DEEP LEARNING-BASED CONTINUOUS AUTHENTICATION SYSTEM USING MULTI-MODAL BIOMETRICS

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b. The work has not been submitted to any other Institute for any degree or diploma.

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ABSTRACT

The rapid evolution of technology has exposed the vulnerabilities of traditional authentication mechanisms like passwords, which are prone to security threats such as brute force attacks, phishing, and dictionary attacks.

To mitigate these risks, Multi-Factor Authentication (MFA) was introduced, combining factors like passwords, tokens, and biometrics. While MFA improves security, it often creates friction, leading to poor user experience and, in some cases, causing users to bypass security measures.

Password-less authentication methods, such as facial recognition and fingerprint scanning, were developed to improve convenience but are not without limitations. These methods remain susceptible to spoofing, device theft, and frequent re-authentication, which disrupts workflows. Moreover, they rely on static, one-time validations, making sessions vulnerable to hijacking by unauthorized users.

This project proposes a **continuous, deep learning-based authentication system** that leverages multiple biometric factors for real-time identity verification throughout a user session. Unlike traditional methods, this continuous system ensures the user remains authenticated while active. It combines facial recognition, voice analysis, and behavioral biometrics (e.g., typing rhythms, and file download frequency) to provide a higher level of security with minimal disruption.

The system uses advanced deep-learning techniques to ensure accurate verification. Convolutional Neural Networks (CNNs) process facial images, while Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) models analyze voice and behavioral patterns. Generative AI augments the biometric dataset during training, generating synthetic data to help the model adapt to diverse real-world scenarios. OpenCV handles real-time image processing, and frameworks like TensorFlow or PyTorch are used to develop and deploy the models.

By continuously monitoring biometric data, the system dynamically adapts to the user's unique traits, reducing false positives and negatives common in traditional systems. This also minimizes risks such as session hijacking or unauthorized access during active sessions.

This solution is particularly relevant in today's landscape, where robust, secure authentication is critical for industries like remote work, online banking, and healthcare. As remote work expands, securing data from unauthorized access has become more vital. Likewise, the healthcare sector demands seamless yet secure authentication to protect sensitive patient data.

In conclusion, the proposed deep learning-based continuous authentication system offers a groundbreaking solution to the limitations of traditional and password-less methods. Combining multi-modal biometrics with advanced AI techniques, it ensures continuous, high-security authentication with minimal user disruption, making it an ideal fit for industries that require uninterrupted, secure sessions.

CONTENTS

TIMELINE AND MILESTONES – PROGRESS REPORT

The following table summarizes the completed tasks, pending tasks, and areas that need further improvement:

Task	Status	Comments	Estimated Time of Completion	Priority
Custom Face Model	Completed	A custom face model has been built and evaluated.	June 13, 2024	High
Custom Voice Model	Completed	Voice model created; accuracy needs improvement.	August 16, 2024	High
Keystroke Dynamics Model	Completed	Keystroke dynamics model built, showing 83% accuracy.	September 24, 2024	High
Integration of Multimodal Authentication	Completed	The end-to-end flow is ready waiting for other modules to be plugged in	October 11, 2024	Medium
Custom Random Forest Classifier	Work In Progress	Random forest classifier is ready, once human activity recognition is built, it needs to be integrated	January 15, 2025	High
Human Activity Recognition using UCI HAR	Work In Progress	Implementation in Progress, Accuracy needs improvement	January 31, 2025	High
Data Augmentation and Fine tuning for Custom Models	Work In Progress	Need additional data for training to improve robustness.	February 28, 2025	Medium
Deployment as an application	Pending	Build and deploy as an application for prototype	April 30, 2025	High

Priority Focus

1. **Current Tasks** (High Priority, *Work in Progress*):

   Custom Random Forest Classifier: Complete integration post-human activity module.
   Human Activity Recognition (UCI HAR): Focus on improving accuracy.
   Data Augmentation and Fine-Tuning: Gather and process additional data.

2. **Future Tasks**:

   Deployment as an Application: Once all models are finalized, prioritize development and testing for deployment.

Suggested Milestones

1. **October 2024**: Finalize all model integrations.
2. **January 2025**: Achieve target accuracy for Random Forest and HAR models.
3. **April 2025**: Complete prototype deployment as a working application.

CHAPTER 1: INTRODUCTION AND LITERATURE REVIEW

1.1 Introduction

1.1.1 Background and Motivation

As technology evolved and the internet became a battlefield against cyber security threats, traditional authentication mechanisms for websites and mobile applications with the invention of the Internet of Things (IoT) became prone to security threats. The authentication landscape evolved and is now embracing the **paradigm shift to continuous authentication**.

Traditionally, passwords and Personal Identification Numbers (PINs) have been the de facto authentication factors of user authentication. However, their reliance on static credentials made them vulnerable to threats such as brute force attacks, phishing, and credential stuffing.

Recent developments in the Identity and Access Management domain(IAM) have seen IAM platforms encourage end users for multi-factor authentication(MFA) registration. MFA usually entails a combination of authentication factors according to the authentication strength requirement. As an example, administrators in a system would be required to use both biometric and device verifications but regular users will only use combinations of device authentication factors.

a. **Knowledge-based factors**, such as passwords or PIN codes, while effective when securely stored, are still vulnerable to social engineering attacks. Users are always vulnerable to security threats as it is not uncommon to forget passwords/PINs.
b. **Possession-based factors** are physical authentication factors used in modern IAM space i.e. RFID tokens or smart cards. While this provides enhanced security, it does disrupt the user experience as users always need to carry it with them.
c. **Biometric factors** or inherence factors are metrics intrinsically owned by authorized individuals. These often take the form of biometrics – such as fingerprint readers, retina scanners, or voice recognition. These are designed to ensure unauthorized parties cannot pass the authentication process and these factors are almost 100% unique to the authorized user. However, once compromised, it could turn into a single point of failure.

Continuous Authentication is a security paradigm that evolved from traditional, static methods of authentication. Instead of relying solely on authentication factors at the point of login to a session, Continuous Authentication continuously monitors, verifies, and authenticates the user’s identity throughout the entire duration of their interaction with the application. It is dynamic and adaptable.

Even if continuous authentication seems to be the golden answer it is not void of any shortcomings. End-user experience, the computational complexity of the system itself, and the delayed response time are a few of the areas where it still demands further research and study.

Characteristics	Traditional Authentication Methods	Continuous Authentication
Authentication Frequency	One-time, at login	Continuous, throughout the session
User Interaction	Active, requires user input	Passive, seamless
Security Level	Static, vulnerable to attacks	Dynamic, risk-based
User Experience	Intrusive, interrupts workflow	Frictionless, transparent
Adaptability	Limited, fixed security measures	High, context-aware

These challenges could be overcome by recent waves of research and exploratory studies on continuous authentication coupled with Machine Learning (ML) and Deep Learning (DL) techniques. It can monitor the behavioral metrics of the user i.e. keystroke dynamics and can track human activity recognition if the user is using a mobile phone. With this biometric information coupled with contextual parameters i.e. session duration, login time, etc. it can be well equipped to classify the risk of a user session. Moreover, it can use multi-modal biometrics i.e. face recognition and voice similarity checks to further verify the user. The continuous, dynamic, and comprehensive nature of continuous authentication makes it a promising solution against spoofing attacks and other session-based attack vectors.

1.1.2 Problem Statement

Traditional As discussed above, the **one-time authentication method fails** to address the challenge of continuous authentication. Therefore, the application becomes vulnerable to session-based attack vectors i.e. session hijacking, and privilege escalation. Biometric and Multi-factor Authentication factors do effectively secure the initial login, but they disrupt the user experience and are still vulnerable to limitations of device theft and spoofing attacks.

Logins can be secured with a combination of MFA, complex passwords, and risk-based conditional access policies with an acceptable user-friendly workflow, but it remains a point-in-time authentication and not continuous throughout the session. It can lead to **session hijacking** (where attackers steal an authenticated session token), **session fixation** (where attackers inject a valid session ID into a victim's session), and **man-in-the-middle** (MITM) attacks (where attackers intercept and modify communications) that can compromise security.

These scenarios highlight a **critical gap** once a user logs into a new session, there is no continuous verification, validation, or authentication to ensure the authenticity of the user. To address this gap, we need a **dynamic, adaptive, customized,** and real-time authentication framework that would continuously verify and authenticate a user throughout the session with minimal user disruption and reduced window of session attacks.

1.1.3 Objectives

The objective of this research or project is to ideate and develop a **Deep Learning-Based Continuous Authentication System using multi-modal biometrics** to address the current challenges of traditional authentication frameworks. The key objectives are as follows:

a. To design and implement a continuous authentication system that operates seamlessly throughout the entire user session.
b. To integrate **multiple biometric modalities**—facial recognition, voice analysis, and behavioral biometrics i.e. keystroke dynamics, and human activity recognition using mobile devices—into a unified framework for enhanced security and user experience.
c. To apply machine learning and deep learning models, such as **Convolutional Neural Networks (CNNs)**, and **LTSMs** for dynamic, real-time user verification.

An additional objective of the system is to address and mitigate session-based attacks by leveraging continuous authentication mechanisms. With real-time verification and authentication of the user, this authentication framework will ensure that only the authentic user is controlling the session and will eliminate the window for session-based attack vectors i.e. Session hijacking, MIM attacks, etc.

1.1.4 Contributions

a. A novel continuous authentication system that integrates multi-modal biometrics with a risk classification system for enhanced security and acceptable user experience.
b. A hybrid architecture utilizing CNNs for visual data processing and RNNs for behavioral pattern analysis to ensure accurate, dynamic verification coupled with LTSMs for keystroke dynamics,
c. A prototype implementation using OpenCV and deep learning frameworks (TensorFlow or PyTorch), demonstrating the feasibility and practicality of the proposed system in real-world applications.
d. A detailed exploration of key challenges such as computational efficiency, data collection challenges, and system scalability in the deployment of this continuous authentication solution.

1.2 Literature Review

1.2.1 Overview of the Field

Authentication is an important aspect in the current world especially as we digitally evolve. Traditionally, we have been using various methods such as passwords, PINs, and security questions to establish our identity. But all these measures are slowly being rendered ineffective given the advancing tactics of today’s cyber criminals including session hijacking, phishing, and credential stuffing. The main **challenge with these traditional static factors** is that they can only prove that it is me at a given time when I am attempting to log in. This is where Continuous Authentication comes in as a better option to the traditional authentication methods.

Continuous Authentication (CA) provides a new and improved way of authentication as it performs the identification process during a user’s session. Unlike one-time verification, CA systems are adaptive and monitor the user’s activity in real time to detect any irregular behavior and therefore prevent the attacker from further controlling the user’s session. These systems use various types of biometric information including the behavior and the physical attributes to make the process more dynamic and effective.

The CA systems have been greatly enhanced by developments in machine learning, deep learning, sensors, and biometrics. With the advancement in technology and the increasing use of mobile devices, wearables, and the Internet of Things (IoT), CA is rapidly finding its application in these smaller and constrained devices. Nevertheless, the CA systems must find a way of balancing efficiency and flexibility in different conditions, the privacy of users, and high-security standards.

1.2.2 Thematic Organization

1.2.2.1 Biometric Authentication Approaches

Biometric authentication has been an important milestone in the ever-evolving authentication space. These factors are almost 100% unique and personal for users. **Physiological biometrics** (Facial recognition, voice recognition, fingerprints) provide the highest accuracy and reliability. Whereas **behavioral biometrics** (keystroke dynamics, human activity recognition) provide continuous passive authentication by analyzing user's behavior at rest and in motion.

a. Physiological Biometrics:

Facial Recognition has played a pivotal role in strengthening reliability in authentications. It is non-intrusive and provides a seamless experience i.e. Windows Hello. IoTCAF integrates facial recognition with IOT-based data to cope with the dynamic and robust nature of IoT ecosystems. However, despite being highly reliable, it is vulnerable to spoofing with high-resolution images or prone to less accuracy in case of poor lighting or movements [4][6][8].

Fingerprint recognition is highly reliable but still is susceptible to device displacement, spoofing attacks, 3-D printed fake fingerprints, or artificial fingerprint replicas [6][8].

This summarizes the fact even though physiological biometrics elevates security with acceptable user-friendliness, it is vulnerable to sophisticated identity attack vectors. Therefore, a robust combination of multiple biometric modalities and contextual factors (i.e. IP reputation, average session duration) has proven to be an effective strategy to overcome the limitations.

b. Behavioral Biometrics:

Behavioral Biometrics such as keystroke dynamics and human activity recognition offer continuous passive authentication in the background. This is highly effective when users are constantly interacting with devices.

Gargoyle Guard [5] has researched the use of Real-Time Activity Fingerprinting (RTAF), which analyzes keystroke dynamics and mouse behavior, using Bi-LSTM RNNs to model temporal dependencies in real-time behavior.

Michail Kaseris and Kostavelis [22] documented the systematic identification and classification of activities undertaken by individuals based on diverse sensor-derived data for human activity recognition.

However, on studying both citations, it was presented that both approaches face challenges due to user variability. i.e. Keystroke dynamics model may not be interpreted accurately if the user is multitasking or in a different emotional state (Stress, anger). Similarly, human activity recognition is also susceptible to device use (desktop vs laptop) and the user's physical state [5][7].

Gait recognition systems can also be effective when users carry wearable sensors or use cameras, but they also suffer from challenges i.e. placement variability and environmental factors (terrain or footwear) [7][9].

Behavioral Biometric Modality	Key Features
Keystroke Dynamics	Typing speed, dwell time, flight time
Mouse Dynamics	Movement speed, acceleration, click duration
Touchscreen Gestures	Swipe speed, touch pressure, gesture patterns
Gait Recognition	Walking speed, stride length, body movements
Voice Recognition	Pitch, tone, speaking rhythm

1.2.2.2 Multi-Modal Systems

Multimodal authentication improves security and usability by combining multiple biometric factors i.e. gait recognition, facial recognition, and accelerometer data, to overcome the limitations of individual modalities.

a. **Benefits:** This approach significantly improves performance [2], where the integration of accelerometer data with facial recognition achieved a high authentication accuracy of 98.3%. This kind of approach resolves respective modality-based challenges (Poor lighting for facial recognition, device placement issues in gait analysis [8]). IoTCAF framework extends these capabilities by integrating behavioral biometrics with contextual data which includes environmental conditions(i.e. IP reputation) and device location, to enable scalable and adaptive authentication. This real-time adjustment of thresholds improves both accuracy and efficiency, particularly in resource-constrained environments i.e. IoT deployments [4].

b. **Challenges:** On the other hand, multimodal systems face many challenges.

    i. Increased **computational complexity**, and multiple data sources, can limit scalability on low-power devices like smartphones and IoT sensors. IoTCAF framework mitigates this by optimizing feature extraction and using lightweight machine-learning models to balance accuracy with efficiency [4][10]. Another critical issue is that it is difficult to synchronize data across different modalities i.e. gait and facial recognition.

    ii. **Privacy** concerns also present a significant hurdle, as biometric data(i.e. voice and facial images) needs to be stored in **compliance with GDPR** and other regional compliances along with inherent ethical and security issues. While frameworks like IoTCAF implement privacy-preserving measures (anonymization and retention policies) these require continuous maintenance and notifications to ensure user trust and compliance [4][5].

It can be concluded from the relevant citations that even if Multimodal systems significantly enhance authentication accuracy and adaptability, there are challenges with computational resources, data synchronization, and privacy.

1.2.2.3 Continuous Authentication Techniques

Continuous authentication enables continuous verification and authentication throughout the session, providing real-time protection against session-based cyber-attack vectors.

a. **Dynamic Verification Models**: IoTCAF uses a dynamic approach to continuous authentication, using **semantic rules** and **ontology-driven frameworks** to adjust authentication levels based on contextual data. i.e. when a user attempts to access sensitive information from an unfamiliar device or location, the system increases the verification frequency or triggers additional checks for better authentication strength[4]. This dynamic approach is very effective in **resource-constrained** environments (IoT) and balances authentication security with computational efficiency.

    Similarly, Gargoyle Guard's Real-Time Activity Fingerprinting **(RTAF)** uses **Bi-LSTM RNNs** to model the real-time sequential nature of user behavior. By continuously monitoring **typing patterns**, **mouse movements**, and other interaction data, the framework performs continuous passive authentication without the need for active input or prompts from the user [5]. This continuous authentication can also adjust dynamically to the user's behavior.

b. **Challenges in Continuous Authentication**:

i. **Latency**: Real-time continuous authentication systems struggle with latency while processing multiple data sources that need extensive computations. Selected ML models must be lightweight and effective as used by IoTCAF to maintain a balance between accuracy and computational complexity[4].
ii. **Adaptability**: Continuous systems must be able to adjust t user behavior fluctuations. Adaptive machine learning algorithms need to be deployed to attain acceptable accuracy over time.

Continuous authentication systems offer robust security and acceptable ease of use after point-in-time authentication during login, but challenges related to latency, adaptability, and computational efficiency need to be addressed for practical deployment and further adaptations.

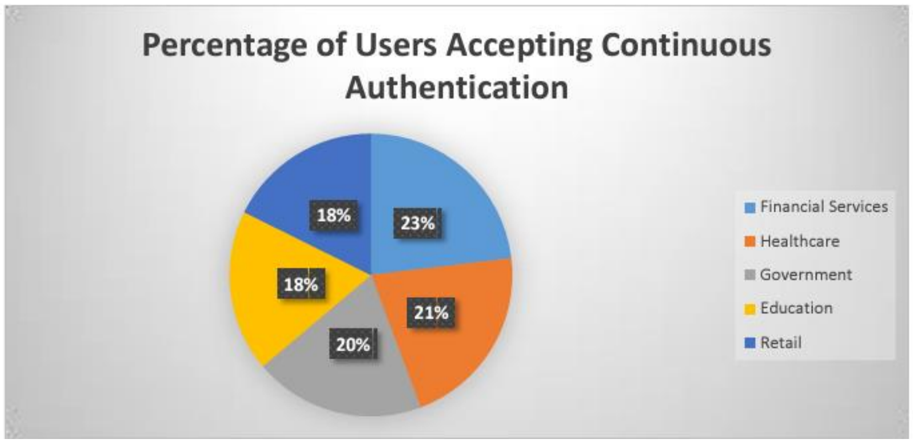
1.2.2.4 Machine Learning in Authentication

Machine learning (ML) plays a significant role in many modern continuous authentication systems as it enables the authentication framework to process biometric and behavioral data to identify users accurately and dynamically.

a. **Role of Deep Learning Models:** Deep learning models play a significant role in continuous authentication frameworks. CNNs are effectively used for facial recognition to learn complex patterns and features from images. Recurrent Neural Networks (RNNs), specifically Long Short-Term Memory (LSTM) and Bi-directional LSTMs (Bi-LSTMs) are used for sequential analysis of speech data for voice recognition. Bi-LSTM RNNs are used (Gargoyle Guard [5]), to process keystroke dynamics and gait recognition as they can capture temporal dependencies and detect anomalies in user behavior over time. Lightweight ML models aided with distributed computing are used in resource-constrained IoT environments i.e. smart homes or wearable devices [4].

b. **Challenges:**

i. Machine learning models are prone to **overfitting** when trained on small or non-diverse datasets unless data augmentation and cross-validations are used to mitigate it.
ii. **Data quality** is a challenge for ML models as biometric data can often be noisy or incomplete leading to compromised accuracy. Data augmentation and transfer learning techniques are used to overcome this issue by adding synthetic or cross-domain data to the training dataset[6].
iii. **Model Interpretability** is another practical challenge, especially considering regional compliance policies i.e. GDPR, CCPA, and ethical usage of users' biometric data. It becomes pivotal that the decision-making process is made transparent and consistent to governing bodies and end users. Explainable AI(XAI) is a solution that helps achieve transparency in black-box ML models. Below is a diagram of much-needed **user education and awareness** to enable faster adoption of CA frameworks.



