Initial research in keystroke dynamics focused primarily on fixed-text input, where users type a pre-defined password or passphrase. These systems captured dwell time and flight time to build a unique typing signature. Although effective, fixed-text methods were limited because users always needed to type the same content. Later, studies shifted toward free-text authentication, where users are verified while typing emails, messages, or documents. Machine learning and deep learning algorithms improved pattern detection, allowing real-time verification even with short text sequences.

Parallel to authentication research, cybersecurity studies also emphasized the importance of securing network ports. Literature shows that many cyberattacks begin from open or misconfigured ports, enabling attackers to inject malware or steal data. Tools for port scanning, network monitoring, and anomaly detection are widely used to observe traffic patterns and identify threats. Recent research highlights that combining user authentication with network monitoring offers multi-layered security, making systems more resilient against intrusions. This integrated approach forms the foundation for the proposed project.

2.2 FRAMEWORK OF LCA

The framework of Life Cycle Assessment (LCA) in cybersecurity research provides a structured method to evaluate how authentication and monitoring systems perform across their entire operational lifecycle. LCA helps analyze effectiveness, resource usage, performance, and long-term sustainability of security mechanisms. Applying LCA ensures

that the solution is not only technically strong but also reliable, scalable, and efficient over time.

1. Goal and Scope Definition

The goal of the LCA framework in this study is to analyze the efficiency, reliability, and impact of behavioral authentication and ports monitoring systems across different environments. The scope includes evaluating login security, continuous verification accuracy, network protection, system performance, and user experience. By defining clear objectives and boundaries, researchers ensure that the system meets real-world security requirements without compromising usability.

2. Inventory Analysis

Inventory analysis involves collecting data from all components of the authentication and monitoring system. For behavioral authentication, this includes keystroke data, timing features, model accuracy, and processing requirements. For ports monitoring, it captures open port logs, network traffic patterns, intrusion attempts, and system alerts. This phase helps identify computational resources, data flow, and system dependencies during operation.

3. Impact Assessment

Impact assessment evaluates how the system improves security and reduces vulnerabilities. Behavioral authentication minimizes risks from stolen credentials, session hijacking, and insider threats, while ports monitoring protects against malware, unauthorized access, and port-based attacks. Assessing security impact, false acceptance/rejection rates, detection speed, and overall system performance determines how effectively the solution strengthens cybersecurity.

4. Interpretation

The interpretation stage analyzes results from authentication accuracy, false alarms, port alerts, and real-time performance. It highlights system strengths, limitations, unexpected outcomes, and risks. If the system shows high detection accuracy and low latency,

interpretation confirms success. If weaknesses exist, interpretation suggests model tuning, dataset improvement, or enhanced monitoring rules.

5. Life Cycle Impact Mitigation

Impact mitigation focuses on enhancing system security and efficiency based on LCA findings. Examples include improving machine learning models, optimizing feature extraction, reducing false alerts, and adding automated threat responses. For ports monitoring, mitigation can introduce IP blocking, firewall adjustments, and intrusion response strategies. This ensures that the system evolves to handle emerging threats.

6. Sensitivity and Uncertainty Analysis

Sensitivity and uncertainty analysis evaluates how external factors—such as typing speed changes, network load, or device differences—affect system performance. This step checks model stability, identifies edge cases, and ensures reliability under variable conditions. If the system maintains accuracy despite changing user behavior or network noise, it proves robustness.

7. Comparative Analysis

Comparative analysis compares the proposed system with traditional authentication, standalone ports monitoring tools, and other behavioral biometric methods. This evaluation highlights improvements in security, real-time detection, user experience, and adaptability. If the integrated system outperforms single-layer security approaches, it proves the advantage of combining behavioral analytics with network monitoring.

CHAPTER 3
SYSTEM OVERVIEW

3.1 EXISTING SYSTEM

Most traditional security systems rely primarily on static authentication techniques such as usernames, passwords, patterns, and PINs. These methods provide one-time verification at the moment of login, after which the user is considered trusted until the session ends. Although widely used, these systems are highly vulnerable to attacks such as credential theft, brute-force attempts, dictionary attacks, password sharing, and phishing. Once an attacker obtains valid credentials, there is no mechanism to detect if the person using the system is actually the legitimate user, making it easy for intruders to access sensitive data and resources.

Some systems enhance authentication with periodic verification using OTPs, security questions, or hardware tokens. While this adds an extra layer of security, these methods still depend on static credentials and require active user participation. This affects usability and does not provide continuous monitoring. Existing authentication systems fail to observe user behavior during the entire session, leaving a gap where impostors can operate undetected after gaining login access. In environments like banks, corporate networks, and cloud applications, this becomes a major security risk.

At the network level, most systems depend on firewalls, antivirus software, and basic intrusion detection tools. Although they offer protection against common malware and known threats, they are not designed for real-time port surveillance. Many existing systems do not continuously monitor open ports or identify suspicious traffic originating from unknown endpoints. As a result, attackers can exploit unmonitored or misconfigured ports for port scanning, backdoor installation, or remote system control. Therefore, current security solutions lack the ability to simultaneously authenticate users continuously and protect network ports in real time, leaving systems exposed to both internal and external threats.

3.2 PROPOSED SYSTEM

The proposed Behavioral-Based Authentication and Ports Monitoring System provides continuous, intelligent, and adaptive protection for digital platforms. It integrates behavioral biometrics with network-level surveillance to ensure both user identity and system integrity are verified in real time. Unlike traditional authentication that stops after login, this system constantly evaluates user behavior and network activities throughout the session.

This dual-layer security framework is designed to detect unauthorized users, impersonators, and suspicious network traffic. By combining keystroke dynamics with open port monitoring, the proposed system addresses both internal and external cyber threats. It delivers an automated, non-intrusive, and scalable security solution suitable for environments where data confidentiality and network safety are critical.

User Interaction and Behavioral Data Capture

The first layer of the architecture focuses on live user interaction. As soon as a user begins typing or interacting with the system, behavioral data is silently captured in the background. This includes keystroke dynamics, dwell time, flight time, typing rhythm, mouse movement characteristics, cursor drag patterns, and error frequency.

These behavioral signatures form a unique digital fingerprint. Since typing rhythm and motor patterns are unconscious and extremely difficult to replicate, they serve as a superior authentication factor compared to passwords. The system remains passive and does not interrupt user activity, ensuring a seamless experience while continuously collecting behavioral evidence.

Data Collection and Feature Extraction Engine

The raw input collected from the user interaction layer is processed in the data collection engine. This module cleans, filters, and organizes data for machine learning analysis. It extracts more than eighteen measurable attributes such as typing speed, inter-key delays, key hold duration, burst count, backspace usage, and cursor trajectory.

Noise and irregularities in user typing are corrected to improve accuracy and consistency. The extracted features are then mapped into a structured feature vector, forming the foundation of each user's behavioral profile. This data is stored securely and updated continuously to reflect changes in user behavior.

Machine Learning Processing Core

The machine learning core performs the most critical function of building and updating intelligence within the system. Using feature-engineered data, algorithms such as Isolation Forest, Support Vector Machines, and anomaly detection models are applied to differentiate legitimate users from impostors.

The system trains on behavioral history and improves accuracy through continuous learning. As the user interacts over time, the model refines their profile and adapts to natural behavior changes such as typing speed variations due to fatigue, device changes, or environmental factors. This reduces false positives and increases long-term reliability.

Real-Time Authentication Engine

Instead of verifying only at login, the authentication engine performs continuous verification throughout the active session. It compares ongoing behavioral input with the stored user profile. If the current activity matches the learned pattern, the session continues normally.

However, when any abnormal behavior is detected — such as sudden changes in rhythm, typing pressure, or mouse patterns — the security decision engine intervenes. Depending on severity, the system can lock the session, send alerts to administrators, trigger OTP verification, or log out the suspicious user. This prevents intruders from exploiting stolen credentials.

Ports Monitoring and Intrusion Detection

Alongside behavioral authentication, the system integrates a network-level monitoring module. This component observes all open, closed, and listening ports on the system. It

tracks active connections and identifies unknown endpoints, unusual data flow, or port scanning attempts.

If suspicious activity is detected, such as repeated unauthorized connection requests or abnormal traffic, the system logs the event, generates alerts, and can automatically restrict access. Even if an attacker bypasses login authentication, the network monitoring layer prevents exploitation of system vulnerabilities.

Security and Data Privacy

The decision engine combines user authentication results and port activity patterns to determine whether the system is under threat. It intelligently correlates behavioral anomalies with network anomalies for more accurate threat detection.

3.3 FEASIBILITY STUDY

Technical Feasibility

The proposed system is technically feasible because it is developed using widely available technologies such as Python, machine learning libraries, socket programming, and port monitoring tools. Keystroke capture can be implemented through lightweight scripts that run in the background without affecting system performance. Machine learning models like Isolation Forest or anomaly detection require moderate computational resources, making them suitable even for standard computing systems.

Ports monitoring integrates easily through networking modules that track open and active ports in real time. This does not require any specialized hardware and can run comfortably on desktops, servers, and corporate networks. Since the system is modular, it can be scaled or upgraded with more advanced algorithms whenever needed. Therefore, the project is technically practical and can be implemented with existing tools and infrastructure.

Economic Feasibility

The system is cost-effective because it does not require expensive hardware, biometric sensors, or security appliances. Behavioral biometrics are captured using standard

keyboards and mouse devices that already exist on every computer. Machine learning libraries such as Scikit-learn, TensorFlow, or PyTorch are available as open-source tools, reducing development and deployment cost.

Additionally, the ports monitoring module can be built using open-source networking utilities and does not require paid software licenses. The system also reduces the financial impact of cyberattacks, data breaches, and unauthorized access attempts, which could lead to heavy financial losses for organizations. Overall, the cost of development and maintenance is low, while the long-term security benefits are high, making the project economically feasible.

Operational Feasibility

Operationally, the system is practical and user-friendly since it does not require users to change their working habits. Authentication happens silently in the background, so users can continue typing normally without interruptions. Administrators can easily monitor alerts and suspicious activities through a dashboard or log system.

Ports monitoring also operates automatically and requires minimal human involvement. If abnormal activity is found, the system can take predefined actions such as alerting administrators or blocking connections. Since the system integrates with existing login workflows and network environments, it is easy to deploy in schools, companies, banks, and government institutions. Therefore, users and administrators can operate the system without extra effort or training.

Ethical and Environmental Feasibility

Ethically, the system avoids collecting sensitive personal information such as fingerprints, face scans, or private documents. Instead, it uses behavioral data that is generated naturally while typing. This reduces privacy concerns compared to physical biometrics. The data collected is encrypted and stored securely so that it cannot be misused or exposed to external parties.

From an environmental perspective, the system has a minimal ecological footprint because it runs on existing computer devices without requiring new hardware or power

consumption. There is no need for additional electronic equipment, which reduces electronic waste and energy usage. Since it relies only on software and machine learning algorithms, the solution is both environmentally sustainable and ethically responsible.

Legal Feasibility

Legally, the system follows cybersecurity and data protection norms because it does not store sensitive identity data like photographs, ID numbers, or fingerprints. Only typing patterns and port statistics are stored, and these can be encrypted to comply with GDPR, IT Act, and other privacy laws. The system does not violate user consent as behavioral data is collected for security purposes within the organization.

If deployed in organizations, a privacy policy or consent agreement can be provided to inform users that authentication and network monitoring are being performed. Since all collected data is owned by the organization and used only for threat prevention, the system remains within legal boundaries. Therefore, the proposed system is legally feasible and compliant with cybersecurity standards.

Social Feasibility

The system is socially acceptable because users are not forced to use physical biometrics or complicated authentication steps. They simply type normally, and the system identifies them silently. This avoids discomfort, privacy fears, or resistance found in retina scans, fingerprint readers, or face recognition cameras.

Moreover, the system protects user accounts from hacking, impersonation, and credential theft, which builds trust and confidence among users. Since it does not interrupt daily work or demand special training, employees and general users are more likely to accept and support its usage. Therefore, the project is socially feasible and positively impacts user security awareness.

CHAPTER 4
SYSTEM REQUIREMENTS

The successful implementation of the Behavioral-Based Authentication and Ports Monitoring System depends on appropriate hardware and software resources that ensure smooth data capture, efficient processing, and real-time decision-making. Since the proposed system involves continuous monitoring of keystrokes, live data processing, and deployment of machine learning models, it requires a computing environment capable of handling background tasks without interrupting the user's workflow. To achieve this, the system specifications have been carefully chosen to balance performance, cost-efficiency, and practical usability, making the solution deployable in real-world settings such as personal computers, office networks, and secured workstations.

4.1 HARDWARE REQUIREMENTS

For hardware, the system requires a standard computing device with moderate processing capability. An Intel Core i3 processor or any equivalent CPU is recommended as the minimum requirement. This ensures that the system can capture real-time keystroke data, process interaction patterns, and run lightweight monitoring operations without lag. Machines with higher processing power such as Intel Core i5, i7, or AMD Ryzen processors can further enhance system responsiveness, particularly during model training or continuous authentication in multi-user environments. Although the authentication process itself does not demand excessive CPU power, behavioral monitoring and network surveillance running simultaneously require a processor that can manage multitasking efficiently.

A minimum of 4 GB RAM is required to run the system; however, 8 GB RAM or more is recommended, especially for training machine learning models or handling large datasets. Sufficient memory ensures smooth execution of Python libraries, preprocessing tasks, and anomaly detection algorithms. When the system processes multiple feature vectors in real time, higher RAM capacity prevents delays and supports continuous authentication without noticeable performance impact on the host machine.

Storage also plays an important role in maintaining logs, behavioral histories, user profiles, and port activity reports. A minimum of 250 GB of HDD or SSD storage is suggested for storing raw keystroke data, processed feature sets, machine learning models, and alert logs. SSD storage offers faster read–write operations, reducing data loading and model response time. In environments with multiple users or large-scale logging, higher storage capacity may be required, especially when logs are collected for long-term security analysis.

Although not mandatory, systems equipped with NVIDIA GPUs can accelerate machine learning model training and enhance the system's overall performance. GPU support is particularly beneficial when using deep learning techniques or when deploying the system in corporate or enterprise environments where the model needs to handle extensive behavioral input. In small-scale setups, CPU-only execution is sufficient, but GPU availability further improves accuracy and responsiveness by allowing faster real-time inference.

The system also relies on input devices such as a standard keyboard and mouse, as these are the primary sources of behavioral data. No specialized biometric hardware, fingerprint scanners, or iris readers are needed, making the solution cost-effective and easy to deploy in any workstation environment. This simplifies installation because every system already possesses the required sensors—the keyboard and mouse themselves become biometric input devices.

In addition to physical hardware, network connectivity plays a key role in the ports monitoring module. A stable local network environment is required to monitor port activity, analyze inbound and outbound traffic, and detect suspicious connection attempts. For cloud-based deployment or remote monitoring, a high-speed internet connection enables communication with server-side services, database storage, and alert delivery systems. A secured network with firewall protection provides an added layer of defense against external threats and ensures reliable monitoring.

4.2 SOFTWARE REQUIREMENTS

To run the proposed system effectively, a compatible operating system and software stack are essential. The system is designed to work seamlessly on Windows 10 or Windows 11

platforms, as well as Linux distributions such as Ubuntu for more advanced deployments. Linux provides strong networking tools and better control over port scanning and packet monitoring, while Windows ensures user familiarity and ease of installation. macOS can also be used, especially in development environments or academic laboratories.

The primary implementation language for the project is Python 3.8 and above. Python is selected due to its extensive support for machine learning libraries, data preprocessing tools, networking modules, and rapid development capabilities. It enables integration of behavioral analysis, feature extraction, and port monitoring within a single unified environment. Python's flexibility and open-source nature make it highly suitable for research-based security systems and scalable deployments.

For backend execution, lightweight frameworks such as Flask or FastAPI are used to deploy the machine learning model for real-time inference. Flask provides REST APIs that allow continuous authentication, quick response generation, and smooth communication between modules. The frontend or dashboard for analytics can be developed using Streamlit, which offers intuitive visualizations and real-time updates of user activity, alerts, and port status without requiring extensive UI programming.