Relatively Low User Acceptance Rate Across Different Industries Due to lack of transparency and interpretability

1.2.3 Gaps and Challenges in the Literature

Continuous Authentication (CA) frameworks have evolved over the past years. However, there are still critical gaps in the realization of the theoretical concepts in CA systems.

1.2.3.1. Limited Multimodal Integration

a. Most of the explored multi-modal modalities include a maximum of two biometric modalities (i.e. gait recognition and facial recognition [5][8]). Even though these bimodal CA frameworks are more accurate and reliable than unimodal frameworks or MFA systems, they are still inadequate in real-world scenarios.
b. **Critical Analysis:** The integration of additional modalities i.e. keystrokes dynamics, human activity recognition, and contextual factors(IP reputation, average session duration) would aid in robust risk classification enabling continuous authentication by analyzing user behavior at rest(keystroke dynamics [9][10]) and user in motion(Human activity recognition[22]). However, integrating multiple modalities introduces new challenges i.e. data synchronization, increased computational complexity, and complex feature fusion techniques. Studies ([2] [8] [4][7]) show that a combination of accelerometer data with facial recognition has enhanced the reliability of the CA framework.
c. **Recommendation:** To truly embrace the dynamic nature of continuous authentication and to build a robust framework, future research should explore more **comprehensive multimodalities** that integrate physiological traits (e.g., facial recognition, voice recognition) with behavioral traits (e.g., keystroke dynamics, human activity using mobile). These approaches would significantly improve user verification accuracy while maintaining the ease of use.

1.2.3.2. Real-Time Scalability

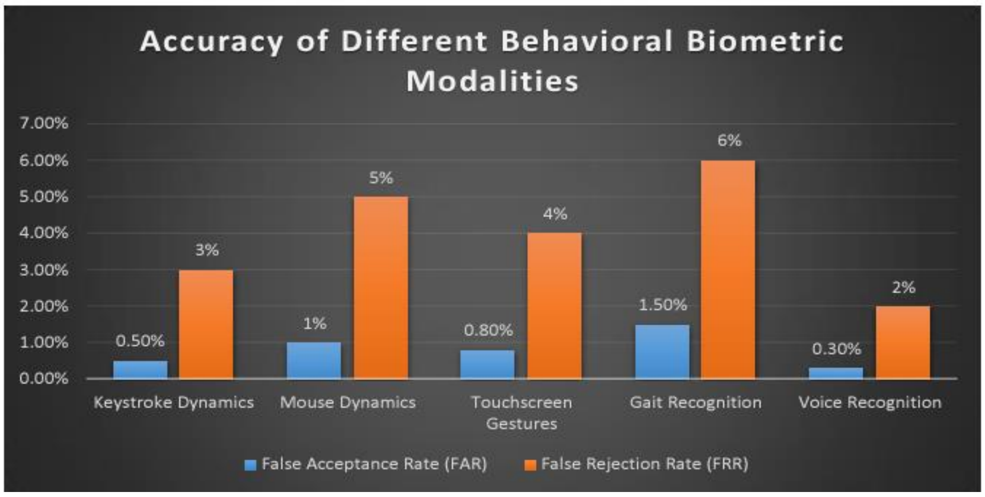
a. Scalability is **one of the prominent challenges** in CA frameworks. Real-time CA frameworks need high computational resources to process multi-modal biometric inputs, classify risk, and verify the user passively throughout the session.
b. The **computational demand of CA frameworks** limits the feasibility of their deployments in resource-constrained environments i.e. smart wearables, mobile, and IoT environments. The impact of compute-heavy models on resource-constrained IoT environments is researched and studied here [5][4].

Deep learning models (e.g., CNNs for facial recognition or RNNs for behavioral biometrics) will also have these limitations. Research [23][4] by IoTCAF focuses on optimizing machine learning models for real-time performance on resource-constrained platforms and demonstrates that lighter models can balance accuracy and efficiency. However, the trade-offs between computational efficiency and accuracy remain a key challenge.

c. **Recommendation:** Future work should explore developing more lightweight and efficient machine learning models that maintain high accuracy while reducing computational overhead. Techniques such as model pruning, knowledge distillation, and edge computing could help address these issues by offloading heavy processing tasks to more powerful servers.

1.2.3.3. Dynamic User Behavior

a. **Dynamic user behavior is another hurdle** in continuous authentication. Behavioral biometrics (e.g. keystroke dynamics, gait patterns, touch gestures) are highly sensitive to environmental and physical factors i.e. stress, fatigue, or multitasking. As a result, CA systems that incorporate dynamic user behavior struggle to produce consistent accuracy or reliability [7][5].



Impact on Accuracy of Different Behavioral Biometrics due to dynamic Behavior [15]

b. **Critical analysis** could be that traditional CA systems use static models or fixed thresholds for behavioral biometric verification. It is often inadequate as it cannot handle the inherent variability of human actions. e.g. A user might type slower than usual under stress or fatigue, which might result in false rejections in a keystroke dynamics-based system. Similarly, changes in a user's gait pattern due to illness or footwear could result in authentication errors [10]. Modern CA systems must be dynamic and should adapt to varied human activity and keystroke dynamics.

c. Research must explore adaptive models that use context-aware learning. These models must use feedback from real users and use it to adjust the threshold of behavioral biometric verification. Transfer learning can be used here to make the models more effective.

1.2.3.4. Security Against Advanced Threats

a. Existing CA frameworks mitigate traditional identity attack vectors i.e. spoofing or impersonation. But there are now more sophisticated adverse identity attack vectors that CA frameworks struggle to account for.
b. **Critical analysis** of these citations revealed two major security threats.
    i. **Adversarial attacks** target the learning weights of deep learning models or data based on epsilon values, inducing misclassification (Chakraborty et al., 2021). Adversarial attacks are so vulnerable that they can induce misclassifications even in images that are difficult for human perception,
    ii. **Deepfake Technology** creates realistic synthetic images or videos that can bypass or confuse facial recognition systems. These deepfakes are not only convincing to human observers but can also manipulate algorithms to authenticate unauthorized users.
c. Emerging research has explored defenses against these advanced threats. Studies have demonstrated methods i.e. adversarial training ([29][9]) and robust feature extraction ([25] [6]) to prevent the injection of synthetic data. However, these methods are still in their infancy and have not been widely adopted.
d. To counter the sophisticated cyber identity attack vectors, future CA frameworks must adopt Adversarial Machine Learning Defenses (To reject adversarial inputs), Anomaly Detection Algorithms, and Synthetic Data Recognition and must involve contextual environmental factors to account for variability in data.

1.2.4 Relevance to Current Research

This project aims to mitigate the gaps above in CA frameworks by proposing a novel multimodal CA system that integrates diverse biometric modalities and contextual environmental factors.

1.2.4.1. Comprehensive Multimodal Integration

One Limited multi-modal integration has been one of the highlights in the literature.

The proposed solution will incorporate behavioral biometrics with keystroke dynamics and human activity recognition with contextual factors that would determine user risk classification. This classification will then trigger face or voice recognition. A combination of these physiological and behavioral biometrics will significantly form a robust framework against sophisticated identity attack vectors and environmental variations as explained in [4][7][10].

A diverse portfolio of biometrics (**physiological and behavioral**) coupled with **explainable AI** ([5][8]) will also mitigate the compliance requirements or ethical concerns leading to a comprehensive multi-modal CA framework.

1.2.4.2. Real-Time Scalability in Resource-Constrained Environments

Scalability is another hurdle in practical deployments of CA frameworks are often resource-intensive and hence, unsuitable for IoT and mobile environments.

The proposed project embraces model compression, feature selection, and distributed learning to ensure that the CA system works efficiently on devices with limited resources i.e. wearables or smart home devices [4][5]. Also, a conscious attempt is made to keep the model lightweight for it to be deployable at ease referring to citations in [4][7].

1.2.4.3. Adaptability to Dynamic User Behavior

Existing Dynamic user behavior is another factor that impacts accuracy during continuous verification. The existing static model relies on static thresholds leading to the variance.

To mitigate this, this project focuses on adaptive CA models (as cited in [5][10]) that would account for typing variations caused by stress, reducing false positives and negatives [7][9].

1.2.4.4. Security Against Advanced Threats

Existing continuous authentication systems are vulnerable to sophisticated cyber-attack vectors i.e. adversarial biometrics, Deepfakes, and synthetic data.

This project explores adversarial machine learning to counter adversarial examples and synthetic data (e.g., deepfakes). Models are trained with adversarial data and use robust feature extraction to reject manipulated biometrics [10][9]. Anomaly detection is also incorporated to detect any probable identity compromise missed by behavioral models.

CHAPTER 2: THEORETICAL STUDY

2.1. Introduction to Continuous Authentication Systems

Overview of Authentication Systems:

Authentication confirms a user's identity to grant access to digital resources. Common methods like passwords, PINs, and single-instance biometrics (e.g., fingerprints, facial scans) are widely used but struggle against modern security threats. Passwords can be stolen or easily guessed, while biometrics, though generally stronger, can be fooled (e.g., with fake fingerprints or photos). These single-check methods verify identity only at login, leaving the session vulnerable to hijacking and unauthorized access afterward.

Continuous authentication (CA) has become a solution to these problems. CA constantly verifies the user's identity during a session, reducing the risk of unauthorized access even after a successful login. As digital systems become more complex and users expect smooth access, balancing security with user experience is essential. CA systems achieve this by constantly monitoring user behaviour like typing rhythm, walking style, and voice patterns, along with standard biometric information.

Need for Continuous Authentication:

The growing number of cyberattacks i.e., session hijacking, stolen credentials, and man-in-the-middle attacks, demonstrates the need for stronger identity verification. Continuous authentication is vital to ensure that the users are constantly verified throughout their active session. Standard login procedures only check identity once, at the start, creating opportunities for unauthorized activity later. By watching user behaviour in real-time, continuous authentication takes a proactive stance on security. This helps stop malicious actions that happen after the initial login, such as session hijacking and spoofing.

Furthermore, continuous authentication makes security less intrusive. Unlike traditional methods, CA systems check a user's identity without interrupting their workflow, only requiring further authentication if something unusual is spotted. This reduces the need for constant manual checks and improves the overall user experience.

Multimodal Authentication:

Combining several biometric methods in multimodal authentication systems boosts both accuracy and security. Using just one method (unimodal), like fingerprint scanning, is susceptible to being tricked or failing in certain situations (like poor lighting affecting face recognition). Multimodal systems, by using combinations of face, voice, and typing patterns, become more resistant to attacks and work more reliably in different environments. This is especially important for continuous authentication, providing multiple checks so that if one method is compromised or unreliable, others can take over.

For instance, if it's too dark for facial recognition to work, voice recognition can still be effective. Similarly, adding behavioural biometrics like typing patterns and activity recognition creates an additional layer of security, making it significantly harder for an attacker to imitate various aspects of a user's identity.

2.2. Deep Learning in Authentication Systems

2.2.1. Role of Deep Learning:

Deep learning is crucial for enhancing continuous authentication systems. Especially when dealing with large and complex sets of data from multiple sources. Older machine learning techniques require manually designed features to categorize data. In contrast, deep learning models, like Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) automatically learn complex features directly from the raw data. This leads to better classification accuracy and more robust systems.

For example, CNNs are excellent at image recognition, making them ideal for facial recognition. RNNs and Long Short-Term Memory (LSTM) networks are well-suited for handling sequential data, such as voice patterns and typing rhythms.

The ability of deep learning to extract intricate, high-level features from unprocessed data helps continuously monitor and confirm user identity. This allows CA systems to adapt to changes in user behaviour in real time.

2.2.2. Applications of Deep Learning in Biometrics:

Deep learning has proven effective for various biometric methods. For facial recognition, Convolutional Neural Networks (CNNs) are commonly used to analyze facial images and extract unique features that can be compared to stored user profiles. In voice authentication, Recurrent Neural Networks (RNNs), especially LSTMs, analyze aspects like pitch, rhythm, and tone to create distinctive voiceprints. For keystroke dynamics, deep learning models can detect subtle patterns in typing speed, rhythm, and key pressure that are unique to each person. These models can also learn and adapt to changes in a user's behavior over time, leading to improved authentication accuracy.

2.2.3. Challenges in Deep Learning-based Authentication:

While deep learning offers many advantages for biometric authentication but it also presents some challenges. One key issue is the need for large training datasets which might not always be available. Another challenge is the computational cost: these models often require powerful hardware that may not be present in devices with limited resources, i.e., smartphones or IoT devices. Additionally, deep learning models can be sensitive to poor-quality data, such as blurry images or distorted audio which can negatively affect authentication accuracy.

To address these challenges, techniques like data augmentation (creating artificial variations of existing data), transfer learning (leveraging pre-trained models), and model pruning (reducing the model's complexity) can be used to improve the efficiency and robustness of deep learning for biometric authentication.

2.3. Multimodal Biometrics for Continuous Authentication

2.3.1. Concept of Multimodal Biometrics:

Multimodal biometrics combines multiple biometric traits to authenticate users, providing a more secure and accurate method compared to unimodal systems. By fusing data from several biometric sources—such as **facial recognition**, **voice patterns**, and **keystroke dynamics**—the system benefits from redundancy, making it more resistant to attacks such as **spoofing** or **environmental disruptions** [15]. In continuous authentication, multimodal systems offer continuous validation by monitoring multiple aspects of user behavior.

2.3.2. Advantages of Multimodal Approaches:

The key advantage of multimodal systems lies in their **robustness** and **security**. Using multiple biometric traits makes the system **more resistant to spoofing attacks**, as it becomes exponentially harder to spoof multiple traits (e.g., both face and voice). Additionally, multimodal systems perform better in **real-world conditions**, as they are less likely to be affected by a single form of environmental noise, such as poor lighting or background noise.

For example, combining **voice** and **keystroke dynamics** allows a system to authenticate a user even when one modality (such as facial recognition) fails due to poor lighting conditions, as seen in some biometric systems [9].

2.3.3. Fusion Techniques in Multimodal Systems:

In multimodal biometric systems, **fusion techniques** are employed to combine the data from multiple modalities. The most common approaches include **feature-level fusion**, **score-level fusion**, and **decision-level fusion**. In **feature-level fusion**, raw data from different modalities are combined before classification. In **score-level fusion**, separate classifiers are trained on different modalities, and their outputs are combined to make a final decision. **Decision-level fusion** involves making individual decisions for each modality and then combining these decisions to produce the final output.

The proposed system uses **feature-level fusion** to integrate **keystroke dynamics** and **human activity recognition** before classification. This method allows the system to capture both behavioral and contextual aspects of the user's identity, ensuring that authentication remains robust and accurate even in the face of session-based attacks or other environmental disruptions.

2.3.4. Real-World Applications and Case Studies:

Several real-world applications utilize multimodal biometrics for continuous authentication, such as the combination of **face and voice recognition** or **fingerprint and voice recognition**. These systems have shown success in improving security by reducing the risk of spoofing and providing more reliable user identification in varying environmental conditions. However, many systems face challenges such as **computational complexity** and the difficulty of **integrating diverse data types** efficiently, especially when deployed on mobile or IoT devices with limited processing power.

2.4. Keystroke Dynamics and Human Activity Recognition

2.4.1. Keystroke Dynamics:

Keystroke dynamics involves the analysis of **typing patterns** to authenticate users. Unlike traditional biometrics, keystroke dynamics analyzes the **rhythm**, **speed**, and **pressure** exerted during typing. These behavioral patterns are unique to each individual and can serve as a reliable method for **continuous authentication**. Changes in a user's **typing behavior**, such as a significant delay between key presses or variations in typing rhythm, can signal unauthorized access or session hijacking.

2.4.2. Human Activity Recognition (HAR):

Human activity recognition (HAR) uses **mobile sensors** and **IoT devices** to capture **user movements**, such as walking patterns, gestures, or posture. HAR adds an additional layer of behavioral authentication, monitoring activities like **walking speed**, **gait**, and **posture** to continuously verify the user's identity. HAR is particularly valuable in **mobile environments** where a user's movement can be tracked in real-time to provide ongoing identity

verification.

2.4.3. Challenges in Keystroke and Activity Recognition:

While both keystroke dynamics and human activity recognition offer valuable data, they are prone to challenges such as **data variability** (e.g., **typing under stress** or **multitasking**) and **environmental factors** (e.g., walking on different surfaces). For keystroke dynamics, factors like stress or fatigue can change typing patterns, making it difficult to distinguish between legitimate user behavior and anomalies. Similarly, HAR systems must account for varying walking speeds, environmental conditions, and changes in posture, which can introduce noise into the system. To address these challenges, adaptive algorithms that continuously learn and adjust to each user's behavior are essential for improving accuracy and robustness.

2.5. Solution Overview and Module Integration

The proposed solution introduces a novel CA system that integrates **keystroke dynamics** and **human activity recognition** data from mobile and IoT devices into a **Random Forest Classifier** to assess user risk levels as **Low**, **Medium** or **High**. **Medium Risk** prompts voice verification via a **Voice Matcher**, while **High Risk** or failed voice verification triggers facial recognition through a **Face Matcher**. If facial authentication fails, the system terminates the session, ensuring robust security against unauthorized access. This dynamic approach balances security with user convenience by escalating authentication only when required.

This dynamic approach helps mitigate session-based attacks by continuously verifying the user's identity throughout the session. By integrating real-time authentication checks based on user behavior and environmental context, the system detects anomalies that could indicate session hijacking, session fixation, or replay attacks.

For example, if the system detects a change in the user's **keystroke dynamics** or **human activity** patterns that differ significantly from prior behavior, it triggers an immediate re-authentication or session termination. This ensures that the system remains vigilant to potential threats even after the initial login, minimizing the risk of session hijacking and other forms of attack.

2.5.1. Unique Aspects of the Solution

What sets this solution apart is its adaptability and user-centric design. The system learns and evolves over time by incorporating user-specific data, reducing disruptions and providing a seamless, customized security experience. As the system becomes increasingly trained on user behavior, it minimizes false positives, ensuring a balance between security and usability. Moreover, the modular, deep learning-based pipeline is application-agnostic, enabling its reuse across diverse platforms without modification. This scalability, combined with its emphasis on personalization, makes the solution uniquely effective in addressing the limitations of existing CA frameworks.

By bridging gaps in the literature and offering an adaptive, scalable, and user-friendly CA system, this solution represents a significant step forward in securing digital interactions across diverse environments while also mitigating risks from session-based attacks and other relevant security threats.

2.5.2. Data Acquisition Module

The **Data Acquisition Module** serves as the foundation of the continuous authentication system by collecting raw biometric, behavioral, and contextual data. This module captures **facial data** via cameras, **voice data** through microphones, and **keystroke dynamics** by monitoring typing patterns. Additionally, it incorporates **human activity recognition** using sensors from mobile devices, such as accelerometers and gyroscopes, and IoT devices like motion detectors and wearables. Contextual information, including device type, IP address, session duration, and network conditions, further complements the collected data. This comprehensive input ensures a robust dataset that reflects both biometric and environmental factors, facilitating accurate downstream processing.

2.5.3. Preprocessing Module

The Preprocessing Module gets the raw data collected by the Data Acquisition Module ready for analysis. Facial data is normalized and has key features extracted to make the input consistent. Voice data is cleaned up using noise reduction and important features like Mel-frequency cepstral coefficients (MFCCs) are extracted. Typing data is analyzed to find timing and rhythm patterns. For activity data from mobile and IoT devices, specific methods like gait analysis and activity labeling are used. This module makes sure all the different types of data are converted into consistent, usable formats for the machine learning models, keeping the important information from the original data while making it suitable for processing.

2.5.4. Matcher Modules

The **Matcher Modules** authenticate users by evaluating the preprocessed data from individual modalities.

a. **Face Matcher:** This component uses pre-trained models like FaceNet or VGGFace to create facial embeddings, which are compared to stored templates. These embeddings capture unique facial features for accurate authentication. Advanced face recognition algorithms are used to handle variations in lighting, angles, and expressions, ensuring robust performance in different conditions.

b. **Voice Matcher:** This component utilizes pre-trained systems like Deep Speech, enhanced with custom LSTM-based models, to analyse voice characteristics for authentication. It extracts unique vocal attributes like pitch, tone, and cadence for accurate identification. Techniques for handling background noise are also included to improve reliability in real-world settings.

c. **Keystroke Dynamics Matcher:** This component analyses typing patterns to detect deviations in a user's rhythm and timing. It captures keypress durations, intervals, and sequences to create unique behavioural profiles. This adds an extra layer of security by monitoring subtle behavioural cues that are difficult to replicate.

d. **Activity Recognition Matcher:** This component processes human activity data from mobile and IoT sensors to identify behavioural patterns. It analyses data like walking patterns, gestures, and movement dynamics to detect deviations from typical user behaviour, adding contextual security by using physical activity as another authentication factor.

2.5.5. Feature Fusion and Integration Module

The **Feature Fusion and Integration Module** consolidates outputs from the **Keystroke Dynamics Matcher** and **Activity Recognition Matcher** to form a unified vector for classification. This module integrates these specific modalities at the feature level, ensuring a comprehensive representation of behavioral and activity data. By focusing on these modalities, it effectively captures subtle behavioral deviations without over-relying on biometric inputs. The output is passed to the **Random Forest Classifier** for risk-level categorization.

2.5.6. Random Forest Classifier

The **Random Forest Classifier** serves as the decision-making core of the system, categorizing authentication attempts based on the consolidated input vector from the **Feature Fusion and Integration Module**. Trained on a diverse dataset of labeled behavioral and activity patterns, the classifier assigns each authentication attempt to one of three risk levels: **Low**, **Medium**, or **High**. A **Low-Risk** classification permits seamless access, while a **Medium-Risk** result triggers additional verification via the **Voice Matcher**. **High-Risk** classifications either deny access immediately or escalate to further verification using the **Face Matcher**, depending on the outcome of the **Medium-Risk** check. This module ensures dynamic and adaptive responses tailored to the confidence in the user’s legitimacy.

2.5.7. Decision and Feedback Module

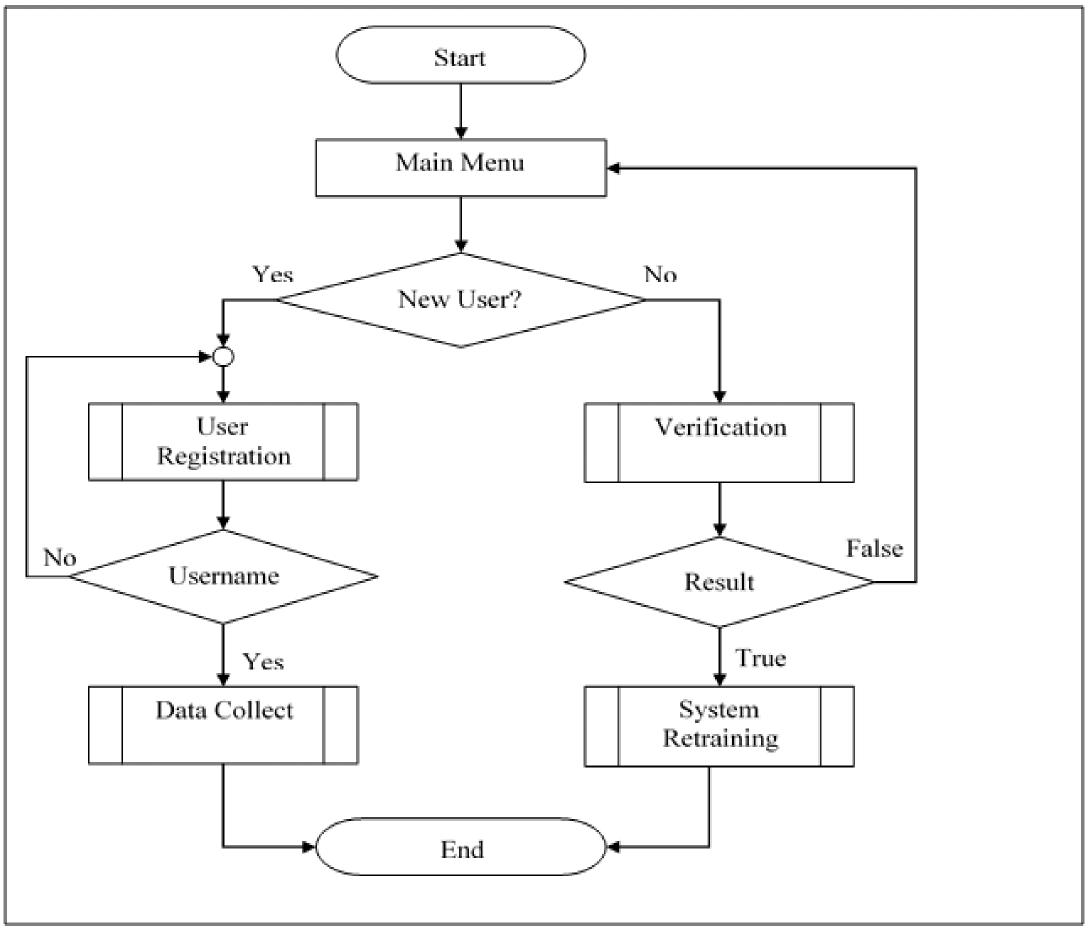
The **Decision and Feedback Module** enforces risk-level decisions from the **Random Forest Classifier** and manages user interactions accordingly.

Low Risk: Users are granted uninterrupted access without any extra security checks. This prioritizes convenience while maintaining security based on the confidence level provided by the risk assessment. Minimal logging and alerts are generated to keep the process efficient and unobtrusive.

Medium Risk: The system requests an additional verification step using the Voice Matcher. The user must provide a voice sample for authentication. This balances security and user experience by only requiring a quick second check when needed. If the voice verification fails, the risk level is escalated to High Risk.

High Risk: If the initial risk assessment is High or the Medium Risk voice verification fails, the Face Matcher is used for further authentication. If the Face Matcher also fails, access is immediately denied, and a security alert is sent for manual review and investigation. This strict response blocks unauthorized access and provides useful information to the security team.

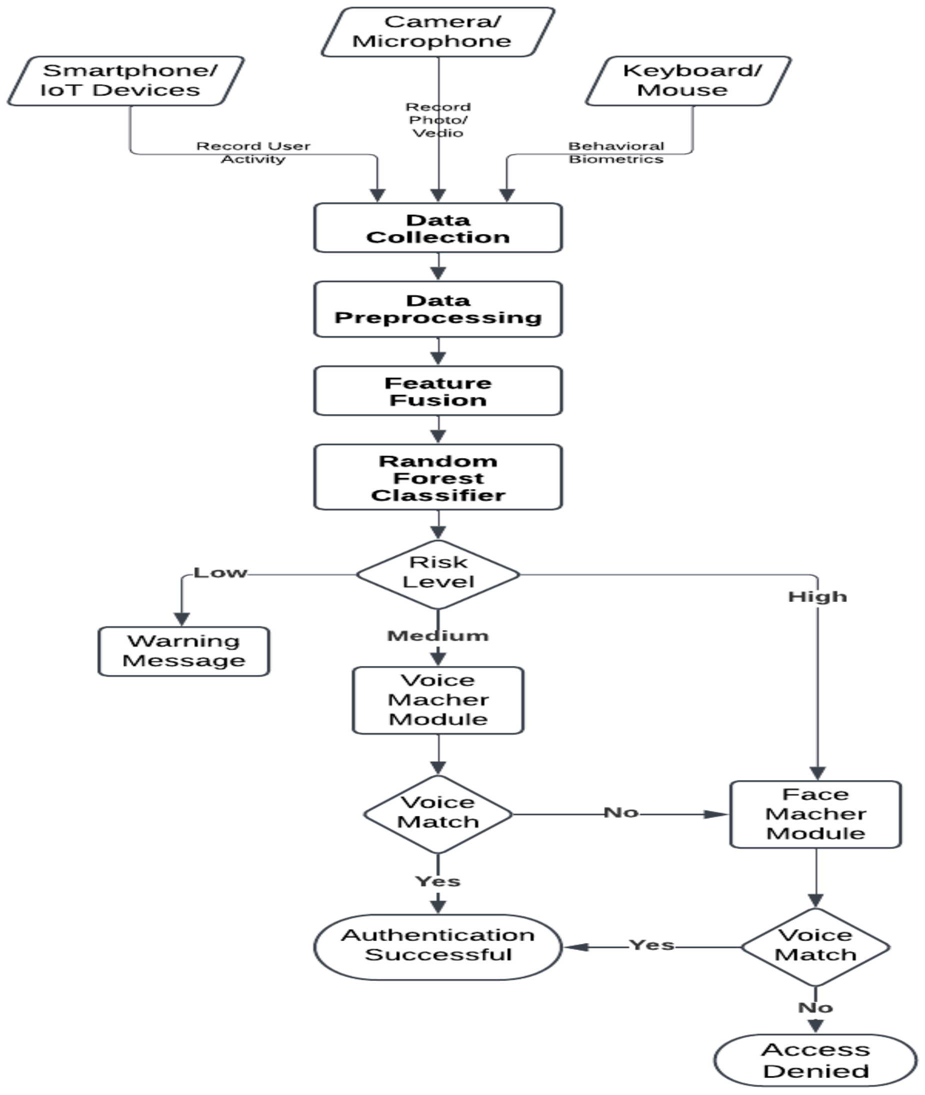
Web flow of user experience:



This diagram shows the process flow of the keystroke dynamic prototype system. Mainly there are involve in two main parts. First, a user needs to register into the keystroke dynamic system if he/she is a new user. For new user, he/she need to key in his/her name, email, contact number, username, and password. Once he/she is successfully registered as a new user, he/she requires to key-in his/her username, password, and standard phrase for 10 times to capture his/her keystroke dynamic typing data and reference template which to be stored in the server’s database.

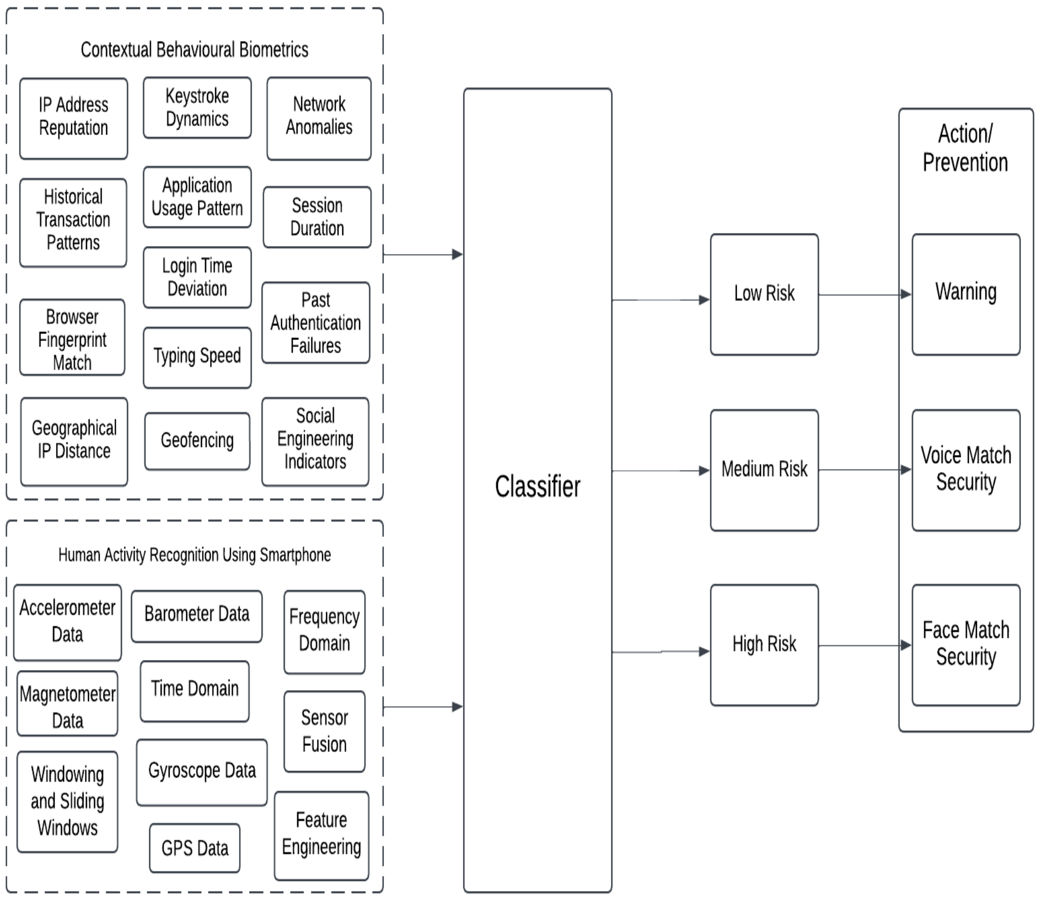
Second, a normal user which has registered can log in to the Keystroke Dynamic system which the username and password. The keystroke info will be captured and send from the client to the server. The verification process will be done on the server-side to verify the user keystroke dynamic info is matching with the username and password reference template. If his/her result is matched, then able to login to the web-based system. After that, the system will do the retraining process to recalculate the user reference template Otherwise, the result is negative which below the score limit, he/she will prompt that does not allow to proceed with the next step.

Module Integration Diagram:



This diagram shows how the different parts of the continuous authentication system work together to decide access. The process begins with the Data Acquisition Module collecting data from various sources like smartphones, cameras, microphones, and keyboards/mice. This raw data is then cleaned and prepared by the Data Preprocessing Module. The Feature Fusion Module combines this processed data into a single format, which is then sent to the Random Forest Classifier. The classifier assesses the risk level. If the risk is low, a simple warning is shown. If the risk is medium, the system performs Voice Matching, and if the voice matches, authentication is successful. If the risk is high, or voice matching fails, Face Matching is used. If both voice and face checks fail, access is denied. These modules work in sequence to dynamically assess and secure the system based on the current risk level.

Decision Workflow Diagram:



This diagram depicts a continuous authentication system that combines Contextual Behavioural Biometrics and Human Activity Recognition using smartphone sensors. The system collects various data points related to user behaviour and context, including IP address reputation, typing patterns (keystroke dynamics), app usage, session length, browser fingerprint match, and geographical IP distance. It also uses smartphone sensor data (accelerometer, magnetometer, gyroscope, GPS, and barometer) processed through techniques like sensor fusion and feature engineering to recognize human activity. A classifier analyses this combined information to determine a risk level, categorizing it as:

- **Low Risk:** A warning is issued, indicating a low-risk session with no immediate action needed.
- **Medium Risk:** A voice match verification step is triggered to add a layer of authentication.
- **High Risk:** A face match verification is required for higher confidence in user identity validation.

By dynamically assessing risk, the system provides adaptive security measures for continuous authentication throughout the user's session.

2.6. Model Study

2.6.1. Keystrokes Dynamics

2.6.1.1. Introduction

To keep your digital life secure, we have developed a custom model that analyzes your unique typing patterns. This model, powered by LSTM networks, focuses on understanding the rhythm and pace of your keystrokes. By recognizing these individual differences, it can reliably identify you and protect your accounts.

2.6.1.2. Model Architecture

Our model analyzes your unique typing patterns to identify you. It uses a special type of neural network called LSTM to understand the rhythm and timing of your keystrokes. This network is designed to process sequential data, like the order and speed of your keypresses.

The model has multiple layers that work together to extract meaningful features from your typing data. The first layer captures quick changes in your typing speed and rhythm, while the second layer focuses on more subtle variations.

To prevent the model from memorizing the training data too closely, we use a technique called dropout. This helps the model generalize better to new, unseen data.

Finally, the model assigns a probability to each user based on your typing pattern. The user with the highest probability is identified as you.

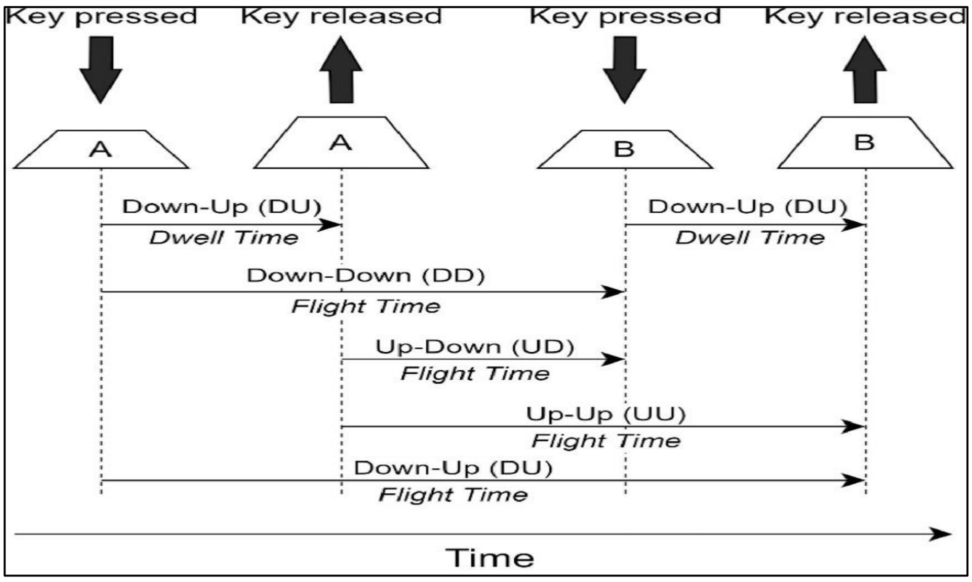
We train the model using a loss function called Sparse Categorical Cross entropy. This helps the model learn to distinguish between different users by minimizing the error between its predictions and the true labels.

2.6.1.3. Training Pipeline

The training process for the keystroke dynamics model involves several steps to ensure it learns unique typing patterns, avoids overfitting, and generalizes well to new data:

Data Collection:

Inter-key latencies, representing the time in seconds between key press (D) and key release (U) events, are calculated for all possible two-key combinations (digraphs). For example, for keys "A" and "B", features like "DU.A.A", "DU.B.B", "DD.A.B", "UD.A.B", "UU.A.B", and "DU.A.B" are generated. The model is trained on keystroke data containing both hold times and flight times. Due to the limited dataset size, data augmentation techniques like adding small random variations (jittering) to timing intervals may be used to simulate natural typing variability and improve model robustness.



Preprocessing:

Input features are normalized for consistency and to prevent bias towards certain features. Temporal features are carefully extracted to capture the typing variations that distinguish users.

Model Training:

Cross-validation is used to ensure the model generalizes well to unseen data. The learning rate and number of training cycles (epochs) are adjusted based on validation performance to prevent overfitting. Early stopping (halting training when validation performance stops improving) and model checkpointing (saving the best model during training) are also employed to further combat overfitting and ensure the best model is retained.

2.6.1.4. Evaluation Metrics

Several metrics are used to evaluate the model's accuracy in classifying typing patterns:

Accuracy: This measures the overall proportion of correctly classified users out of all predictions.
Precision, Recall and F1-Score: These metrics provide a more detailed view of the model's ability to correctly identify individual users, particularly useful when dealing with imbalanced datasets or the risk of false positives.
Confusion Matrix: This visual tool shows the counts of true positives, false positives, true negatives and false negatives, providing a clear picture of classification performance across all users.
ROC-AUC: The Receiver Operating Characteristic (ROC) curve and the Area Under the Curve (AUC) measure the model's ability to distinguish between different users and assess its discriminatory power.

2.6.1.5. Why LSTM for Keystroke Dynamics

The LSTM model was chosen for keystroke dynamics because of its ability to capture long-term dependencies in sequential data, crucial for understanding how typing behaviour changes over time. LSTMs excel at processing sequences, retaining information over extended periods, making them suitable for tasks like speech and keystroke recognition. Keystroke dynamics exhibit both short-term variations (like typing speed during short bursts) and long-term habits (like consistent rhythm over longer sessions), which the LSTM architecture handles well.