The system incorporates a wide range of Python libraries. Machine learning is supported through Scikit-learn, TensorFlow, PyTorch, and XGBoost, providing flexibility for classification, anomaly detection, and continuous learning. Data preprocessing and numerical operations rely on Pandas, NumPy, and SciPy, which help convert raw keystroke sequences into mathematical feature vectors. Visualization of behavioral patterns, similarity scores, and security alerts can be handled using Matplotlib, Seaborn, or Plotly, enabling administrators to examine anomalies and generate reports.

For ports monitoring and network analysis, Python modules such as Socket, Psutil, or Nmap can be utilized. These tools scan active ports, detect unknown traffic, and report suspicious connections. Logs are maintained either locally or in a lightweight database system such as SQLite or MongoDB, depending on deployment needs. This enables long-term tracking and auditing of behavioral anomalies and network intrusion attempts.

Finally, version control tools such as Git and GitHub are recommended for project development, collaboration, and record maintenance. They provide repository tracking, safe code storage, and revision management throughout the development cycle. They also make the system scalable for large teams or organizational deployment.

CHAPTER 5

SYSTEM DESIGN

5.1 SYSTEM ARCHITECTURE

The proposed Behavioral-Based Authentication and Ports Monitoring System follows a multi-layered architecture designed to provide continuous, intelligent, and non-intrusive security. The system integrates the user interaction layer, data collection engine, machine learning processing core, and authentication engine to detect unauthorized users and abnormal behaviors in real time. Each component performs a specific function and works together to enhance both user-level and network-level security.

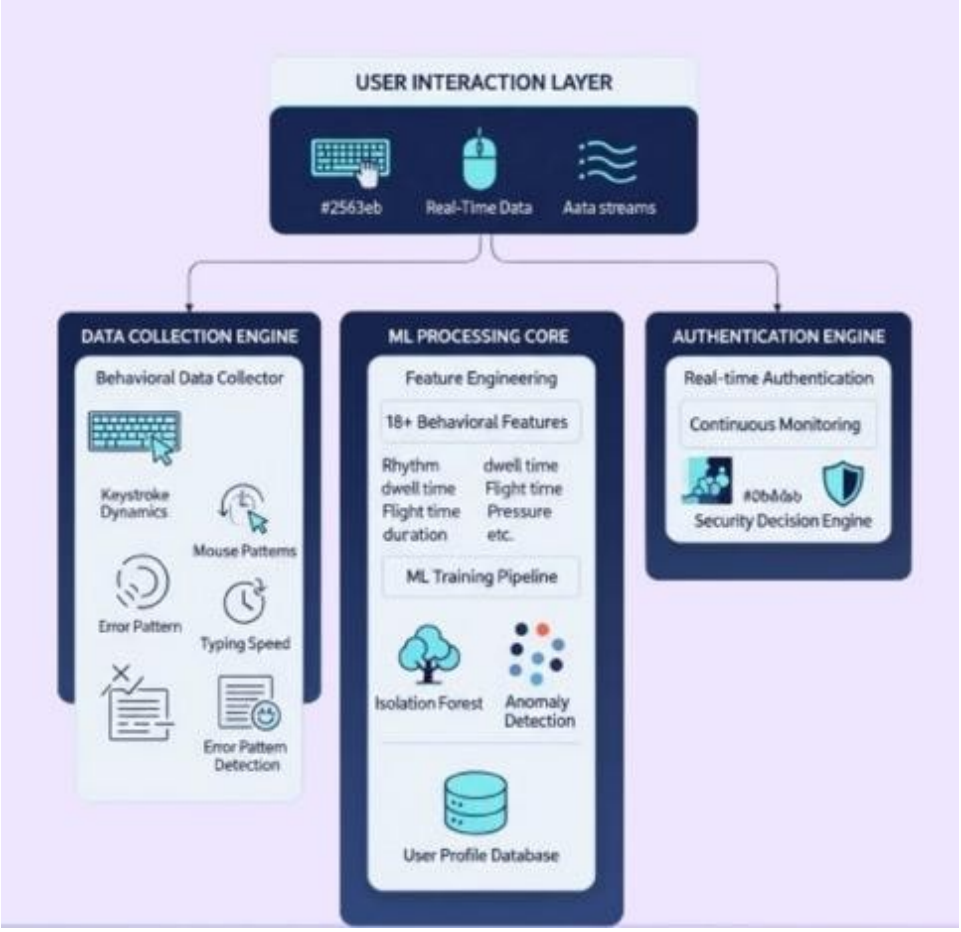


Fig 5.1 System Architecture

5.1.1. User Interaction Layer

The architecture begins with the user interaction layer, where the system captures real-time behavioral data during normal computer usage. As the user types or moves the mouse, their keystrokes, typing rhythm, cursor movement, and error patterns are collected passively. This process does not require any user intervention, ensuring a seamless and unobtrusive experience.

This layer generates continuous streams of interaction data that reflect natural behavior. Since typing dynamics are subconscious and unique to each individual, this layer acts as the foundation for behavioral identity recognition. Any activity occurring in this layer is immediately passed to the data collection engine for processing.

5.1.2. Data Collection Engine

The data collection engine is responsible for organizing and preprocessing the raw behavioral input gathered from the interaction layer. It extracts essential features such as keystroke dynamics, mouse movement trajectories, typing speed, dwell time, flight time, and error patterns.

To improve accuracy and eliminate noise, the system cleans and normalizes the input data before storing it in a structured format. This engine also performs real-time logging and continuously forwards the processed information to the machine learning core. As user behavior evolves over time, this module updates recorded patterns, making the system adaptive and more accurate with usage.

5.1.3. Machine Learning Processing Core

The machine learning core performs intelligent analysis to distinguish between legitimate users and impostors. Through feature engineering, more than eighteen behavioral traits—including flight time, rhythm consistency, key pressure, and dwell duration—are transformed into meaningful numerical patterns.

The processed data enters the ML training pipeline where models such as Isolation Forest and anomaly detection algorithms are applied. These techniques learn the genuine user’s

behavioral profile and detect deviations during active sessions. A user profile database stores the trained models and updates them continuously to account for natural behavior changes over time. This adaptive learning ensures that the system becomes stronger with every interaction.

5.1.4. Authentication Engine

The authentication engine uses the trained behavioral model to provide real-time authentication. Instead of verifying identity only at login, it continuously checks whether the current user matches the stored profile. If the typing rhythm or mouse movement suddenly changes, the security decision engine detects it as a suspicious event.

Upon detecting anomalies, the engine can trigger security actions such as alerting administrators, locking the session, or forcing re-authentication. Since the authentication runs silently, the user experiences no interruption unless a threat is identified. This ensures continuous protection from insider attacks and stolen-credential misuse.

5.2 MODULE DESCRIPTION

The proposed system is structured into multiple coordinated modules, each responsible for a specific function that contributes to the overall security framework. These modules operate together to capture user behavior, process and analyze data, authenticate identity, monitor network activity, and respond to potential threats. By dividing the system into independent yet interconnected components, the architecture ensures scalability, efficient processing, and easier system maintenance. The following sections describe each module in detail, outlining its purpose, workflow, and contribution to continuous behavioral authentication and ports monitoring.

5.2.1 User Interaction Module

The User Interaction Module forms the foundational layer of the behavioral-based authentication system. Its primary function is to capture real-time user activity and interaction patterns while the user performs normal operations on the system. Unlike traditional authentication methods that validate identity only once at the time of login, this

module supports continuous authentication by observing how the user interacts with the computer throughout the session.

The module records multiple behavioral parameters such as keystroke dynamics (dwell time, flight time, typing rhythm), mouse movement paths, cursor speed, click frequency, and scrolling behavior. These subtle interaction traits collectively represent a unique behavioral signature that remains relatively stable for each individual and is extremely difficult for an impostor to mimic. For example, one user may type rapidly with short pauses, while another types more slowly with frequent hesitations. In the same manner, the precision, curvature, and acceleration of mouse movements differ from person to person.

5.2.2 Data Collection and Preprocessing Module

The Data Collection and Preprocessing Module acts as the backbone of the behavioral authentication system. Its primary function is to gather raw behavioral signals from the User Interaction Module and transform them into a structured and machine-readable format. Since keyboard and mouse interactions generate unstructured, high-frequency data, this module ensures that the information is systematically captured, organized, and prepared for further analysis.