Two LSTM layers are used to capture these different patterns. The first layer detects immediate changes in typing, such as speed or rhythm. The second layer learns more sustained typing habits, improving classification accuracy by learning both short-term and long-term typing characteristics, which is key to distinguishing users based on both temporary and consistent typing behaviour.

Dropout regularization after the LSTM layers helps prevent overfitting, especially given the relatively limited dataset size. By preventing the model from relying on any single feature too much, dropout improves its ability to generalize to new typing samples. A 32-unit dense layer then reduces the complexity of the time-based features, passing only the most important information to the final output layer.

The SoftMax activation function in the output layer enables multi-class classification, essential for assigning each typing pattern to a specific user. By producing a probability distribution, the model confidently classifies users based on the likelihood of each user, which is critical for accurate authentication.

In summary, the LSTM-based model provides an effective method for continuous user authentication using keystroke dynamics. By leveraging long-term dependencies in typing, the model distinguishes users based on both short-term fluctuations and long-term habits. Dropout regularization and the SoftMax output layer ensure robust performance and generalization. This architecture makes the model well-suited for real-time authentication systems using keystrokes as a biometric. The use of LSTMs ensures the model effectively captures and classifies unique typing behaviours, providing a reliable, secure, and efficient solution for continuous user authentication.

2.6.1.6. Challenges and Future Enhancements

The LSTM-based keystroke dynamics model faces challenges related to data variability and how users change over time. Typing differences between devices (like phones vs. desktops) hinder the model's ability to generalize. Users' typing can also change due to physical condition, stress, or environment, requiring the model to adapt without complete retraining. Imbalanced datasets, where some users have much more data than others, can create bias. Finally, processing keystrokes in real-time on devices with limited resources (like phones or IoT devices) requires low latency and minimal computing power, which can be difficult to achieve.

Future improvements could include:

Domain adaptation: Techniques to help the model work better across different devices and environments.
Incremental learning: Allowing the model to adapt to changing typing habits without full retraining.
Multimodal biometrics: Combining keystrokes with other biometrics like voice or face recognition to improve reliability.
Advanced regularization and data augmentation: Using better regularization methods or creating synthetic data to address imbalanced datasets and overfitting.
Model optimization: Compressing the model to make it more efficient for resource-constrained devices, enabling real-time authentication on mobile and IoT platforms.

2.6.2. Human Activity Recognition (HAR) Using UCI HAR Dataset

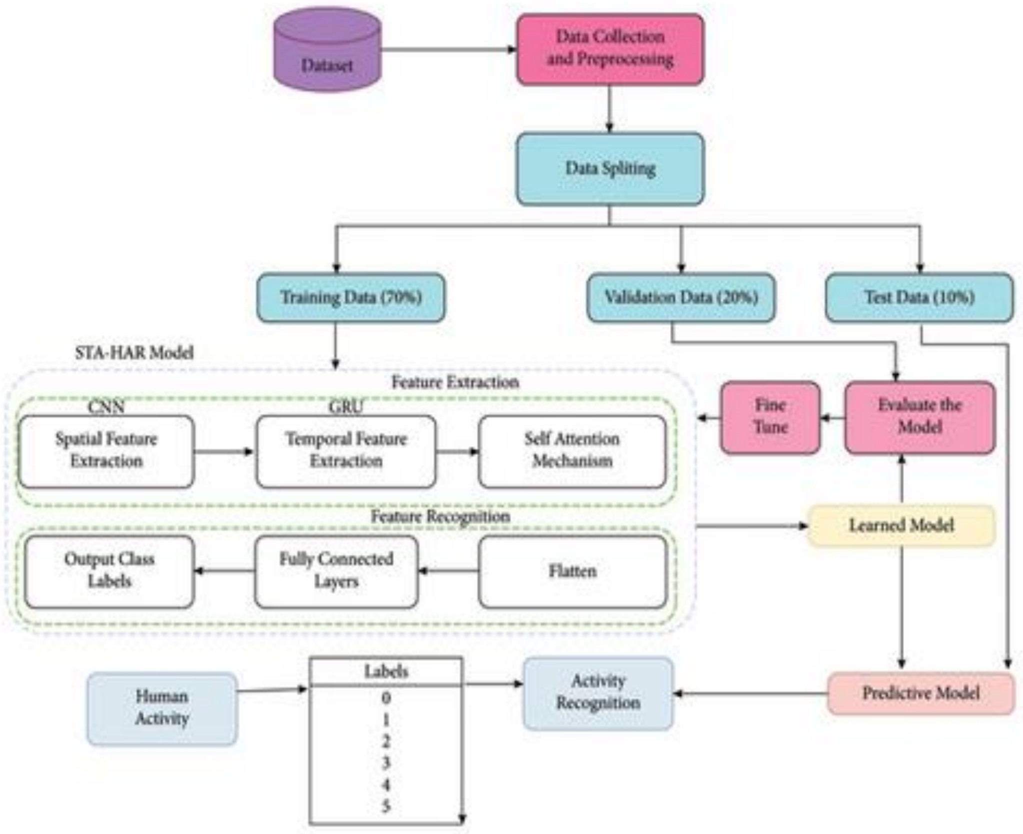
2.6.2.1. Introduction

Human Activity Recognition (HAR) is a critical task for continuous authentication and context-aware systems. In this context, we developed a custom machine learning model using the **UCI HAR dataset** to classify human activities based on data collected from mobile sensors. The **UCI HAR dataset** contains time-domain signals from accelerometers and gyroscopes, which provide essential information about an individual's movement patterns. By training a model on this data, we aim to recognize a variety of activities, such as walking, running, sitting, and standing. This model is an integral part of multimodal continuous authentication systems, where **human activity recognition** helps provide additional context to the authentication process.

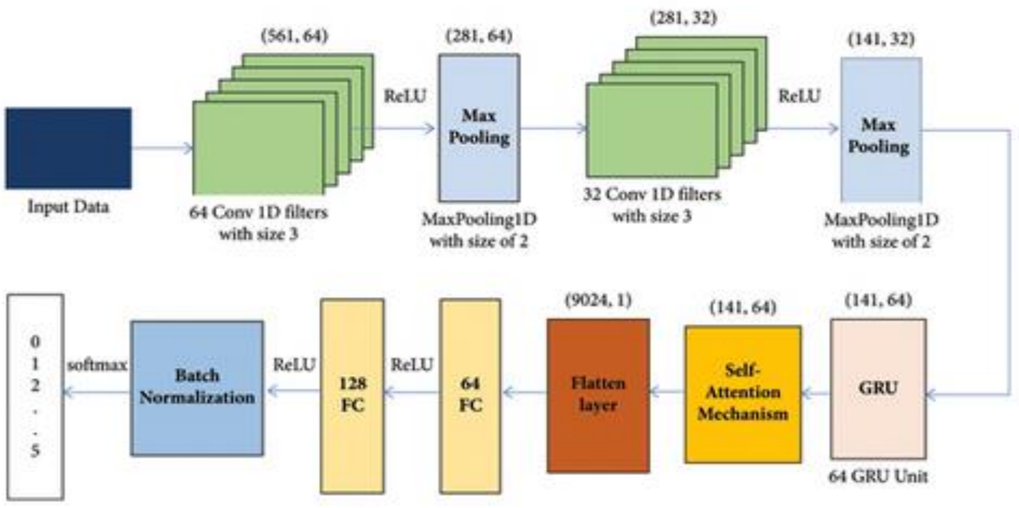
2.6.2.2. Model Architecture

The HAR (Human Activity Recognition) model starts with raw sensor data: time-series accelerometer and gyroscope readings on three axes (x, y, z). These raw readings capture the physical movement patterns during different activities. The model's architecture includes:

a. **Input Layer:** This layer receives the time-series sensor data from the accelerometer and gyroscope, collected during activities like walking, running, and standing.
b. **Preprocessing:** The data is cleaned and made consistent. Normalization scales the sensor data to ensure standardized input across different users and recording sessions. Features like mean, standard deviation, and signal magnitudes are calculated from the raw data to create a feature vector for each time window of sensor measurements.
c. **Model Architecture:** While Convolutional Neural Networks (CNNs) or Long Short-Term Memory (LSTM) networks could be used for this type of sequential data, this model uses a fully connected neural network (FNN). It has two dense layers with ReLU activation, followed by a SoftMax output layer for activity classification. The dense layers extract higher-level features from the sensor data, and the SoftMax layer outputs probabilities for each activity.



The proposed human activity recognition model uses a spatiotemporal attention mechanism. It extracts spatial features from raw sensor data using a convolutional neural network (CNN) and temporal information using a gated recurrent unit (GRU) over time. This design aims to efficiently identify and categorize human activities from sequential data. The attention mechanism then weighs the spatial and temporal features at each time step, optimizing for the specific activity being recognized. By focusing on both spatial and temporal information, the model aims to improve activity recognition accuracy. The workflow of this framework is shown in the diagram above.



When applied to the UCI-HAR dataset, the proposed framework uses two 1D convolutional layers followed by pooling layers to extract relevant features from the sequential sensor data (X) for human activity recognition. Here, X = $\{x_1, x_2, \ldots, x_t\}$ represents the input signals, where x_t is a sequential representation of sensor readings captured across multiple dimensions or features at each time-step *t* for various activities performed by subjects. Each x_t has 561 features. Dropout regularization is applied after the dense layers to prevent overfitting, which is a concern given the dataset's limited size and the high number of input features. A dropout rate of 20% is used, randomly omitting some units during training to encourage the model to generalize well to unseen data.

2.6.2.3. Training Pipeline

The **training pipeline** for the **human activity recognition** model consists of several important steps to ensure optimal performance:

a. **Dataset Preparation:**
The **UCI HAR dataset** contains labeled sensor data, where each instance is associated with a specific activity label. The data is divided into training and testing sets to evaluate the model's ability to classify unseen data. **Data augmentation** is applied to simulate slight variations in activity performance (such as different walking speeds or running styles).
b. **Feature Extraction and Scaling:**
The raw time-series data is processed to extract relevant features such as **mean, standard deviation, and skewness** of accelerometer and gyroscope readings over time windows (typically 1-second windows). These features are then **normalized** to ensure that the model is not biased by different scales in the raw data.
c. **Model Training:**
The model is trained using **cross-validation** to ensure that the model does not overfit to the training data and performs well on unseen data. **Early stopping** is used to halt training if the validation loss does not improve after a certain number of epochs, thus preventing unnecessary computation and overfitting.
d. **Hyperparameter Tuning:**
The model's hyperparameters, including the number of layers, units, and dropout rates, are tuned using a **grid search** strategy. The best-performing hyperparameters are selected based on validation performance.

2.6.2.4. Evaluation Metrics

To evaluate the **HAR model's performance**, several metrics are used to ensure a comprehensive assessment:

a. **Accuracy:**
This is the most straightforward metric and calculates the proportion of correct predictions to the total number of predictions. It is crucial for determining the overall performance of the classifier in distinguishing activities.
b. **Precision, Recall, and F1-Score:**
These metrics help evaluate the classifier's performance for each activity class. **Precision** measures how many of the predicted activity labels are correct, while

recall assesses how many of the true activity labels were successfully predicted. The **F1-score**, being the harmonic mean of precision and recall, provides a balanced view of the model's classification ability.

c. **Confusion Matrix:**
   A confusion matrix is used to visualize how the model classifies each activity and highlights any misclassifications, providing valuable insight into specific activities where the model may be performing poorly.
d. **ROC-AUC:**
   Receiver Operating Characteristic (ROC) curves and the **Area Under the Curve (AUC)** score are calculated to assess the model's ability to discriminate between activity classes at different thresholds.

2.6.2.5. Why LSTM/CNN for Human Activity Recognition

The use of **Long Short-Term Memory (LSTM)** or **Convolutional Neural Networks (CNN)** is particularly suited for **time-series classification tasks** like **human activity recognition**. Both LSTM and CNN architectures are well-suited for extracting features from sequential data, such as accelerometer and gyroscope signals, where the order of the sensor readings and their temporal relationships play an important role.

a. **LSTM for Temporal Dependencies:**
   LSTM networks are ideal for processing sequential data with long-term dependencies, like those found in human activity. LSTMs are designed to remember patterns over long-time intervals, which is essential when recognizing activities that involve continuous motion, such as walking or running. Their ability to capture both short-term and long-term dependencies makes them effective in understanding activity transitions, such as when a person switches from walking to running (Hochreiter & Schmid Huber, 1997).
b. **CNN for Feature Extraction:**
   CNNs, on the other hand, are highly effective in learning spatial features and are commonly used for processing data that has spatial hierarchies, like images and time-series data. CNNs help in identifying patterns in the sensor data across multiple time steps, allowing for the efficient extraction of features from raw sensor readings [16].
c. **Regularization and Generalization:**
   The **dropout** technique is employed to address the risk of overfitting, particularly given the small dataset size. It ensures that the model doesn't become overly reliant on any particular feature, which allows for better generalization to new data.
d. **SoftMax Output Layer:**
   The final **SoftMax layer** is used to classify the input into different activity classes, providing class probabilities. This ensures that the model outputs not only the predicted activity but also the likelihood of the prediction, which aids in decision-making processes in real-world applications [5].

The **LSTM-based model** for **human activity recognition** using the **UCI HAR dataset** offers an effective solution for continuous authentication systems. By capturing temporal dependencies in keystroke and movement data, the model provides a robust framework for activity recognition. The use of **LSTM layers** ensures that the system can learn both short-term and long-term patterns in human movement, while regularization techniques like dropout improve its generalization capabilities. The **SoftMax output layer** enables multi-class classification, crucial for differentiating between various human activities. This architecture is ideal for integrating with other authentication systems, enhancing the accuracy and reliability of continuous user verification.

2.6.2.6. Challenges and Future Enhancements

Deploying the HAR model in real-world scenarios presents several challenges. One major issue is device variability: sensor readings differ between devices (like smartphones and wearables), making it difficult for the model to generalize. Domain adaptation techniques could help adjust the model to new devices or sensor setups. Another challenge is noise in the sensor data, which can create variations that confuse the model. Data augmentation and denoising techniques can mitigate this. Imbalanced activity labels, where some activities are more frequent than others, can also bias the model. Integrating other biometrics, such as keystroke dynamics and voice recognition, could enhance the system's reliability by adding more context for authentication.

Future improvements could include:

Incremental learning: This would allow the model to adapt to changes in user behaviour over time without needing to be completely retrained.
Real-time feedback loops: This would enable continuous model updates, improving accuracy and efficiency in dynamic environments.
Edge computing: Optimizing the model to run on devices with limited resources, ensuring real-time performance even on mobile and IoT systems.

2.6.3. Random forest classifier

2.6.3.1. Introduction

Our Risk Classification System is designed to keep your digital life secure by constantly evaluating your authentication attempts. It is like a guard wall which sorting these attempts into three categories: low-risk, medium-risk and high-risk. This smart system uses a powerful tool called a Random Forest Classifier which is trained on a variety of data including your typing patterns, phone movements and even the device and network you're using.

2.6.3.2. Model Architecture

Imagine the Random Forest Classifier as a team of expert detectives. Each detective (or decision tree) examines different clues (features) from your authentication attempt. These clues include how you type, how you hold your phone, and where you're accessing your account from. The detectives then vote on the risk level, and the final decision is based on the majority vote.

2.6.3.3. Training Pipeline

To train these detective trees, we fed them a massive dataset of real-world authentication attempts. We taught them to recognize patterns associated with different risk levels. We also used techniques like data normalization and feature selection to ensure the model learns effectively.

2.6.3.4. Evaluation Metrics

We rigorously tested our model to ensure its accuracy and reliability. We used metrics like accuracy, precision, recall and F1-score to measure its performance. We also visualized its decision-making process using techniques like ROC curves and confusion matrices.

2.6.3.5. Why Random Forest is Best for This Use Case

We chose the Random Forest model for several reasons:

Robustness: It's great at handling noisy and diverse data, making it perfect for real-world scenarios.
Efficiency: It is computationally efficient, allowing for real-time decision-making.
Flexibility: It can handle various data types, including numerical and categorical data.
Interpretability: While not as interpretable as simpler models, it provides insights into the decision-making process.

2.6.3.6. Conclusion

By combining these powerful techniques, our Risk Classification System provides a robust and adaptable solution for continuous authentication. It strikes a balance between security and user experience. Ensuring that you stay protected without compromising convenience.

2.6.4. Voice Matcher

2.6.4.1. Introduction

Our custom GRU-based voice matching model is a key part of our continuous authentication system. It uses mel spectrograms to analyze the sound of your voice. These spectrograms are like a visual representation of the sound, showing how the energy of different frequencies changes over time. We use a special type of neural network called a GRU to process this information efficiently and accurately, making it perfect for real-time voice authentication.

2.6.4.2. Model Architecture

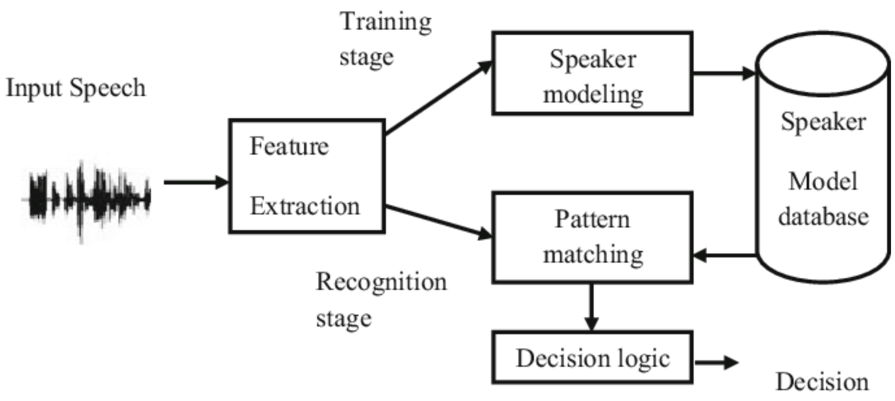
The model utilizes mel spectrograms as input features to capture the time-frequency representation of speech. These spectrograms are essential for modelling the temporal dynamics and energy distributions in voice signals, making them well-suited for speaker verification tasks.

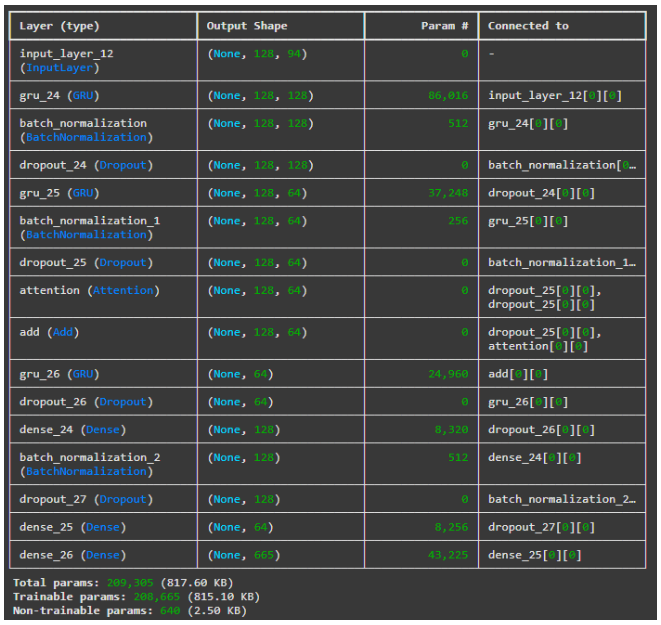
The network comprises three GRU layers to effectively process voice data with varying lengths and complexities. The first layer, with 128 GRU units, captures short-term temporal dependencies. The second and third layers, each with 64 GRU units, refine sequential patterns and model long-term temporal dependencies, respectively.

An attention mechanism is integrated into the architecture, enabling the model to focus on the most critical segments of the input sequence, prioritizing features that are most indicative of speaker identity.

To stabilize training and enhance generalization, batch normalization is applied to normalize the output of each GRU layer, reducing internal covariate shifts. Dropout layers with a rate of 30% are included to mitigate overfitting and ensure robustness to unseen data.

The network includes fully connected dense layers to extract meaningful features and classify the speaker. The first dense layer, with 128 units and ReLU activation, refines features. The second dense layer, with 64 units, further compresses the feature space. The final SoftMax output layer outputs class probabilities for multi-class classification, enabling confidence-based decision-making.





```
┃ Layer (type)                ┃ Output Shape           ┃     Param # ┃ Connected to            ┃
│ input_layer_12              │ (None, 128, 94)        │           0 │ -                       │
│ (InputLayer)                │                        │             │                         │
│ gru_24 (GRU)                │ (None, 128, 128)       │      86,016 │ input_layer_12[0][0]    │
│ batch_normalization         │ (None, 128, 128)       │         512 │ gru_24[0][0]            │
│ (BatchNormalization)        │                        │             │                         │
│ dropout_24 (Dropout)        │ (None, 128, 128)       │           0 │ batch_normalization[0…  │
│ gru_25 (GRU)                │ (None, 128, 64)        │      37,248 │ dropout_24[0][0]        │
│ batch_normalization_1       │ (None, 128, 64)        │         256 │ gru_25[0][0]            │
│ (BatchNormalization)        │                        │             │                         │
│ dropout_25 (Dropout)        │ (None, 128, 64)        │           0 │ batch_normalization_1…  │
│ attention (Attention)       │ (None, 128, 64)        │           0 │ dropout_25[0][0],       │
│                             │                        │             │ dropout_25[0][0]        │
│ add (Add)                   │ (None, 128, 64)        │           0 │ dropout_25[0][0],       │
│                             │                        │             │ attention[0][0]         │
│ gru_26 (GRU)                │ (None, 64)             │      24,960 │ add[0][0]               │
│ dropout_26 (Dropout)        │ (None, 64)             │           0 │ gru_26[0][0]            │
│ dense_24 (Dense)            │ (None, 128)            │       8,320 │ dropout_26[0][0]        │
│ batch_normalization_2       │ (None, 128)            │         512 │ dense_24[0][0]          │
│ (BatchNormalization)        │                        │             │                         │
│ dropout_27 (Dropout)        │ (None, 128)            │           0 │ batch_normalization_2…  │
│ dense_25 (Dense)            │ (None, 64)             │       8,256 │ dropout_27[0][0]        │
│ dense_26 (Dense)            │ (None, 665)            │      43,225 │ dense_25[0][0]          │
 Total params: 209,305 (817.60 KB)
 Trainable params: 208,665 (815.10 KB)
 Non-trainable params: 640 (2.50 KB)
```

Loss Function:
We trained the model using a technique called categorical cross-entropy loss. This helps the model learn to assign the correct speaker to each voice clip by comparing its predictions to the actual labels. It's a great way to train models for tasks like speaker identification.

2.6.4.3. Training Pipeline

The training pipeline was designed to optimize the model’s performance while ensuring robustness to real-world variations. The model was trained on the VoxCeleb dataset, a large-scale speaker recognition dataset featuring diverse environments and speaker variations. The dataset provides extensive labelled voice samples, enabling the model to generalize effectively to real-world scenarios. Data augmentation techniques, such as noise injection and speed perturbation, were employed to simulate challenging acoustic environments, improving the model’s adaptability to noisy and dynamic conditions.

To optimize the training process, several callbacks were implemented:

Early Stopping: To halt training when the validation loss plateaus, preventing overfitting.
ReduceLROnPlateau: To dynamically adjust the learning rate, enhancing convergence.
Model Checkpointing: To save the model with the best validation performance for deployment.

2.6.4.4. Evaluation Metrics

To comprehensively assess the model’s performance, the following metrics were employed:

Accuracy: To assess the overall correctness of predictions on both training and testing datasets.
Precision, Recall, and F1-Score: To provide detailed insights into the model’s performance for each speaker class, balancing the trade-off between false positives and false negatives.
ROC Curve and AUC: To evaluate the model’s ability to discriminate between positive and negative speaker pairs across varying thresholds.
Real-Time Performance: To measure the model’s processing speed and ensure it meets the latency requirements of real-time applications.
t-SNE Visualization: To visualize high-dimensional embeddings in a lower-dimensional space, enabling the evaluation of clustering quality and the discriminative power of learned features.

2.6.4.5. Why the Model Architecture: GRU for Voice Matching

The **GRU (Gated Recurrent Unit)** was chosen for its computational efficiency over **LSTMs (Long Short-Term Memory)**, while still retaining the ability to capture long-term dependencies in sequential voice data. GRUs, which use fewer parameters than LSTMs, reduce the computational load without sacrificing performance, making them more suitable for real-time applications like voice verification, where processing speed and efficiency are critical [6]. This efficiency is particularly beneficial when processing voice data with varying lengths and temporal patterns, as GRUs can capture relevant features more effectively than simpler models like traditional **RNNs (Recurrent Neural Networks)** [7].

The **attention mechanism** incorporated into the model allows it to focus on the most important segments of the input sequence, enhancing interpretability and performance by prioritizing the most relevant features of the voice input [7][8]. This mechanism helps the model learn which parts of the voice signal are most indicative of a user's identity, further improving classification accuracy. Additionally, **batch normalization** and **dropout layers** are used to stabilize training and mitigate overfitting, especially with a large number of speaker classes. These techniques improve the model's generalization capabilities, allowing it to adapt to unseen voice samples and diverse speaker characteristics [4][9].

Finally, the **SoftMax output layer** produces class probabilities, which are essential for multi-class classification tasks and provide a confidence-based decision-making approach, ensuring that the model can handle uncertain or ambiguous cases in real-world scenarios [5]

2.6.4.6. Challenges and Future Enhancements

While the custom GRU-based voice matching model exhibits robust performance in real-world scenarios, several challenges hinder its scalability and adaptability. Noisy environments, such as background noise and low-quality microphones, can degrade performance, despite the application of data augmentation techniques. The model also struggles with unseen speakers, particularly those with accents or speech patterns not represented in the training data. Computational constraints remain a significant challenge, as deploying the model on resource-limited devices, such as mobile phones or IoT devices, can lead to performance bottlenecks during real-time inference. Balancing security and usability are a delicate task, as selecting the optimal cosine similarity threshold is crucial. A lower threshold may increase the risk of false acceptances, while a higher threshold may lead to false rejections. Additionally, the model lacks personalization, which could improve accuracy but requires additional storage and computational resources.

Future research directions include improving noise robustness through the integration of denoising autoencoders or speech enhancement techniques. Domain adaptation could optimize the model for specific environments, and model optimization for edge devices, such as through quantized GRUs or knowledge distillation, could address computational limitations. Personalization and incremental learning could enable the model to adapt to specific users over time, enhancing accuracy. Introducing dynamic thresholding mechanisms would allow the system to adjust the verification threshold based on environmental factors or session risk. Multi-modal biometric data integration, combining voice with facial recognition or behaviour patterns, could provide multi-factor authentication, reducing false positives and negatives. Lastly, explainable AI techniques could improve the model's transparency, and real-world testing in applications like smart assistants and IoT devices would ensure scalability and operational feasibility.

2.6.5. Face Matcher

2.6.5.1. Introduction

A **Custom FaceNet model** was developed to enhance face matching and verification within a multi-factor authentication system. Inspired by the original FaceNet architecture, the model employs MobileNetV2 as the backbone for feature extraction, utilizing transfer learning to optimize computational efficiency and performance. The model architecture integrates several components specifically designed to facilitate optimal functionality in real-time continuous authentication tasks.

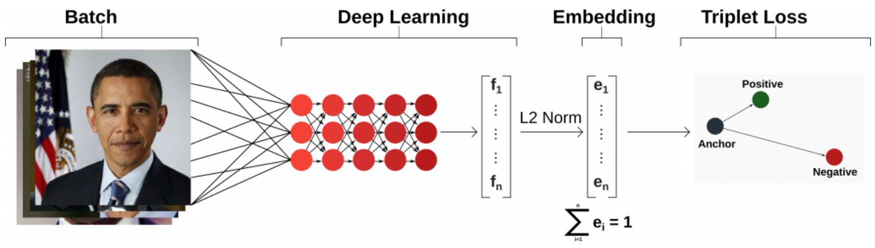
2.6.5.2. Model Architecture

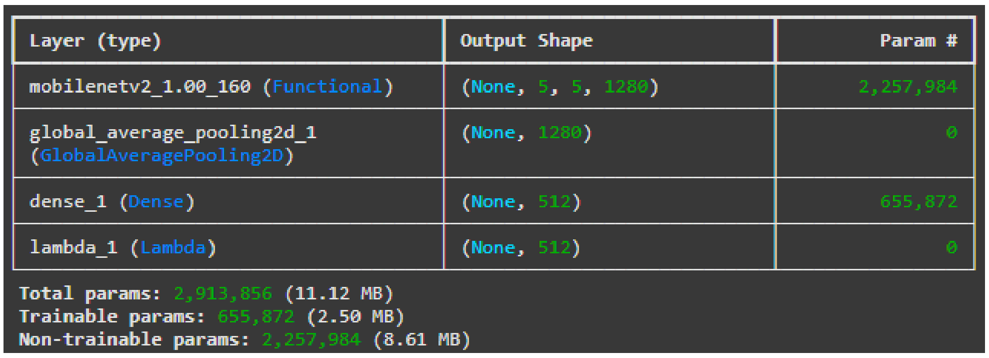
2.6.5.3. Base Model:

The **FaceNet model** is built on a deep **convolutional neural network (CNN)** specifically designed for face recognition and verification. The model architecture comprises three key components: the Inception **ResNet v1** network, the **embedding layer** and a **cosine similarity comparison** mechanism. The backbone, **Inception ResNet v1**, combines **Inception modules** and **ResNet-like architectures** to extract robust facial features. These features are processed through several convolutional and pooling layers, resulting in a compact representation of the face. The **embedding layer** generates a **128-dimensional vector** for each input face image, capturing unique facial characteristics [10].

In the **custom model**, **MobileNetV2** is employed as the base model, pretrained on the **ImageNet** dataset. MobileNetV2's efficiency, particularly through **depthwise separable convolutions**, reduces the model's computational load while maintaining high accuracy, which is essential for mobile and embedded systems [10]. The **top layers** of MobileNetV2 are excluded using `include_top=False`, and the **pretrained weights** are frozen during training to leverage learned features and prevent unnecessary adjustments.

Following feature extraction, a **Global Average Pooling** layer aggregates spatial information into a compact vector, reducing the model's parameters and helping prevent overfitting, while ensuring that essential spatial features are retained for face matching. A **Dense Layer** with **512 units** and **ReLU activation** is then used to project the features into a high-dimensional embedding space. Finally, an **L2 Normalization** layer constrains the embeddings to a **unit hypersphere**, ensuring that the **Euclidean distance** between embeddings reflects facial similarity accurately. This step simplifies the computation of **cosine similarity**, which is critical for verification tasks and enables efficient distance-based decision-making [12].





```
┏━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━┳━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━┳━━━━━━━━━━━━━━━━━┓
┃ Layer (type)                           ┃ Output Shape                 ┃         Param # ┃
┡━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━╇━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━╇━━━━━━━━━━━━━━━━━┩
│ mobilenetv2_1.00_160 (Functional)      │ (None, 5, 5, 1280)           │       2,257,984 │
├────────────────────────────────────────┼──────────────────────────────┼─────────────────┤
│ global_average_pooling2d_1             │ (None, 1280)                 │               0 │
│ (GlobalAveragePooling2D)               │                              │                 │
├────────────────────────────────────────┼──────────────────────────────┼─────────────────┤
│ dense_1 (Dense)                        │ (None, 512)                  │         655,872 │
├────────────────────────────────────────┼──────────────────────────────┼─────────────────┤
│ lambda_1 (Lambda)                      │ (None, 512)                  │               0 │
└────────────────────────────────────────┴──────────────────────────────┴─────────────────┘
 Total params: 2,913,856 (11.12 MB)
 Trainable params: 655,872 (2.50 MB)
 Non-trainable params: 2,257,984 (8.61 MB)
```

Loss Function

We trained the model using a technique called triplet loss, which is a key part of the FaceNet-like architecture. The idea is to make sure the model learns to pull similar faces closer together, while pushing different faces further apart. This is achieved by minimizing the distance between anchor and positive samples, and maximizing the distance between anchor and negative samples. The margin, α, helps ensure a clear separation between the two. The triplet loss function is defined as:

$$L = \max\left(\left\|f(a) - f(p)\right\|^2 - \left\|f(a) - f(n)\right\|^2 + \alpha, 0\right)$$

2.6.5.4. Training Pipeline

The model was trained on the **Labeled Faces in the Wild (LFW)** dataset, comprising **13,000 labeled images** of **5,749 individuals** [14].

Dynamic Triplet Sampling: Ensures the model focuses on hard examples (anchor, positive, negative) during training.

Data Augmentation: Techniques like **random cropping**, **flipping**, and **resizing** enhance the model's robustness against variations.

2.6.5.5. Evaluation Metrics

To comprehensively assess the model’s performance, the following evaluation metrics were employed:

Verification Accuracy and Loss:

Evaluated using the optimal **Euclidean distance threshold** to determine the model’s ability to correctly identify positive matches while minimizing errors.

Receiver Operating Characteristic (ROC) Curve and Area Under the Curve (AUC):

The ROC curve illustrates the trade-off between the **true positive rate (sensitivity)** and the **false positive rate**, showing the model's performance across various thresholds.

The AUC quantifies the overall discrimination capability of the model, with higher values indicating better performance.

t-SNE Visualization of Embeddings:

Used to observe the quality of the learned embeddings by mapping the high-dimensional embedding space into a two- or three-dimensional representation.

Clearly separated clusters in the visualization indicate strong discriminative power of the model for face verification tasks.

Cosine Similarity for Embedding Comparison:

A metric for comparing the embeddings to assess similarity. Cosine similarity is computed between the stored and live input face embeddings using the formula:

$$\text{Cosine Similarity} = \frac{A \cdot B}{\|A\|\|B\|}$$

where AA and BB are the two face embeddings being compared.

2.6.5.6. Comparative Analysis and Justification

We built the model with speed and accuracy in mind, making it perfect for real-time continuous authentication. We chose **MobileNetV2** as the backbone because it is a great balance of power and efficiency. It uses a technique called depth wise separable convolutions to keep things lean and mean, while still delivering top-notch performance. This makes it ideal for devices like smartphones and IoT gadgets.

We compared **MobileNetV2** to other popular architectures, including the original FaceNet model. While the original model is powerful, it is also resource dependable. On the other hand, **MobileNetV2** is more lightweight and efficient and making it better suited for our needs.

To further optimize the model, we used global average pooling instead of flattening the output. This helps us keep the model compact while preserving important spatial information. We also normalized the embeddings to ensure consistent distances and improve numerical stability.

Finally, we trained the model using triplet loss, which is a technique that focuses on learning the differences between faces. This helps the model become better at recognizing and verifying users in real-time.

2.6.5.7. Challenges and Future Enhancements

The model must address edge cases like poor lighting, extreme facial expressions, and obstructions that can hinder recognition accuracy. Incorporating **adaptive learning** for personalized embeddings. Developing solutions for scenarios with limited or low-quality data.

2.7. Conclusion of Theoretical Study

This study outlines a new approach to continuous authentication that blends the power of multimodal biometrics and deep learning. We've reviewed existing research to understand the strengths and weaknesses of these techniques. Our proposed solution aims to fill these gaps, offering a secure, flexible, and easy-to-use method for ongoing authentication. By addressing the risks of session hijacking and spoofing, while keeping user experience smooth, our solution enhances overall security.

CHAPTER 3: EXPERIMENTAL STUDY

3.1. Introduction

This experiment aims to test and confirm that the models we built for the continuous authentication (CA) system actually work. Our main goal is to assess each part individually- the face matcher, voice matcher, and keystroke dynamics matcher. And also, how they work together within the overall CA system. We ran tests using both pre-trained and custom-built models. The pre-trained models gave us a starting point to measure performance, while we are developing our custom models to try and match or even beat that performance. So far, we have built and tested several models, including the Keystroke Dynamics Matcher, the Face Matcher (using FaceNet), the Voice Matcher (using the ECAPA-TDNN design), and a Random Forest Classifier to assess risk levels.

3.2. Experimental Setup

System Configuration

The experiments took place in a system specifically set up for machine learning and deep learning tasks:

a. **Hardware:** The experiments were conducted on a machine with an Intel Core i7 processor, 16GB of RAM, and an NVIDIA GTX 3060 GPU.
b. **Software:** Development was carried out using Python, along with the machine learning libraries TensorFlow and PyTorch, the computer vision library OpenCV, and the data analysis library scikit-learn.
c. **Data:** The data used came from a combination of publicly available datasets, such as UCI HAR, VoxCeleb, and LFW, and also included user-specific data collected for facial recognition, voice recognition, and keystroke dynamics.

Data Collection Process

Data was collected for each biometric modality to ensure diversity and quality:

a. **Facial Data**: Extracted from the LFW dataset and augmented with user-specific facial images captured using a webcam.
b. **Voice Data**: Gathered from the VoxCeleb dataset, complemented by user-provided audio samples recorded in a controlled environment.
c. **Keystroke Dynamics**: User-specific data was collected by logging typing patterns during pre-designed typing tasks.

The dataset was enriched with synthetic samples where necessary to improve diversity, and a balanced distribution of classes was ensured for training and testing phases.

3.3. Implementation of Models

3.3.1 Face Matcher

The Face Matcher utilizes a convolutional neural network (CNN) architecture based on MobileNetV2, which was fine-tuned to generate facial embeddings for recognition tasks. The model was trained to handle variations in lighting, angle, and occlusion, although performance degradation was observed in extreme conditions.

Dataset Analysis

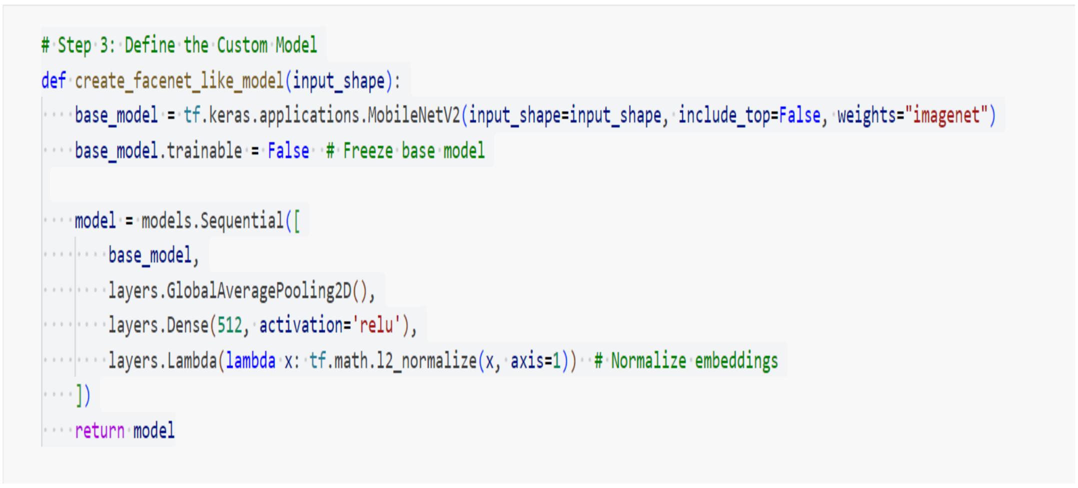
A successful FaceNet-like model relies on a diverse and well-prepared dataset with variations in demographics, lighting, pose, and occlusions. Balanced classes are crucial, especially when using triplet or contrastive loss. Preprocessing involves resizing images to 224*224*3, normalizing pixel values, and applying data augmentation like flips and rotations. Datasets should be split into training (70-80%), validation (10-15%), and testing (10-15%) subsets. Exploratory data analysis is important to ensure balanced classes, feature diversity, and to detect any anomalies. Metrics like accuracy and similarity thresholds are used to assess the quality of the embeddings. Public datasets like CASIA-WebFace, LFW, and VGGFace2, or carefully collected custom datasets, are suitable for training robust face recognition and verification systems.