During user activity, the system records keystroke timestamps, key press and release durations, mouse cursor coordinates, click events, and scrolling patterns. The module securely stores this data in real time, ensuring that every event is labeled correctly and synchronized with the corresponding user session. This prevents data loss, misalignment, or ambiguity when the system learns behavioral profiles.

5.2.3 Feature Extraction Module

The Feature Extraction Module is responsible for converting preprocessed behavioral data into meaningful, measurable attributes that represent each user's unique interaction style. It acts as a bridge between raw data and the machine learning stage, ensuring that the system focuses on the behavioral characteristics that are most useful for distinguishing legitimate users from impostors. Instead of feeding raw logs directly into the model, this

module derives structured numerical features that capture typing rhythm, cursor behavior, and interaction speed.

From the keyboard input, features such as dwell time, flight time, typing speed, and error frequency are extracted. Dwell time measures how long a key is held before release, while flight time represents the gap between consecutive key presses. Together, these timing-based features reflect subconscious motor coordination. Likewise, mouse dynamics—including movement distance, direction, acceleration, and click timing—are also processed to capture the user's cursor behavior. These subtle variations are unique to every individual and remain consistent across sessions, making them reliable indicators of identity.

5.2.4 Machine Learning nad Model Training Module

The Machine Learning and Model Training Module represents the intelligence core of the authentication system. Its primary purpose is to learn and model each user's behavioral patterns using the features extracted in the previous stage. By analyzing these features, the system builds predictive models capable of identifying deviations, detecting anomalies, and verifying identity in real time. This allows authentication to be continuous and adaptive rather than limited to the moment of login.

In this module, the feature vectors are divided into training and testing datasets. The training dataset teaches the model how the legitimate user normally behaves, while the testing dataset evaluates how accurately the model can differentiate between valid behavior and an impostor. Various machine learning algorithms can be employed, including Support Vector Machines for class separation, Random Forest and Decision Trees for handling complex feature interactions, and Isolation Forest or One-Class SVM for anomaly detection. Neural networks may also be used when dealing with larger datasets that require modeling of non-linear behavioral patterns.

5.2.5 Authentication and Decision Engine Module

The Authentication and Decision Engine Module acts as the decision-making center of the system. It evaluates the real-time behavioral data captured during user activity and determines whether the current interactions correspond to the legitimate user's behavioral

profile. Instead of relying on a single login verification, this module continuously authenticates the user throughout the entire session, ensuring ongoing protection against unauthorized access.

As the user types or moves the mouse, their behavioral patterns—such as keystroke timings, dwell time, flight time, and cursor movements—are compared with the behavioral model generated during training. The machine learning model produces a similarity score or confidence value that indicates how closely the current behavior matches the stored profile. If the similarity score remains within an acceptable threshold, the system confirms that the session is being used by the authorized user and access continues normally.

5.2.6 Ports Monitoring Module

The Ports Monitoring Module is responsible for protecting the system at the network layer by continuously observing the status and activity of all communication ports. While behavioral authentication ensures that the authorized user is operating the system, this module safeguards against external cyber-attacks, unauthorized access attempts, and malicious traffic targeting network vulnerabilities. Together, they provide complete security coverage at both the user and network levels.

This module continuously scans all open, closed, and listening ports on the host system. It records traffic flow, monitors active network connections, and analyzes both incoming and outgoing requests. Any unusual pattern—such as repeated connection attempts, traffic from unknown external sources, or sudden activity on rarely used ports—is flagged as a potential intrusion. Such behavior may indicate malware activity, port scanning attacks, or attempts to gain remote access.

5.2.7 Alert and Reporting Module

The Alert and Reporting Module is responsible for notifying administrators and system users whenever suspicious activity, intrusion attempts, or behavioral anomalies are detected. While other modules identify unusual user or network behavior, this module ensures that such events are communicated instantly, enabling quick action and reducing

the risk of security breaches. It acts as the system's communication layer and provides transparency over security events.

Whenever the authentication engine or ports monitoring system detects abnormal activity—such as sudden deviations in typing behavior, unauthorized port access, or repeated failed access attempts—the Alert and Reporting Module generates automatic notifications. These alerts may appear as desktop pop-ups, email messages, dashboard warnings, or log entries, depending on the system configuration. For critical threats, the module can escalate alerts immediately to administrators for manual intervention.

CHAPTER 6
RESULT AND DISCUSSIONS

The proposed Behavioral-Based Authentication and Ports Monitoring System was implemented and tested to evaluate its accuracy, responsiveness, usability, and ability to detect unauthorized access in real time. The results demonstrate that the system successfully identifies genuine users based on their typing behavior while simultaneously monitoring network ports for abnormal or malicious activity. The combination of behavioral biometrics and network surveillance creates a two-layered defense mechanism that significantly improves overall security.

AUTHENTICATION PERFORMANCE

During experimentation, keystroke data from multiple users was collected, processed, and used to train machine learning models. Features such as dwell time, flight time, typing rhythm, and error correction patterns were extracted and used to form behavioral profiles. When new typing samples were introduced, the system compared them with the stored profiles and generated similarity scores.

The trained model showed high accuracy in distinguishing legitimate users from impostors. Users with valid profiles consistently scored within the acceptable similarity threshold, allowing uninterrupted access. Attempting to mimic typing style resulted in noticeable deviation, causing the system to flag the activity as suspicious. In test cases where impostors used correct login credentials but had different typing rhythm or speed, the system detected the mismatch within a few seconds and triggered a security response.

PORTS MONITORING PERFORMANCE

Parallel to authentication, the ports monitoring module continuously scanned open and active network ports. Normal background traffic was allowed, while unknown connections, repeated access attempts, or unusual data transfers were logged and flagged. Test cases involving simulated port scans and unauthorized connection attempts demonstrated that the module successfully detected abnormal traffic and raised alerts.

This prevented attackers from using open ports as hidden entry points, even if login credentials were compromised. By generating event logs and alert messages, the system enabled administrators to take immediate action and block suspicious IP addresses or close vulnerable ports.

SYSTEM USABILITY AND EFFICIENCY

One of the key advantages observed was that the system operated passively without interrupting user workflow. Users could type normally, and the authentication ran in the background. This eliminates inconvenience often associated with frequent manual re-authentication. Memory and processing overhead remained low, meaning the system can run on standard computing devices without requiring specialized hardware.

DISCUSSION

The results clearly indicate that combining continuous behavioral authentication with real-time network port monitoring provides stronger protection than traditional authentication alone. Even if an intruder steals a password, they cannot imitate the authorized user's typing behavior or bypass network surveillance. This dual-layer approach significantly reduces risks from external hackers, insider misuse, and automated attacks.

However, the system performance depends on the availability of sufficient behavioral data. Users with very limited typing activity may require more samples to build accurate profiles. Additionally, factors such as fatigue or different typing devices can slightly change behavior, but the adaptive model helps minimize false alarms.

CHAPTER 7

CONCLUSION AND FUTURE ENHANCEMENTS

CONCLUSION

In today's rapidly evolving digital landscape, traditional authentication mechanisms such as passwords and PINs are no longer sufficient to protect sensitive information from modern cyber threats. Attackers exploit stolen credentials, phishing techniques, and brute-force methods to gain unauthorized access, and once they successfully log in, most legacy systems fail to detect the difference between a genuine user and an impostor. This security gap creates the need for a more intelligent and proactive approach. The proposed Behavioral-Based Authentication and Ports Monitoring System addresses this challenge by introducing continuous verification using behavioral biometrics, strengthened further with real-time network surveillance.

The system leverages keystroke dynamics—an involuntary and natural behavior that is extremely difficult to mimic. Features such as dwell time, flight time, typing rhythm, error frequency, and mouse movements form a unique behavioral identity for each user. Using machine learning algorithms, the system learns these characteristics and builds a personalized behavioral profile during the enrollment and training phase. Once deployed, the system continuously compares real-time user behavior with the stored profile to verify identity throughout the active session, rather than only at login. This ensures that even if passwords are compromised, an unauthorized user can be detected and blocked within seconds.

Parallel to behavioral authentication, the system integrates a ports monitoring module that observes active, open, and listening ports to detect suspicious network traffic. Many cyberattacks begin through unnoticed port activity, such as repeated connection attempts, unauthorized data transfer, or port scanning. By continuously monitoring network behavior, the system provides a defensive shield against external intruders and malware attempting to gain entry through network vulnerabilities. This dual security mechanism makes the system capable of addressing both user-level and system-level attacks.