Data Processing

We used the **Labeled Faces in the Wild (LFW)** dataset and prepared it for use with machine learning models. Each image was resized to 160*160 pixels, a common size for facial recognition. We then turned the images into numerical arrays representing the brightness of each pixel and scaled these values to be between 0 and 1 for faster and more consistent training. We assigned labels to each image based on the person's folder, so we knew which image belonged to which person. The processed images and their labels were then stored in arrays, making the dataset ready for training and testing in our machine learning process.

Defining Model

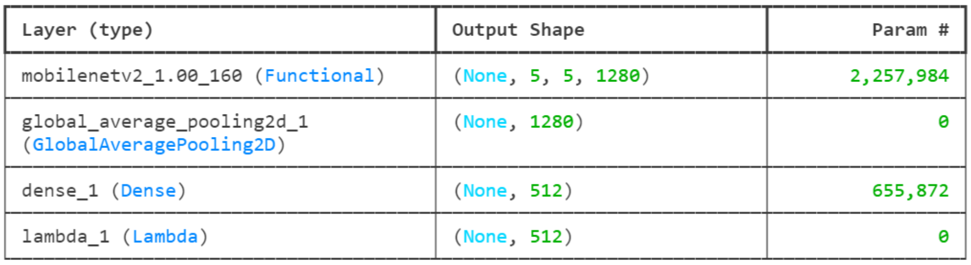
We created a specialized deep learning model using the MobileNetV2 architecture as a foundation. This base model had already been trained on ImageNet. We removed the top layers of the pre-trained model and kept its learned information fixed. Our model includes a global average pooling layer, followed by a dense layer with 512 units and ReLU activation. A Lambda layer then performs L2 normalization on the output, which is important for face recognition because it creates standardized feature representations.



```python
# Step 3: Define the Custom Model
def create_facenet_like_model(input_shape):
    base_model = tf.keras.applications.MobileNetV2(input_shape=input_shape, include_top=False, weights="imagenet")
    base_model.trainable = False  # Freeze base model

    model = models.Sequential([
        base_model,
        layers.GlobalAveragePooling2D(),
        layers.Dense(512, activation='relu'),
        layers.Lambda(lambda x: tf.math.l2_normalize(x, axis=1))  # Normalize embeddings
    ])
    return model
```

This code creates a deep learning model for facial recognition. It starts with MobileNetV2, a model already trained on a large image dataset called ImageNet. This pre-trained model is used to extract important features from faces, and its internal settings are kept fixed. The code then adds a global average pooling layer, a dense layer with 512 units and ReLU activation, and finally a Lambda layer that standardizes the output. This L2 normalization makes the output suitable for comparing faces and determining if they match.

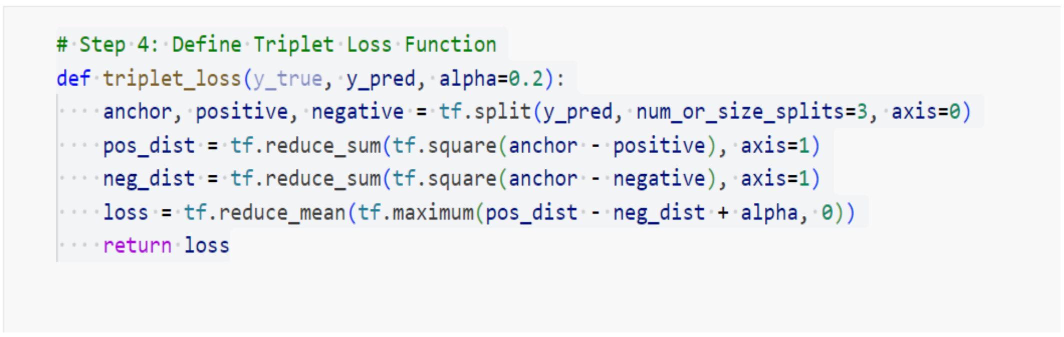
Model Summary



Layer (type)	Output Shape	Param #
mobilenetv2_1.00_160 (Functional)	(None, 5, 5, 1280)	2,257,984
global_average_pooling2d_1 (GlobalAveragePooling2D)	(None, 1280)	0
dense_1 (Dense)	(None, 512)	655,872
lambda_1 (Lambda)	(None, 512)	0

Triplet Loss Function

The triplet loss function is a comparison tool, which operates by contrasting a base input, a positive input, and a negative input. It encourages the model to minimize the distance between anchor and positive samples while maximizing the distance between anchor and negative samples, with a margin (alpha).

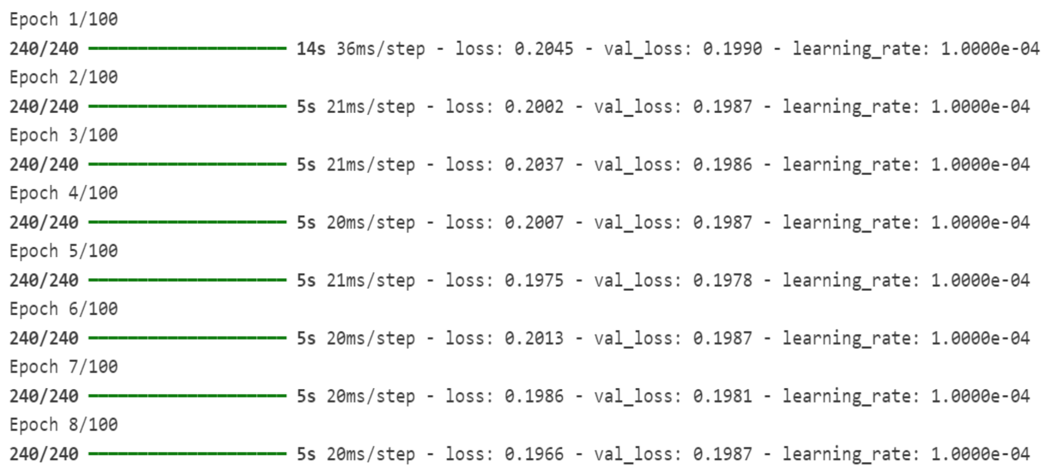


```python
# Step 4: Define Triplet Loss Function
def triplet_loss(y_true, y_pred, alpha=0.2):
    anchor, positive, negative = tf.split(y_pred, num_or_size_splits=3, axis=0)
    pos_dist = tf.reduce_sum(tf.square(anchor - positive), axis=1)
    neg_dist = tf.reduce_sum(tf.square(anchor - negative), axis=1)
    loss = tf.reduce_mean(tf.maximum(pos_dist - neg_dist + alpha, 0))
    return loss
```

Triplet Data Generation
The `generate_triplets` function creates training triplets by randomly selecting an anchor, positive (same class), and negative (different class) samples, ensuring diverse positive and negative pairs for effective training.

Training Strategy

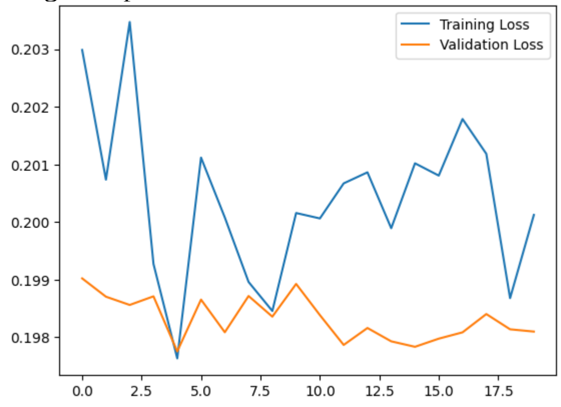
The model uses three training callbacks: **EarlyStopping**, which halts training if validation loss doesn't improve for 15 epochs; **ReduceLROnPlateau**, which reduces the learning rate by 0.5 if the validation loss plateaus for five epochs; and **ModelCheckpoint**, which saves the model with the best validation loss. The model is compiled with the Adam optimizer and triplet loss, trained with a batch size of 30 for 100 epochs, and uses 20% of the data for validation, with the callbacks enhancing performance and preventing overfitting.



```
Epoch 1/100
240/240 ━━━━━━━━━━━━━━━━━━━━ 14s 36ms/step - loss: 0.2045 - val_loss: 0.1990 - learning_rate: 1.0000e-04
Epoch 2/100
240/240 ━━━━━━━━━━━━━━━━━━━━ 5s 21ms/step - loss: 0.2002 - val_loss: 0.1987 - learning_rate: 1.0000e-04
Epoch 3/100
240/240 ━━━━━━━━━━━━━━━━━━━━ 5s 21ms/step - loss: 0.2037 - val_loss: 0.1986 - learning_rate: 1.0000e-04
Epoch 4/100
240/240 ━━━━━━━━━━━━━━━━━━━━ 5s 20ms/step - loss: 0.2007 - val_loss: 0.1987 - learning_rate: 1.0000e-04
Epoch 5/100
240/240 ━━━━━━━━━━━━━━━━━━━━ 5s 21ms/step - loss: 0.1975 - val_loss: 0.1978 - learning_rate: 1.0000e-04
Epoch 6/100
240/240 ━━━━━━━━━━━━━━━━━━━━ 5s 20ms/step - loss: 0.2013 - val_loss: 0.1987 - learning_rate: 1.0000e-04
Epoch 7/100
240/240 ━━━━━━━━━━━━━━━━━━━━ 5s 20ms/step - loss: 0.1986 - val_loss: 0.1981 - learning_rate: 1.0000e-04
Epoch 8/100
240/240 ━━━━━━━━━━━━━━━━━━━━ 5s 20ms/step - loss: 0.1966 - val_loss: 0.1987 - learning_rate: 1.0000e-04
```

Evaluation Metrics:

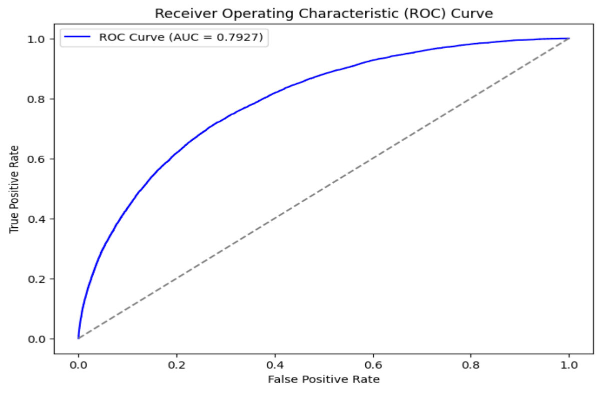
<u>Verification Accuracy and Loss</u>
The model's accuracy in distinguishing between matching and non-matching pairs was evaluated using the optimal Euclidean distance threshold.



This graph shows the model is learning effectively because the training loss goes down over the time. The validation loss stays consistently low, which means the model is generalizing well to new data. The training loss has some ups and downs, probably because of how the optimizer works and variations in the training data. But the validation loss is stable. Towards the end of training, suggesting the model has found a good balance and is not underfitting or overfitting.

ROC Curve

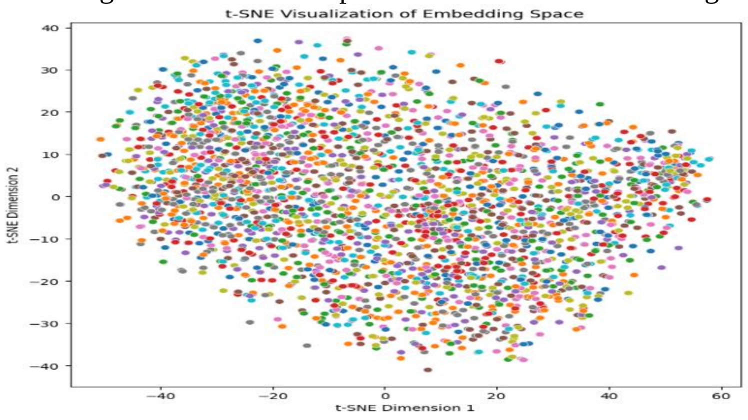
The Receiver Operating Characteristic (ROC) curve and Area Under the Curve (AUC) were used to assess to discriminate between positive and negative pairs across thresholds.



The ROC curve visualizes the trade-off between true positives and false positives. The AUC of 0.7927 shows reasonably good performance (closer to 1 is better). The curve's shape and position above the diagonal indicate effective differentiation and performance better than random guessing. While the AUC is good, further interpretation depends on the specific application's needs regarding false positives and negatives. The ROC curve helps choose a good threshold and compare models (higher AUC is better), but it doesn't show other important metrics like accuracy, precision, or recall. For imbalanced datasets, other metrics like precision-recall curves or F1-scores might be more useful. If false positives and negatives have different costs, cost-sensitive metrics should be used.

t-SNE Visualization

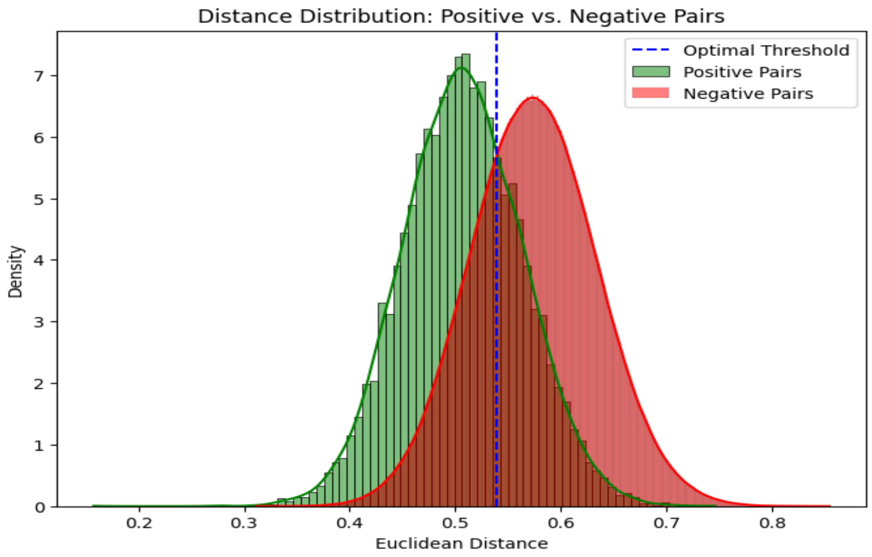
A t-SNE plot of embeddings provided insights into the clustering of embeddings by class, validating the discriminative power of the learned embeddings.



The t-SNE plot shows some data points clustered together, suggesting the algorithm has identified patterns in the data. The wide spread of points indicates high data variability or limitations of the visualization method. The color-coded clusters, representing different categories, show successful separation between them. Further analysis could look at data density, identify outliers and consider information lost during the simplification process. Trying different settings for t-SNE might also reveal more. Overall, the plot gives useful information about the data's structure but more investigation is needed.

Optimal Threshold

The best threshold was found to be 0.5392, which is also shown in the plot. Using this threshold, the training accuracy is now 99.72% and the validation accuracy is 99.74%.



The graph shows the Euclidean distance distributions for positive (same identity) and negative (different identities) pairs. Positive pairs (green) have lower distances, indicating similarity, while negative pairs (red) have higher distances, reflecting dissimilarity. The blue dashed line represents the **optimal threshold** that separates the two distributions. This threshold helps classify pairs as the same or different identity. The overlap near the threshold suggests some ambiguity, indicating that fine-tuning is needed for optimal performance in face recognition tasks.

3.3.2. Voice Matcher

To address the challenge of voice-based authentication, we developed a **custom GRU-based model** that utilizes **Mel spectrograms** as input features. This model is designed to identify and verify users based on their unique vocal characteristics. The inclusion of an **attention mechanism** ensures that the model focuses on the most relevant temporal features of the voice data.

Model Architecture

a. **Input:** The model receives a Mel spectrogram, which is a way of representing the sound's energy across different frequencies over time. This is a good way to represent voice data for speaker identification.

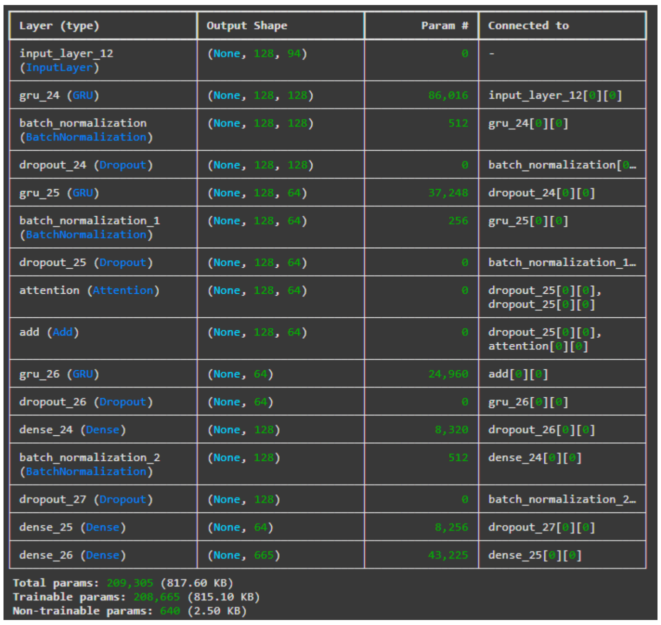
b. **Recurrent Layers (GRUs):** Three Gated Recurrent Unit (GRU) layers are used to analyze the sequential nature of voice data, efficiently capturing long-term patterns. The first layer has 128 units and passes information to the next layer, the second has 64 units and further refines the patterns, and the third has 64 units for the final extraction of voice features.

c. **Attention Mechanism:** This layer helps the model focus on the most important parts of the voice signal that are key to identifying the speaker.

d. **Regularization:** Batch normalization stabilizes training and reduces overfitting by normalizing each layer's output. Dropout layers (30%) further prevent overfitting and improve the model's ability to generalize to new, unseen data.

e. **Fully Connected Layers:** A dense layer with 128 units and ReLU activation condenses the extracted features. A subsequent dense layer with 64 units further refines the feature space before the final output.

f. **Output:** A final dense layer with SoftMax activation gives probabilities for each possible speaker, allowing the model to classify the speaker.