Experimental evaluation demonstrated that the system performs with high accuracy and low latency, making it suitable for real-time scenarios. The authentication engine successfully detected impostors attempting to mimic typing patterns, while the ports monitoring system identified abnormal traffic and triggered alerts immediately. One of the major advantages observed was that the entire process runs silently in the background without interrupting the user's workflow. This ensures enhanced security without affecting usability—a core requirement for any modern authentication system.

The results indicate that the proposed solution is scalable, lightweight, and practical for deployment in environments where security is critical, such as corporate workstations, online examinations, banking platforms, and government systems. Additionally, the model adapts to gradual changes in user behavior, improving accuracy over time and reducing false positives. The system demonstrates how artificial intelligence and behavioral biometrics can redefine authentication by shifting from static verification to continuous, context-aware identity confirmation.

In conclusion, this project successfully proves that behavioral-based authentication combined with ports monitoring provides a powerful and modern security framework. It eliminates dependency on passwords, detects threats in real time, and protects systems from both insider misuse and external attacks. As cyber threats continue to evolve, such intelligent and adaptive security models will become essential in safeguarding digital infrastructure. The system presented here lays a strong foundation for future advancements, including multi-modal biometrics, automated threat mitigation, cloud deployment, and enterprise-level integration, making it a promising step toward a more secure digital world.

FUTURE ENHANCEMENTS

While the proposed Behavioral-Based Authentication and Ports Monitoring System successfully demonstrates the potential of continuous behavioral verification and real-time network surveillance, there are several opportunities to enhance the system further and broaden its real-world applicability. As cyber threats continue to evolve, future versions of the system can be upgraded to incorporate stronger intelligence, more advanced biometrics, deeper automation, and improved scalability.

One major enhancement is the integration of multi-modal behavioral biometrics. In addition to keystroke dynamics and mouse movement, the system can incorporate touchscreen gestures, touch pressure, scrolling patterns, or even voice typing for devices such as laptops, tablets, and smartphones. Multi-modal authentication will increase reliability because even if one behavioral trait is affected by fatigue or device changes, other metrics will compensate and maintain accuracy. This expansion will make the system suitable for modern hybrid environments where users frequently switch between devices.

Another improvement involves deep learning and adaptive AI models. Current machine learning models work effectively with structured features, but advanced neural networks such as LSTMs, CNNs, or transformer-based architectures can learn deeper temporal patterns without manual feature engineering. They can also adapt faster to subtle user behavior changes. Implementing self-learning AI will allow the system to automatically retrain and update behavioral profiles, reducing manual configuration and improving long-term performance.

The ports monitoring module can also be enhanced into a fully autonomous intrusion prevention system rather than only detection. Future versions can automatically block malicious IP addresses, close unused ports, isolate suspicious sessions, or trigger firewall rules without waiting for manual administrator intervention. Integration with existing SIEM (Security Information and Event Management) tools can allow real-time sharing of logs, alerts, and threat data for enterprise use.

In terms of scalability, the system can be deployed on cloud platforms with centralized behavioral databases and distributed monitoring across multiple workstations. This will allow organizations to monitor hundreds or thousands of users simultaneously. Cloud deployment also makes remote access secure, which is increasingly important in work-from-home and mobile work environments. Role-based authentication can further be added for multi-user systems where privileged accounts require stronger monitoring.

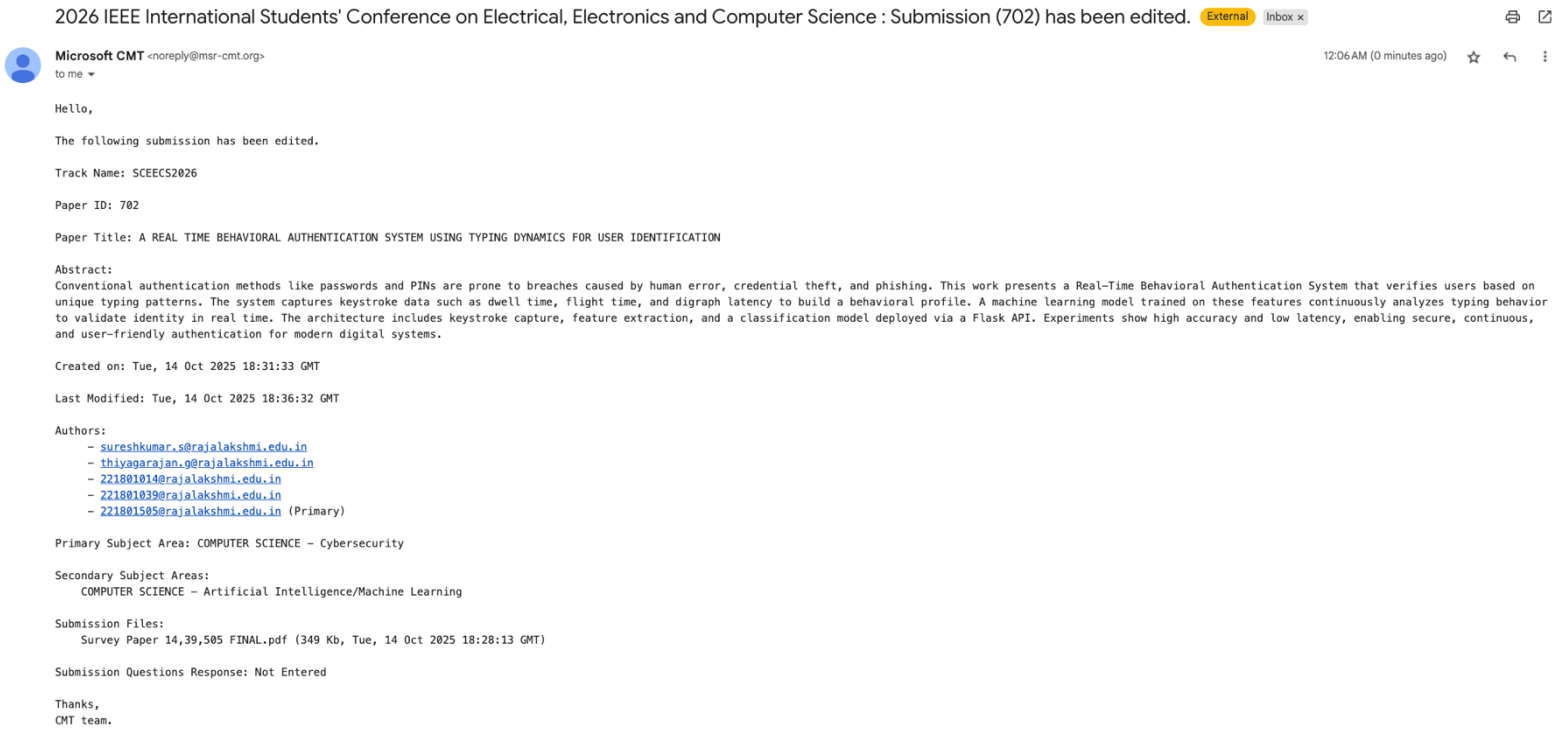
Future improvement can also focus on user privacy and data protection. Techniques like encryption, tokenization, and federated learning can ensure that raw keystroke data never leaves the device and only encrypted behavioral models are shared. This will build user

trust and enable deployment in industries with strict data regulations such as healthcare, finance, and government systems.

Finally, a comprehensive analytics and reporting dashboard can be developed where administrators can visualize authentication statistics, intrusion attempts, open port risks, and behavioral anomalies. Graph-based analysis, heatmaps of mouse activity, and time-based behavioral reports can help organizations understand system usage and better predict security threats.

APPENDEX

PAPER AND PUBLICATION



2026 IEEE International Students' Conference on Electrical, Electronics and Computer Science : Submission (702) has been edited. External Inbox ×

Microsoft CMT <noreply@msr-cmt.org> 12:06 AM (0 minutes ago)
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Hello,

The following submission has been edited.

Track Name: SCEECS2026

Paper ID: 702

Paper Title: A REAL TIME BEHAVIORAL AUTHENTICATION SYSTEM USING TYPING DYNAMICS FOR USER IDENTIFICATION

Abstract:
Conventional authentication methods like passwords and PINs are prone to breaches caused by human error, credential theft, and phishing. This work presents a Real-Time Behavioral Authentication System that verifies users based on unique typing patterns. The system captures keystroke data such as dwell time, flight time, and digraph latency to build a behavioral profile. A machine learning model trained on these features continuously analyzes typing behavior to validate identity in real time. The architecture includes keystroke capture, feature extraction, and a classification model deployed via a Flask API. Experiments show high accuracy and low latency, enabling secure, continuous, and user-friendly authentication for modern digital systems.

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Thanks,
CMT team.

Fig 8.S1 Paper Submission Acknowledgement

A Real-Time Behavioral Authentication System Using Typing Dynamics for User Identification

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Abstract - Conventional authentication mechanisms such as passwords and PINs are highly susceptible to security breaches due to human error, credential theft, and phishing attacks. To enhance user verification, this paper introduces a Real-Time Behavioral Authentication System that identifies users based on their unique typing dynamics. The proposed framework captures keystroke-level data, including dwell time, flight time, and digraph latency, to generate a behavioral profile for each user. A machine learning model trained on these temporal features continuously monitors user typing behavior to validate identity in real time. The system architecture integrates a front-end keystroke capture module, a feature extraction and preprocessing engine, and a classification-based identification model deployed via a lightweight Flask API for real-time inference. Experimental results demonstrate that the system achieves high accuracy in distinguishing genuine users from impostors while maintaining minimal response latency, making it suitable for continuous and unobtrusive authentication. This approach highlights the potential of behavioral biometrics in providing adaptive, secure, and user-friendly access control for modern digital systems.

Keywords — Behavioral Biometrics, Typing Dynamics, Real-Time Authentication, Keystroke Dynamics, Machine Learning, Continuous User Identification.

I. Introduction

In the modern digital era, securing online systems and personal devices is a significant challenge due to the widespread use of passwords and other conventional authentication methods. These traditional mechanisms are increasingly vulnerable to attacks such as phishing, credential theft, and social engineering. Users often create weak or repeated passwords, and the reliance on one-time login credentials does not ensure that the authorized user remains in control throughout a session. Consequently, there is a pressing need for more robust, user-centric, and continuous authentication methods that can enhance security without compromising usability.

Behavioral biometrics offers a promising solution by leveraging the unique behavioral patterns exhibited by individuals. Among various behavioral traits, typing dynamics, also known as keystroke dynamics, is particularly effective for user identification. Typing dynamics capture measurable features such as dwell time (duration of key press), flight time (interval between releasing one key and pressing the next), and n-graph patterns (digraphs, trigraphs). These features are inherently difficult to imitate, making them ideal for verifying a user's identity continuously and unobtrusively.

This project focuses on the design and implementation of a real-time behavioral authentication system using typing dynamics. The system collects keystroke-level data from users, preprocesses it to extract meaningful features, and applies machine learning algorithms to create a unique behavioral profile for each user. During login and active sessions, the system continuously monitors typing behavior to detect anomalies or potential impostors, thereby enhancing security beyond traditional methods. Real-time processing ensures immediate identification and verification, making the system suitable for applications where continuous access control is critical.

The key objectives of the project include real-time user identification, continuous authentication, adaptive behavioral profiling, and achieving high accuracy with low false acceptance and rejection rates. By integrating machine learning with behavioral biometrics, the system not only improves security but also provides a seamless and non-intrusive experience for users. This project contributes to ongoing research in behavioral biometrics and intelligent authentication systems, demonstrating how typing dynamics can be effectively used to build secure, user-friendly digital systems.

II. Related Works

The majority of previous work in behavioral biometrics emphasizes user identification or authentication using fixed-text or free-text keystroke datasets. Classical statistical methods, machine learning models, or deep learning architectures are typically employed to extract and analyze temporal features such as dwell time, flight time, and n-graph patterns, with evaluation metrics including Equal Error Rate (EER), False Acceptance Rate (FAR), False Rejection Rate (FRR), and accuracy. While several works focus on multi-modal fusion, privacy-preserving protocols, or adaptive modeling, most are offline or session-based and do not provide **real-time continuous authentication**. Few existing systems integrate real-time monitoring, adaptive behavioral profile updates, and unobtrusive user verification, leaving a gap that this project seeks to address by developing a fully

real-time, agentic, and adaptive typing-dynamics authentication framework.

A. FIXED-TEXT KEYSTROKE DYNAMICS

Fixed-text keystroke dynamics refers to behavioral biometric systems that authenticate users based on their typing patterns for predefined text, typically passwords, PINs, or passphrases. These systems analyze temporal features such as dwell time (duration a key is pressed) and flight time (interval between releasing one key and pressing the next) to establish a unique typing signature for each user. Because the text input is fixed, the system can more easily capture consistent behavioral patterns across multiple sessions. Early research in fixed-text keystroke dynamics focused primarily on statistical methods, such as distance-based metrics or threshold comparisons, to distinguish genuine users from impostors. These systems proved effective in scenarios with controlled input, providing high accuracy and low error rates while maintaining simplicity in feature extraction and modeling.

One of the main advantages of fixed-text keystroke dynamics is the relative stability of the input. Since the password or fixed text remains constant, variations in typing behavior due to content differences are eliminated, which simplifies feature analysis and improves classification performance. Studies such as Zhong et al. (2012) introduced advanced distance metrics to handle intra-user variability and outliers, demonstrating improved performance compared to traditional Euclidean or Manhattan distances. Similarly, the TKCA system (Yang et al., 2021) employed Bi-LSTM networks to model temporal sequences of keypresses in fixed-text sequences, achieving very low Equal Error Rates (EER) even with short sequences of 30–50 keystrokes. This demonstrates that fixed-text systems can achieve high accuracy with minimal data while maintaining robustness in controlled settings.

However, fixed-text keystroke dynamics also presents notable limitations. One key limitation is the lack of flexibility, as the system depends on a predefined text string for authentication, making it unsuitable for free-text or arbitrary user input scenarios. Users must type the same password or passphrase consistently, which can cause inconvenience and reduce user acceptance. Moreover, while fixed-text systems are resistant to some variations, they can still be vulnerable to attacks if an impostor gains knowledge of the password. Such systems are less effective against sophisticated imitation attacks, such as robotic typing or targeted behavioral spoofing, where attackers attempt to mimic the temporal patterns of genuine users. As a result, many contemporary studies combine fixed-text approaches with additional features or modalities to enhance security.

The implementation of fixed-text keystroke dynamics has been explored extensively in both academic research and practical applications. For instance, continuous authentication frameworks extend the concept of fixed-text typing by repeatedly verifying users during login or session intervals to prevent unauthorized access. Machine learning models, including Support Vector Machines (SVMs), Random Forests, and deep learning architectures like LSTMs, have been applied to improve classification accuracy, handle noise, and adapt to minor behavioral variations.

Research has also examined the effects of typing speed, keyboard type, and environmental conditions on authentication performance, highlighting the need to consider such factors in real-world deployment. Studies consistently show that fixed-text approaches can achieve strong accuracy, often surpassing 90% in controlled experiments.

Despite their limitations, fixed-text keystroke dynamics continues to serve as a foundation for behavioral biometric research, particularly in validating new algorithms and models. These systems provide a controlled environment for testing feature extraction techniques, distance metrics, and machine learning models before extending to more complex free-text or multi-modal scenarios. They also establish benchmark datasets that researchers use to compare methodologies and measure performance improvements. In the context of modern real-time authentication, fixed-text systems inspire hybrid solutions that combine the predictability of fixed text with adaptive profiling and continuous monitoring to enhance security. By understanding the strengths and weaknesses of fixed-text keystroke dynamics, researchers can develop more robust, user-friendly authentication systems suitable for both desktop and mobile applications.

B. FREE-TEXT KEYSTROKE DYNAMICS

Free-text keystroke dynamics refers to behavioral biometric systems that authenticate users based on their typing patterns while entering arbitrary text, rather than a predefined password or passphrase. Unlike fixed-text systems, free-text systems must account for the natural variability in the user's input, making feature extraction and modeling more complex. Key temporal features such as dwell time, flight time, digraphs (two-key sequences), and trigraphs (three-key sequences) are used, along with statistical and frequency-based measures to capture the distinctive behavioral signature of each user. It is particularly important for real-world applications where users interact with a variety of text inputs, such as emails, chat messages, or document editing, making free-text systems more flexible and practical for continuous authentication.