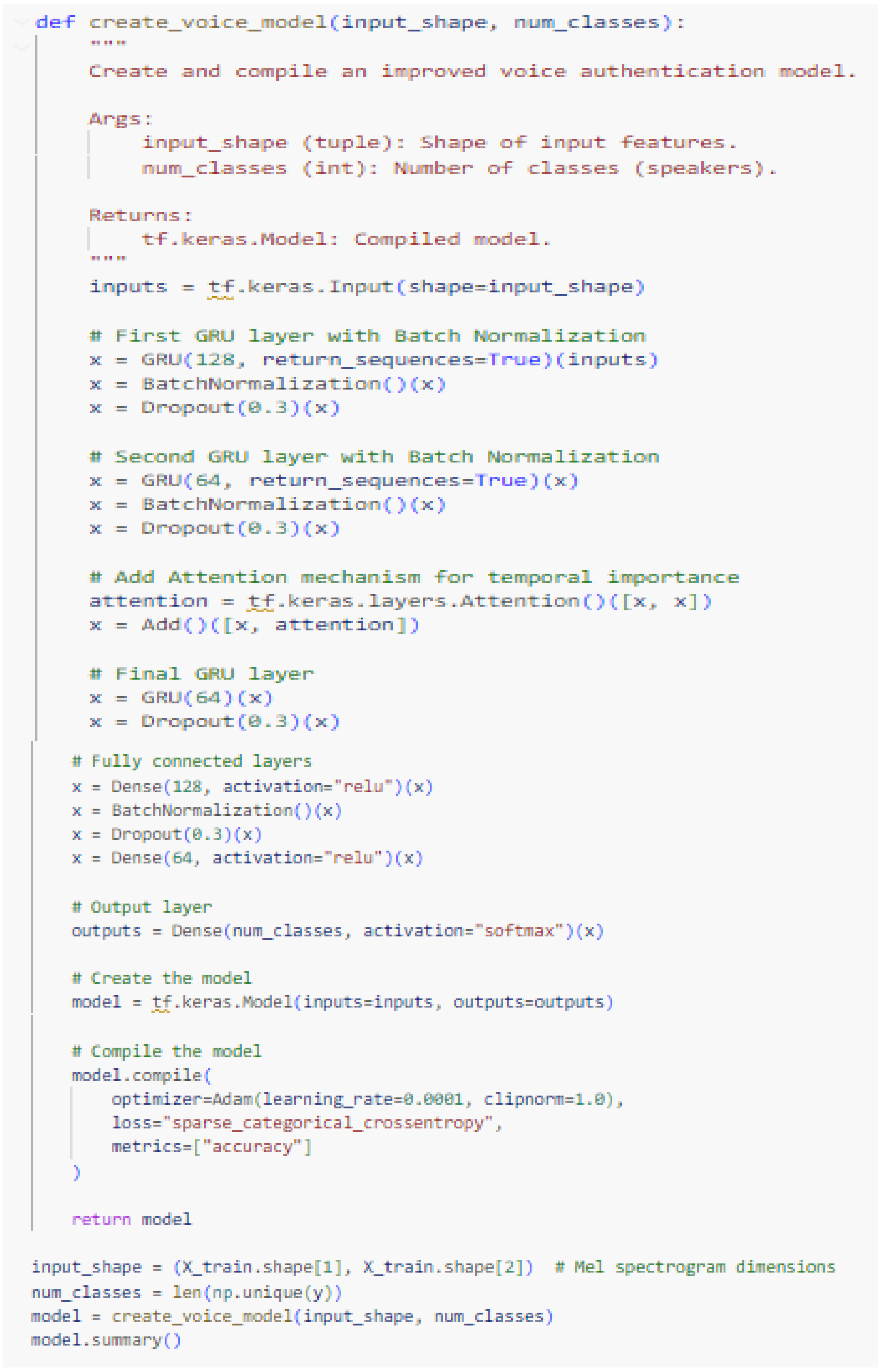
```
┏━━━━━━━━━━━━━━━━━━━━━━━━━━━━┳━━━━━━━━━━━━━━━━━━━━━━━━┳━━━━━━━━━━━━━┳━━━━━━━━━━━━━━━━━━━━━━━━━━┓
┃ Layer (type)               ┃ Output Shape           ┃     Param # ┃ Connected to             ┃
┡━━━━━━━━━━━━━━━━━━━━━━━━━━━━╇━━━━━━━━━━━━━━━━━━━━━━━━╇━━━━━━━━━━━━━╇━━━━━━━━━━━━━━━━━━━━━━━━━━┩
│ input_layer_12             │ (None, 128, 94)        │           0 │ -                        │
│ (InputLayer)               │                        │             │                          │
├────────────────────────────┼────────────────────────┼─────────────┼──────────────────────────┤
│ gru_24 (GRU)               │ (None, 128, 128)       │      86,016 │ input_layer_12[0][0]     │
├────────────────────────────┼────────────────────────┼─────────────┼──────────────────────────┤
│ batch_normalization        │ (None, 128, 128)       │         512 │ gru_24[0][0]             │
│ (BatchNormalization)       │                        │             │                          │
├────────────────────────────┼────────────────────────┼─────────────┼──────────────────────────┤
│ dropout_24 (Dropout)       │ (None, 128, 128)       │           0 │ batch_normalization[0…   │
├────────────────────────────┼────────────────────────┼─────────────┼──────────────────────────┤
│ gru_25 (GRU)               │ (None, 128, 64)        │      37,248 │ dropout_24[0][0]         │
├────────────────────────────┼────────────────────────┼─────────────┼──────────────────────────┤
│ batch_normalization_1      │ (None, 128, 64)        │         256 │ gru_25[0][0]             │
│ (BatchNormalization)       │                        │             │                          │
├────────────────────────────┼────────────────────────┼─────────────┼──────────────────────────┤
│ dropout_25 (Dropout)       │ (None, 128, 64)        │           0 │ batch_normalization_1…   │
├────────────────────────────┼────────────────────────┼─────────────┼──────────────────────────┤
│ attention (Attention)      │ (None, 128, 64)        │           0 │ dropout_25[0][0],        │
│                            │                        │             │ dropout_25[0][0]         │
├────────────────────────────┼────────────────────────┼─────────────┼──────────────────────────┤
│ add (Add)                  │ (None, 128, 64)        │           0 │ dropout_25[0][0],        │
│                            │                        │             │ attention[0][0]          │
├────────────────────────────┼────────────────────────┼─────────────┼──────────────────────────┤
│ gru_26 (GRU)               │ (None, 64)             │      24,960 │ add[0][0]                │
├────────────────────────────┼────────────────────────┼─────────────┼──────────────────────────┤
│ dropout_26 (Dropout)       │ (None, 64)             │           0 │ gru_26[0][0]             │
├────────────────────────────┼────────────────────────┼─────────────┼──────────────────────────┤
│ dense_24 (Dense)           │ (None, 128)            │       8,320 │ dropout_26[0][0]         │
├────────────────────────────┼────────────────────────┼─────────────┼──────────────────────────┤
│ batch_normalization_2      │ (None, 128)            │         512 │ dense_24[0][0]           │
│ (BatchNormalization)       │                        │             │                          │
├────────────────────────────┼────────────────────────┼─────────────┼──────────────────────────┤
│ dropout_27 (Dropout)       │ (None, 128)            │           0 │ batch_normalization_2…   │
├────────────────────────────┼────────────────────────┼─────────────┼──────────────────────────┤
│ dense_25 (Dense)           │ (None, 64)             │       8,256 │ dropout_27[0][0]         │
├────────────────────────────┼────────────────────────┼─────────────┼──────────────────────────┤
│ dense_26 (Dense)           │ (None, 665)            │      43,225 │ dense_25[0][0]           │
└────────────────────────────┴────────────────────────┴─────────────┴──────────────────────────┘
 Total params: 209,305 (817.60 KB)
 Trainable params: 208,665 (815.10 KB)
 Non-trainable params: 640 (2.50 KB)
```

Preprocessing and Training Pipeline

The voice recognition model uses the Mozilla Common Voice dataset, a large collection of labeled voice recordings from many different speakers. The audio is preprocessed by resampling to 16 kHz, truncating or padding to 3-second segments, and converting it into a decibel-scaled Mel spectrogram. These features are then normalized for consistent scaling. Speaker IDs are converted to numerical labels for training efficiency. The Mel spectrogram features are further normalized to have zero mean and unit variance to help the model train faster. The data is split into 80% for training and 20% for testing, with 20% of the training data used for validation. Early stopping halts training if the validation loss doesn't improve for 20 epochs, and model checkpointing saves the best-performing model during training.

Define Model

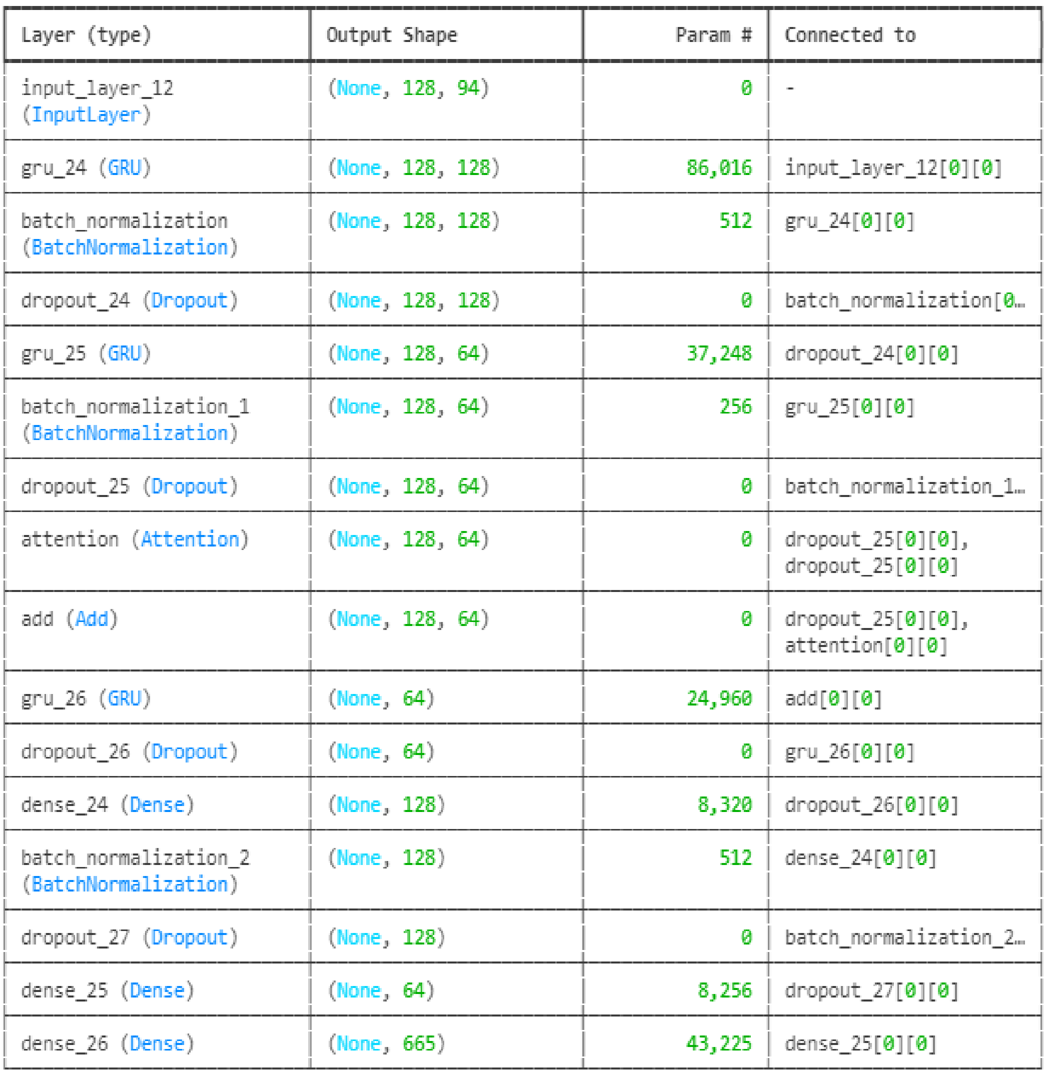
The voice authentication model processes and classifies audio data (Mel spectrograms) using a combination of GRU layers, an attention mechanism, and fully connected (Dense) layers. Two GRU layers initially handle the sequential data, followed by an attention mechanism that highlights key time segments. A final GRU layer and Dense layers then refine the extracted features. Speaker classification is performed by the output layer using SoftMax activation. The model is trained using the Adam optimizer and sparse categorical cross-entropy loss, making it suitable for multi-class classification and accurate speaker identification. Overfitting is mitigated through regularization techniques like Batch Normalization and Dropout.



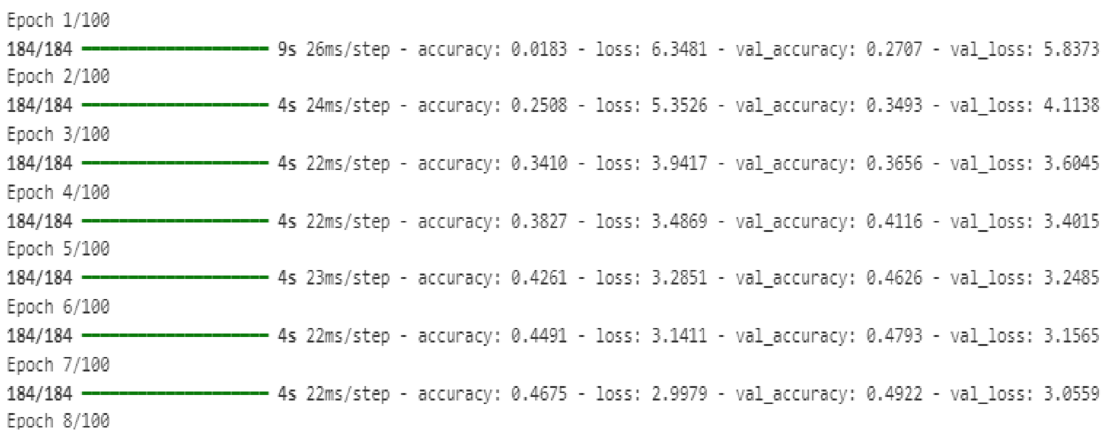
```python
def create_voice_model(input_shape, num_classes):
    """
    Create and compile an improved voice authentication model.

    Args:
        input_shape (tuple): Shape of input features.
        num_classes (int): Number of classes (speakers).

    Returns:
        tf.keras.Model: Compiled model.
    """
    inputs = tf.keras.Input(shape=input_shape)

    # First GRU layer with Batch Normalization
    x = GRU(128, return_sequences=True)(inputs)
    x = BatchNormalization()(x)
    x = Dropout(0.3)(x)

    # Second GRU layer with Batch Normalization
    x = GRU(64, return_sequences=True)(x)
    x = BatchNormalization()(x)
    x = Dropout(0.3)(x)

    # Add Attention mechanism for temporal importance
    attention = tf.keras.layers.Attention()([x, x])
    x = Add()([x, attention])

    # Final GRU layer
    x = GRU(64)(x)
    x = Dropout(0.3)(x)

    # Fully connected layers
    x = Dense(128, activation="relu")(x)
    x = BatchNormalization()(x)
    x = Dropout(0.3)(x)
    x = Dense(64, activation="relu")(x)

    # Output layer
    outputs = Dense(num_classes, activation="softmax")(x)

    # Create the model
    model = tf.keras.Model(inputs=inputs, outputs=outputs)

    # Compile the model
    model.compile(
        optimizer=Adam(learning_rate=0.0001, clipnorm=1.0),
        loss="sparse_categorical_crossentropy",
        metrics=["accuracy"]
    )

    return model

input_shape = (X_train.shape[1], X_train.shape[2])  # Mel spectrogram dimensions
num_classes = len(np.unique(y))
model = create_voice_model(input_shape, num_classes)
model.summary()
```

This code creates a custom voice authentication model that uses GRUs (Gated Recurrent Units), an attention mechanism, and fully connected layers. The model takes Mel spectrograms (visual representations of sound frequencies) as input and identifies the speaker. Two GRU layers process the sequential audio data, with batch normalization and dropout added to prevent overfitting. The attention mechanism helps the model focus on the most important parts of the audio. Finally, a SoftMax layer outputs a probability for each possible speaker, and the model is trained using the Adam optimizer and sparse categorical cross-entropy loss, designed for classifying among multiple speakers.

MODEL SUMMERY



Layer (type)	Output Shape	Param #	Connected to
input_layer_12 (InputLayer)	(None, 128, 94)	0	-
gru_24 (GRU)	(None, 128, 128)	86,016	input_layer_12[0][0]
batch_normalization (BatchNormalization)	(None, 128, 128)	512	gru_24[0][0]
dropout_24 (Dropout)	(None, 128, 128)	0	batch_normalization[0…
gru_25 (GRU)	(None, 128, 64)	37,248	dropout_24[0][0]
batch_normalization_1 (BatchNormalization)	(None, 128, 64)	256	gru_25[0][0]
dropout_25 (Dropout)	(None, 128, 64)	0	batch_normalization_1…
attention (Attention)	(None, 128, 64)	0	dropout_25[0][0], dropout_25[0][0]
add (Add)	(None, 128, 64)	0	dropout_25[0][0], attention[0][0]
gru_26 (GRU)	(None, 64)	24,960	add[0][0]
dropout_26 (Dropout)	(None, 64)	0	gru_26[0][0]
dense_24 (Dense)	(None, 128)	8,320	dropout_26[0][0]
batch_normalization_2 (BatchNormalization)	(None, 128)	512	dense_24[0][0]
dropout_27 (Dropout)	(None, 128)	0	batch_normalization_2…
dense_25 (Dense)	(None, 64)	8,256	dropout_27[0][0]
dense_26 (Dense)	(None, 665)	43,225	dense_25[0][0]



```
Epoch 1/100
184/184 ━━━━━━━━━━━━━━━━━━━━ 9s 26ms/step - accuracy: 0.0183 - loss: 6.3481 - val_accuracy: 0.2707 - val_loss: 5.8373
Epoch 2/100
184/184 ━━━━━━━━━━━━━━━━━━━━ 4s 24ms/step - accuracy: 0.2508 - loss: 5.3526 - val_accuracy: 0.3493 - val_loss: 4.1138
Epoch 3/100
184/184 ━━━━━━━━━━━━━━━━━━━━ 4s 22ms/step - accuracy: 0.3410 - loss: 3.9417 - val_accuracy: 0.3656 - val_loss: 3.6045
Epoch 4/100
184/184 ━━━━━━━━━━━━━━━━━━━━ 4s 22ms/step - accuracy: 0.3827 - loss: 3.4869 - val_accuracy: 0.4116 - val_loss: 3.4015
Epoch 5/100
184/184 ━━━━━━━━━━━━━━━━━━━━ 4s 23ms/step - accuracy: 0.4261 - loss: 3.2851 - val_accuracy: 0.4626 - val_loss: 3.2485
Epoch 6/100
184/184 ━━━━━━━━━━━━━━━━━━━━ 4s 22ms/step - accuracy: 0.4491 - loss: 3.1411 - val_accuracy: 0.4793 - val_loss: 3.1565
Epoch 7/100
184/184 ━━━━━━━━━━━━━━━━━━━━ 4s 22ms/step - accuracy: 0.4675 - loss: 2.9979 - val_accuracy: 0.4922 - val_loss: 3.0559
Epoch 8/100
```

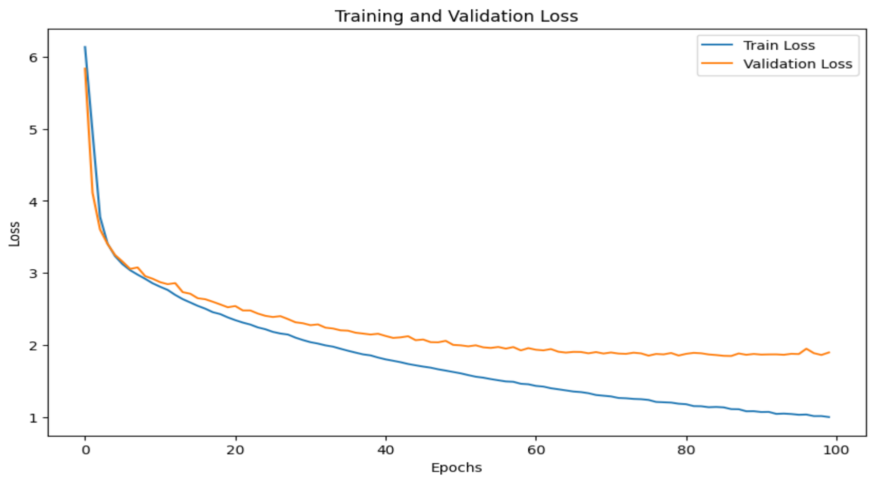
Evaluation Metrics

The model's performance is evaluated using two main metrics:

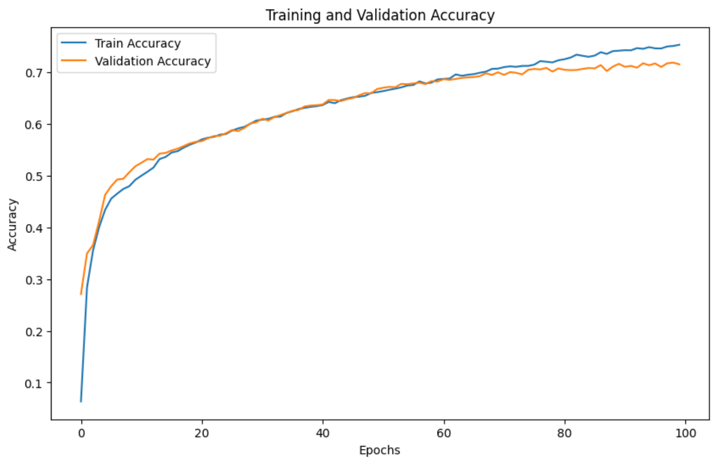
a. **Accuracy:** This is the primary metric, calculated for both the training and testing data.
b. **Classification Report:** This provides a more detailed view, calculating precision, recall and F1-score for each speaker.