One major advantage of free-text keystroke dynamics is its applicability in real-world scenarios. Users can be authenticated seamlessly during normal typing activity without being restricted to a specific password or input sequence, allowing continuous and unobtrusive verification. Recent research leverages advanced machine learning and deep learning techniques, including Random Forests, SVMs, Bi-LSTMs, and transformer-based models, to analyze free-text typing patterns and adapt to the inherent variability. For instance, Recurrent Neural Network-based approaches can model temporal dependencies in variable-length sequences, improving accuracy in free-text authentication. Such systems demonstrate robust performance even when users type different content across sessions, making them suitable for real-time applications.

However, free-text systems face several challenges due to the unpredictability and noise in user input. Variations in typing speed, errors, corrections, keyboard types, and context-specific behaviors introduce significant intra-user variability, which can reduce authentication accuracy. Data sparsity is also a concern, as short free-text segments may not contain enough informative features for reliable classification. Moreover, the system must balance the trade-off between detection speed and accuracy, since longer text sequences provide more

reliable data but delay real-time verification. Researchers have addressed these challenges using feature aggregation, sliding window analysis, and adaptive models that update user profiles over time.

Free-text keystroke dynamics has been extensively studied in recent years, with numerous datasets developed for experimentation and benchmarking. Systems like the ITAD metric approach use graph-based representations of typing sequences combined with Random Forest classifiers to efficiently handle free-text input. Other works explore hybrid approaches, combining statistical analysis with deep learning to capture both local and global typing patterns. Continuous authentication frameworks employ sliding time windows or instance-based evaluation to provide ongoing verification, ensuring that the active user matches the enrolled profile throughout the session. These systems highlight the importance of balancing real-time performance with accuracy and adaptability to changing typing behaviors.

Despite the complexity and challenges, free-text keystroke dynamics offers significant potential for enhancing security in practical applications. By enabling continuous, non-intrusive authentication, these systems reduce reliance on passwords and improve resistance to impersonation attacks. They also provide a rich source of behavioral data that can be leveraged for anomaly detection, multi-modal fusion, or adaptive learning systems. As machine learning models become more sophisticated and computational resources more accessible, free-text keystroke dynamics is increasingly capable of supporting real-time, robust authentication for both desktop and mobile platforms. Understanding its advantages and limitations is essential for designing secure, user-friendly behavioral biometric systems.

C. MACHINE LEARNING APPROACHES

Machine learning and deep learning approaches have become central to modern keystroke dynamics research due to their ability to model complex temporal patterns and adapt to intra-user variability. Traditional statistical techniques, while effective for simple fixed-text scenarios, struggle to capture nonlinear relationships or contextual dependencies in user typing behavior. By contrast, machine learning algorithms such as Support Vector Machines (SVMs), Random Forests (RF), and k-Nearest Neighbors (k-NN) have been successfully applied to both fixed-text and free-text keystroke datasets. These models leverage features like dwell time, flight time, digraph/trigraph sequences, and aggregated statistics to classify users and detect impostors, often achieving high accuracy in controlled environments. For instance, the work by Kiyani et al. (2020) employed an ensemble-based recurrent confidence model (R-RCM) to dynamically assess user authenticity, demonstrating the effectiveness of hybrid ML approaches in continuous authentication systems.

Deep learning methods, particularly Recurrent Neural Networks (RNNs), Long Short-Term Memory networks (LSTMs), and Convolutional Neural Networks (CNNs), have further enhanced keystroke dynamics modeling by automatically extracting temporal and sequential features from raw input. Papers such as "Deep Learning-Based Authentication Using Keystroke Dynamics" (2019–2024) and "BehaveFormer" (Senarath et al., 2023) illustrate the application of Bi-LSTM and transformer-based architectures to both fixed-text and free-text data. These models can learn long-range dependencies between keystrokes, capture subtle behavioral nuances, and adapt to changes in user behavior over time. Transformer-based methods, in particular, integrate attention mechanisms to weigh the importance of specific keystroke sequences, improving identification accuracy in multi-session or noisy environments.

Another advantage of ML and DL approaches is their **scalability and adaptability**. As datasets grow in size and diversity, deep learning models can be fine-tuned or retrained to maintain performance across multiple users and devices. Multi-class classification strategies enable simultaneous verification of multiple users, while anomaly detection frameworks handle unseen or novel typing behaviors. Additionally, these approaches can be integrated into continuous authentication frameworks, where sliding windows of keystroke sequences or streaming data are processed in real time to provide ongoing verification. Studies such as the ITAD metric approach and CNN-RNN hybrids for free-text input demonstrate how ML/DL techniques support robust, non-intrusive, and adaptive authentication in both desktop and mobile contexts.

Despite their advantages, ML and DL methods also face challenges. Deep learning models often require **large volumes of labeled data** for training, which can be difficult to collect in real-world settings, especially for free-text scenarios. Computational complexity and latency are additional concerns, particularly for real-time systems on resource-constrained devices. Moreover, overfitting to specific datasets or user populations can reduce generalizability. Researchers have addressed these issues through techniques such as feature normalization, data augmentation, transfer learning, and lightweight model architectures designed for deployment on personal devices. Hybrid approaches combining classical ML with deep learning have also been proposed to balance accuracy, efficiency, and interpretability.

Overall, machine learning and deep learning approaches have significantly advanced keystroke dynamics research, enabling more accurate, adaptive, and real-time authentication systems. They form the foundation for modern behavioral biometric systems that go beyond static verification, supporting continuous monitoring and dynamic user identification. By leveraging these techniques, current research addresses limitations of fixed-text or free-text systems and opens avenues for multi-modal fusion, privacy-preserving protocols, and deployment in real-world applications. The 20 reviewed papers collectively demonstrate the critical role of ML and DL in achieving high performance and robustness in both experimental and practical keystroke authentication systems.

D. SYNTHESIS – GAPS IDENTIFIED

The literature on keystroke dynamics demonstrates that both fixed-text and free-text approaches provide effective mechanisms for user authentication. Machine learning and deep learning models, including SVMs, Random Forests, LSTMs, and transformers, capture complex temporal and sequential patterns in typing behavior. Multi-modal systems and sensor fusion further enhance robustness by integrating complementary behavioral data, while privacy-preserving techniques protect sensitive user information. Overall, these studies highlight the

high accuracy, adaptability, and potential of typing dynamics for continuous authentication.

Despite these strengths, several limitations persist. Few systems provide real-time, continuous verification, and many adaptive models lack dynamic updating to accommodate behavioral drift. Integration of privacy with adaptive learning is limited, and free-text datasets are often small or homogeneous, reducing generalizability. Additionally, multi-modal and deep learning approaches, while accurate, often compromise usability, computational efficiency, and explainability, leaving room for improvement in practical deployment.

These gaps indicate clear opportunities for innovation. There is scope to develop a real-time, adaptive typing-dynamics system that continuously monitors and updates user profiles, maintains privacy, and operates efficiently across devices. Combining free-text input with robust machine learning models and lightweight multi-modal fusion can enhance accuracy while reducing overhead. Additionally, explainable models can improve user trust and deployment in sensitive applications such as finance or enterprise systems.

In summary, existing research provides a strong foundation in behavioral biometrics, demonstrating the feasibility and benefits of keystroke-based authentication. However, addressing the identified gaps through real-time processing, adaptive learning, privacy integration, and scalable, explainable models presents a significant opportunity to advance the field. The proposed project aims to fill these gaps, creating a practical and secure real-time authentication system suitable for diverse real-world applications.

III. *PROPOSED METHODOLOGY*

The proposed system is designed to perform real-time behavioral authentication based on users' typing dynamics, capturing unique patterns in their keystroke behavior. The process begins with a data collection module that records each keypress and key release event along with associated timestamps. Both fixed-text and free-text inputs are considered, enabling the system to operate in versatile environments such as password entry or normal typing. This module works unobtrusively in the background, ensuring that users are authenticated continuously during their active sessions without interrupting workflow.

The next phase is data preprocessing and feature extraction, where the raw keystroke events are cleaned to remove inconsistencies, errors, or noise. Relevant features, including dwell time, flight time, digraphs, trigraphs, typing speed, and rhythm patterns, are extracted for each user. These features are then normalized to reduce variability caused by factors such as device type, keyboard layout, or user posture. The extracted features are structured and formatted to serve as input for the authentication model, ensuring consistency and reliability for further processing.

The authentication model employs a hybrid approach combining deep learning and classical machine learning algorithms. Long Short-Term Memory (LSTM) networks or Bi-LSTM models are used to capture temporal and sequential dependencies in keystroke sequences, while classical models like Random Forests provide robust decision-making for classification. This dual approach ensures that both local and global patterns in user behavior are captured, improving accuracy and reducing the likelihood of false acceptance or rejection. The system compares real-time keystroke features with stored behavioral profiles to continuously authenticate users and detect impostor activity.

To handle changes in typing behavior over time, the system incorporates adaptive learning mechanisms. User profiles are updated dynamically based on validated recent typing patterns, allowing the system to adjust to natural behavioral drift caused by factors such as fatigue, posture changes, or device switching. This adaptive feature ensures long-term reliability of authentication while maintaining minimal user intervention. Additionally, thresholds for anomaly detection are fine-tuned to balance security with usability, minimizing false alarms without compromising detection of unauthorized users.

Finally, privacy and security measures are integrated into the system to protect sensitive behavioral data. Features are processed and stored securely, and privacy-preserving techniques such as local profile storage or encrypted updates are implemented to prevent data misuse. The entire methodology, from data collection to adaptive authentication, is designed to create a robust, real-time, adaptive, and privacy-conscious behavioral authentication system, suitable for deployment across desktop and mobile environments, providing seamless continuous verification of legitimate users while preventing unauthorized access.

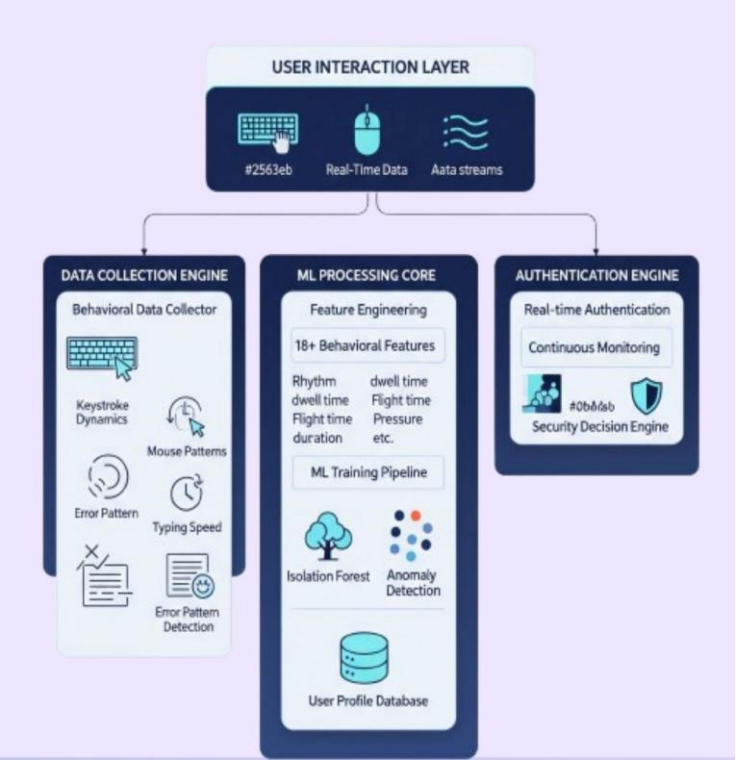

Fig.1. Architecture Diagram

TABLE 1 COMAPRISON TABLE

S. No	Title of the Paper	Methodology Used	Limitations	Advantages	Accuray(%)/ EER
1	BehaveFormer: A Framework with Spatio-Temporal Dual Attention Transformers for IMU enhanced Keystroke Dynamics (Senarath et al., 2023)	Spatio-temporal dual-attention transformers; combines keystroke + IMU; STDAT module	Requires IMU data (mobile); heavier model complexity	Strong performance by fusing IMU with keystrokes; transformer attention captures temporal patterns.	EER reported: 1.80% (Aalto DB) ; 2.95% (HuMIdb).
2	An Agent-Based Modeling Approach to Free-Text Keyboard Dynamics (Dillon & Arushi, 2025)	Agent-based simulation to generate synthetic free-text keystrokes; evaluated with OC-SVM and Random Forest	Synthetic data may not capture all real user variance; cross-keyboard generalization weak	Allows controlled experiments across keyboard types; isolates hardware effects	RF accuracy: **>70%** intra-keyboard (paper)
3	TKCA: Timely Keystroke-based Continuous Authentication (Yang et al., 2021)	Embedding of key name + timing; Bi-LSTM with timely voting aggregation	Works with very short keystroke sequences in uncontrolled settings	Needs per-user training data; majority voting adds latency	EER: **8.28%** (30 keys); **2.78%** (190 keys)
4	Privacy-Preserving Continuous Authentication Using Behavioral Biometrics (Baig et al., 2023)	Cryptographic protocols (homomorphic encryption, oblivious transfer) + biometric scoring	Protects user features/privacy during auth; practical privacy guarantees	Computational/communication overhead; implementation complexity	Biometric performance maintained; specific accuracy varies by dataset (reported as good)
5	Continuous User Authentication Featuring Keystroke Dynamics (Kiyani et al., 2020)	Ensemble learners + Robust Recurrent Confidence Model (R-RCM)	Action-level confidence scoring; quick lockout on impostors	Tuning thresholds sensitive; possible false locks	Reported improved detection; exact % varies by dataset.
6	Keystroke dynamics-based user authentication using freely typed text (Kim et al., 2018)	User-adaptive feature extraction + novelty detection; free-text focus	Works on free text (realistic); novelty detection handles unknown patterns	Free-text noisy; needs more data per user	EER: **~2.46%** (reported in related summaries)
7.	Accurate Continuous and Non-intrusive User Authentication with Multivariate Keystroke Streaming (Alshehri et al., 2017)	Time-series streaming features; RNN+CNN style sequence modelling	Non-intrusive continuous auth; exploits multivariate keystroke streams	Higher compute for streaming; sensitivity to windowing	Reported strong continuous auth performance (metrics in paper)
8	Iterative Keystroke Continuous Authentication: A Time Series Based Approach (2018)	Iterative time-series modeling; sliding windows for continuous decision	Adapts over time; designed for continuous monitoring	Requires parameter tuning for window sizes; drift handling needed	EER / accuracy numbers reported per dataset in paper
9	Authentication on the Go: Effect of Movement on Mobile Keystroke Dynamics (2017)	Empirical study of keystroke on mobile under motion; statistical analysis	Highlights practical degradation under movement; guides robustness design	Movement causes large variability; needs sensor fusion	Quantitative drop in accuracy under movement (paper shows results)
10	Authentication by Keystroke Dynamics: Influence of Typing Language (2023)	Comparative analysis across languages; statistical feature comparison	Shows language impacts features; informs multilingual systems	Language dependence complicates global deployment	Reported differences in EER across languages (paper)

IV. CONCLUSION

This project proposes a real-time behavioral authentication system using typing dynamics to provide continuous and unobtrusive user verification. By capturing keystroke patterns such as dwell time, flight time, and n-graph sequences, and leveraging machine learning and deep learning models, the system can accurately distinguish genuine users from impostors. The inclusion of adaptive learning allows the system to adjust to natural behavioral drift over time, while privacy-preserving measures ensure sensitive typing data remains secure. Multi-modal considerations and hybrid modeling further enhance robustness, making the system suitable for deployment across both desktop and mobile platforms.

The review of literature and identified gaps underscore the need for real-time, adaptive, and privacy-conscious authentication mechanisms in practical applications. By addressing these gaps, the proposed methodology offers a secure and efficient solution capable of continuous user verification without interrupting workflow. Overall, this system demonstrates the potential of typing dynamics as a reliable behavioral biometric, paving the way for future enhancements such as multi-modal integration, explainable AI, and scalable deployment in enterprise, financial, and personal security applications.

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