Key results include:

a. **Test Accuracy:** The model achieved approximately 71% accuracy on the test data, demonstrating its ability to identify speakers from their voice features.
b. **Training History:** The training and validation accuracy improved smoothly over time, indicating no significant overfitting or underfitting.



Analysing the training and validation loss curves for the voice matcher shows a typical learning pattern of decreasing losses over time. However, a large difference between the two curves indicates overfitting: the model is memorizing the training data instead of learning general features. This is shown by a low training loss but a much higher validation loss, meaning it performs poorly on new data.
To fix this a several strategies can be used. Early stopping can halt training when the validation loss starts to increase. Regularization techniques (L1/L2) can discourage overly complex models. Data augmentation, like adding noise or changing pitch, can make the training data more diverse. Finally, adjusting the model's settings (hyperparameter tuning) can improve performance.
It is also important to test how well the model handles different voices and to evaluate its performance in both enrolment (adding a new voice) and verification (checking if a voice matches) scenarios. In short, using these strategies to reduce overfitting will improve the model's ability to generalize and perform well on unseen voice data.



The training and validation accuracy curves both show increasing accuracy over time, indicating the model is learning. The training accuracy is levelling off, suggesting it is close to its best performance. The validation accuracy has also stabilized but with some minor fluctuations. A small difference between the two curves suggests slight overfitting, meaning the model performs very well on the training data but might not generalize perfectly to new data.

To improve this, techniques like early stopping (halting training if validation accuracy drops), regularization (L1 or L2 to discourage complex models), and adjusting model settings (hyperparameter tuning) could reduce overfitting and improve performance on new data. Overall, the model's performance is good, and the small gap between the curves is manageable, but further optimization could improve its ability to generalize.

3.3.3. Keystroke Dynamics Matcher

To provide continuous user authentication using typing patterns (keystroke dynamics), we built a custom model using Long Short-Term Memory (LSTM) networks. This model is specifically designed to recognize the timing patterns in typing, like how long keys are held down and the time between keystrokes, which are unique to each person.

Model Architecture

a. **Input:** The model receives time-based input, where each sample is a sequence of hold times (how long keys are pressed) and flight times (time between key presses), reflecting individual typing patterns.

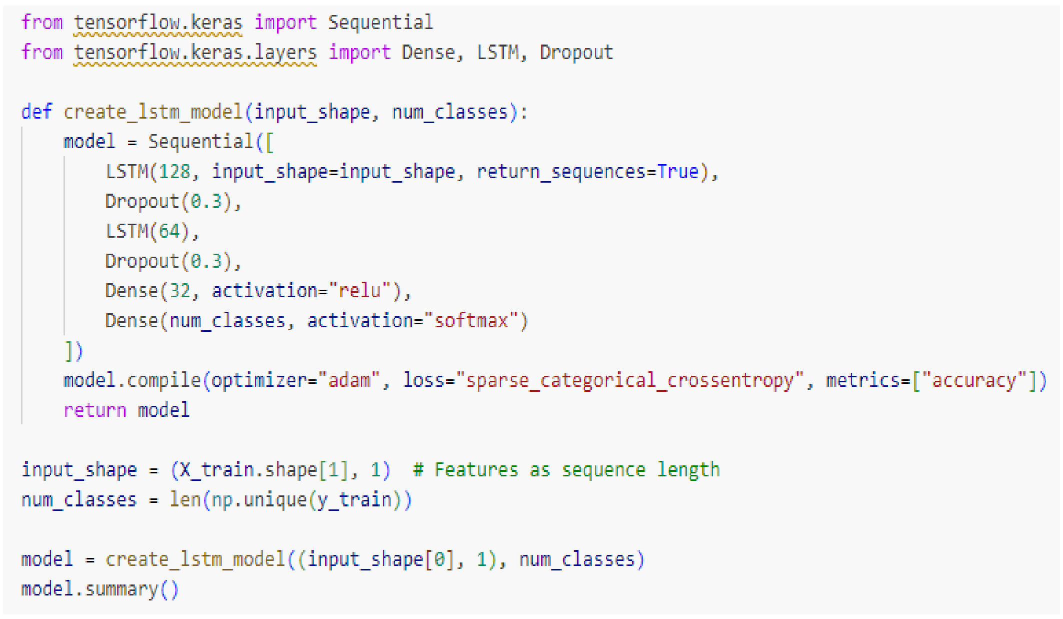
b. **LSTM Layers:** Two LSTM layers analyze the sequence of keystrokes, capturing both short-term and long-term timing dependencies. The first LSTM layer (128 units) processes the input and passes the information to the next layer. The second LSTM layer (64 units) further refines these timing patterns, focusing on subtle typing variations. Dropout layers (30%) are applied after each LSTM layer to prevent overfitting and improve the model's ability to generalize to new typing samples.

c. **Fully Connected Layers:** A dense layer with 32 units and ReLU activation condenses the information extracted by the LSTM layers. The final output layer uses a SoftMax activation function to classify the input, assigning it to a specific user.

d. **Loss Function:** The model uses Sparse Categorical Cross entropy Loss, suitable for multi-class classification where the goal is to match each typing sample to the correct user ID.

Define Model

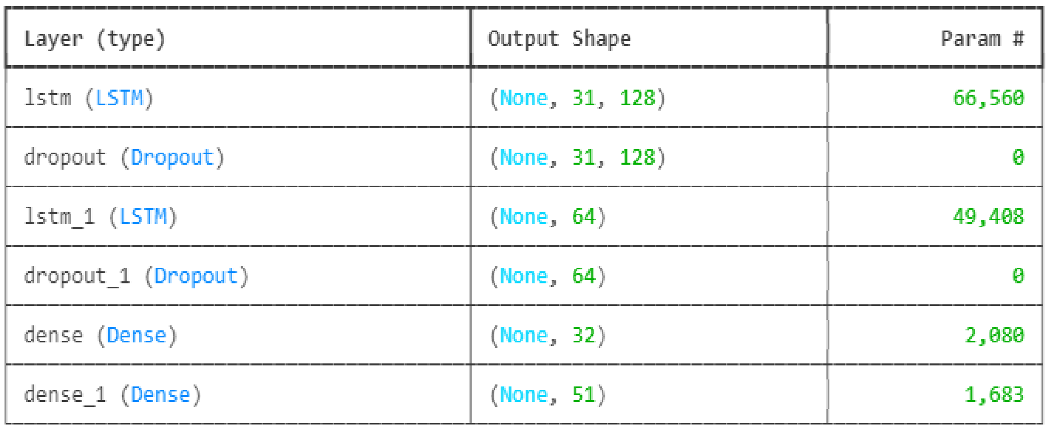
The Keystroke Dynamics Matcher model is built using TensorFlow Keras's Sequential API, which allows for a straightforward, linear stacking of layers. The model uses an LSTM-based neural network, a type of architecture well-suited for sequential data like time series or sequence classification



```python
from tensorflow.keras import Sequential
from tensorflow.keras.layers import Dense, LSTM, Dropout

def create_lstm_model(input_shape, num_classes):
    model = Sequential([
        LSTM(128, input_shape=input_shape, return_sequences=True),
        Dropout(0.3),
        LSTM(64),
        Dropout(0.3),
        Dense(32, activation="relu"),
        Dense(num_classes, activation="softmax")
    ])
    model.compile(optimizer="adam", loss="sparse_categorical_crossentropy", metrics=["accuracy"])
    return model

input_shape = (X_train.shape[1], 1)  # Features as sequence length
num_classes = len(np.unique(y_train))

model = create_lstm_model((input_shape[0], 1), num_classes)
model.summary()
```

This code defines a machine learning model using LSTMs (Long Short-Term Memory networks), which are designed for sequential data like time series. The model starts with a 128-unit LSTM layer that passes its output to a second 64-unit LSTM layer. Dropout layers (30%) after each LSTM help prevent overfitting. A 32-unit dense layer with ReLU activation then processes the LSTM output, followed by a final dense output layer with softmax activation to produce probabilities for each class. The model is trained using the Adam optimizer and sparse categorical cross-entropy loss, suitable for multi-class classification with integer labels. Accuracy is used to measure performance. This setup is ideal for tasks where the model needs to learn temporal relationships in the input data. The create_lstm_model function initializes and compiles the model with a given input shape and number of classes, and model.summary() provides a summary of the model's structure.

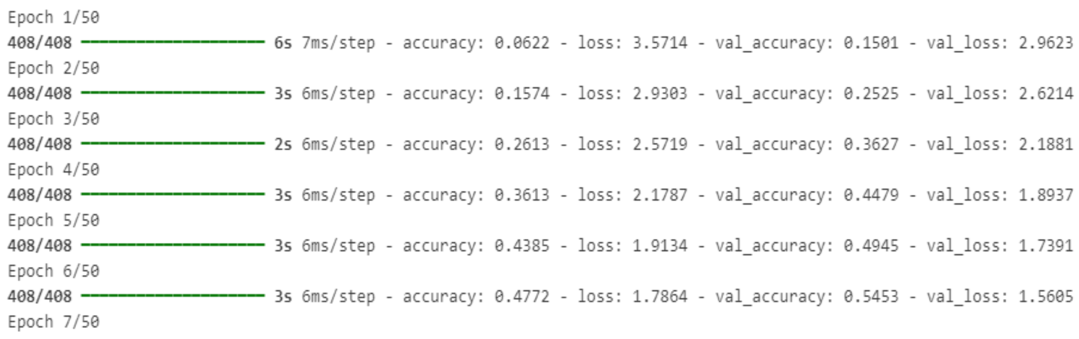
MODEL SUMMERY



Layer (type)	Output Shape	Param #
lstm (LSTM)	(None, 31, 128)	66,560
dropout (Dropout)	(None, 31, 128)	0
lstm_1 (LSTM)	(None, 64)	49,408
dropout_1 (Dropout)	(None, 64)	0
dense (Dense)	(None, 32)	2,080
dense_1 (Dense)	(None, 51)	1,683

Preprocessing and Training Pipeline

The keystroke dynamics model uses the CMU DSL-StrongPasswordData dataset, which contains keystroke data from multiple users typing the same password, providing enough variation to capture individual typing styles. The data is preprocessed by calculating hold times (key press to release duration) and flight times (release of one key to press of the next). These features are then normalized using StandardScaler to improve training. Hold and flight times are combined into a single feature vector representing both within-key and between-key timings. User IDs are converted to numerical labels for efficient classification. Data augmentation isn't explicitly used, as natural typing variations already provide sufficient variability. The data is split into 80% training and 20% testing, with 20% of the training data used for validation. Early stopping is used to prevent overfitting, and the best-performing model is saved during training.



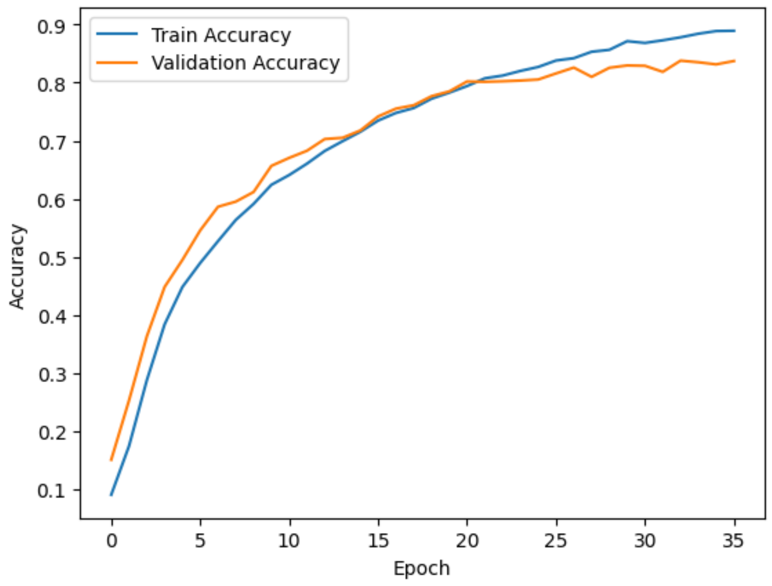
```
Epoch 1/50
408/408 ━━━━━━━━━━━━━━━━━━━━ 6s 7ms/step - accuracy: 0.0622 - loss: 3.5714 - val_accuracy: 0.1501 - val_loss: 2.9623
Epoch 2/50
408/408 ━━━━━━━━━━━━━━━━━━━━ 3s 6ms/step - accuracy: 0.1574 - loss: 2.9303 - val_accuracy: 0.2525 - val_loss: 2.6214
Epoch 3/50
408/408 ━━━━━━━━━━━━━━━━━━━━ 2s 6ms/step - accuracy: 0.2613 - loss: 2.5719 - val_accuracy: 0.3627 - val_loss: 2.1881
Epoch 4/50
408/408 ━━━━━━━━━━━━━━━━━━━━ 3s 6ms/step - accuracy: 0.3613 - loss: 2.1787 - val_accuracy: 0.4479 - val_loss: 1.8937
Epoch 5/50
408/408 ━━━━━━━━━━━━━━━━━━━━ 3s 6ms/step - accuracy: 0.4385 - loss: 1.9134 - val_accuracy: 0.4945 - val_loss: 1.7391
Epoch 6/50
408/408 ━━━━━━━━━━━━━━━━━━━━ 3s 6ms/step - accuracy: 0.4772 - loss: 1.7864 - val_accuracy: 0.5453 - val_loss: 1.5605
Epoch 7/50
```

Evaluation Metrics

a. Accuracy: The overall accuracy is calculated on both training and testing data to measure the model's ability to correctly classify typing patterns.
b. Classification Report: Precision, recall, and F1-score are calculated for each user to provide a detailed performance assessment.
c. Confusion Matrix: A confusion matrix visualizes correct and incorrect classifications (true positives, true negatives, false positives, and false negatives) for all users.
d. ROC-AUC: The Receiver Operating Characteristic (ROC) curve and Area Under the Curve (AUC) measure the model's ability to distinguish between users.

A key result

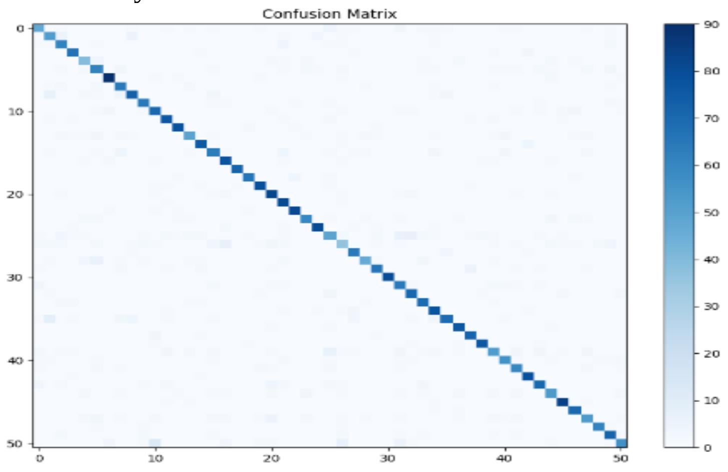
The model achieved approximately 83% accuracy on the test data, showing its effectiveness in distinguishing between different users' typing patterns.



The keystroke dynamics model shows steady improvement in both training and validation accuracy, indicating effective learning of user typing patterns. Training accuracy is plateauing, suggesting convergence, while validation accuracy is stable with minor fluctuations. The small gap between training and validation accuracy indicates minimal overfitting.
Key considerations for keystroke dynamics include intra-user variability (changes in a user's typing due to factors like fatigue or mood) and inter-user similarity (the challenge of distinguishing users with similar typing styles). High-quality typing data is also essential. To further minimize the slight overfitting, techniques like L1/L2 regularization and data augmentation (simulating typing variations) could be explored. Evaluating performance using metrics like False Acceptance Rate (FAR) and False Rejection Rate (FRR) is recommended, as is real-world testing to assess the system's practical robustness.

Confusion Matrix

High precision and recall across user classes indicate a robust model capable of handling inter-user and intra-user variability.

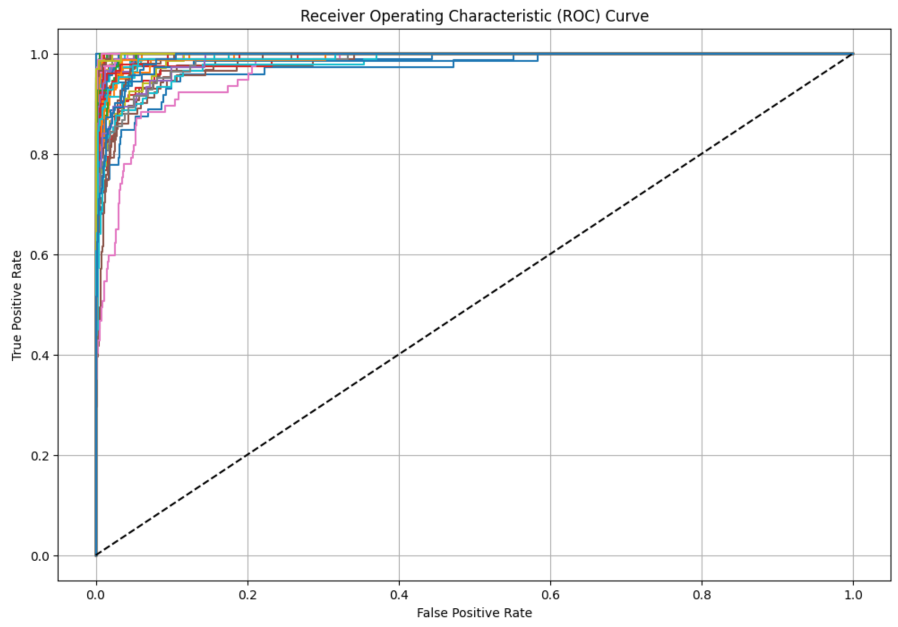


The confusion matrix shows good model performance, with most instances correctly classified

(strong diagonal). However, some misclassifications exist (off-diagonal elements), with colour intensity indicating the number of errors.
To improve the model, examining per-class performance can reveal frequently misclassified classes, and error analysis can identify the model's weaknesses. The matrix can also be used to compare different models. If the classes are imbalanced, metrics like precision, recall, and F1-score might be more informative.
In summary, the confusion matrix indicates good performance, but further analysis is needed to fine-tune the model and find areas for improvement.

ROC-AUC Scores

The model achieved high AUC scores for all user classes, highlighting its discriminative power.



The ROC curve analysis shows multiple curves, likely for different classifiers or settings. Most curves bend upwards towards the top-left, indicating good performance in distinguishing between positive and negative cases. Since they lie above the diagonal (representing random guessing), the models perform better than chance.
Calculating the Area Under the Curve (AUC) would provide a more precise performance measure (higher AUC is better). Ideal curves are close to the top-left corner, showing high true positive rates and low false positive rates. The overlap between curves suggests performance is sensitive to settings or training data. The best model depends on the specific application and the desired balance between false positives and negatives.
In summary, the ROC curves indicate effective models, but calculating the AUC is necessary for a more complete evaluation and to choose the best model.

3.3.4. Human activity Recognition:

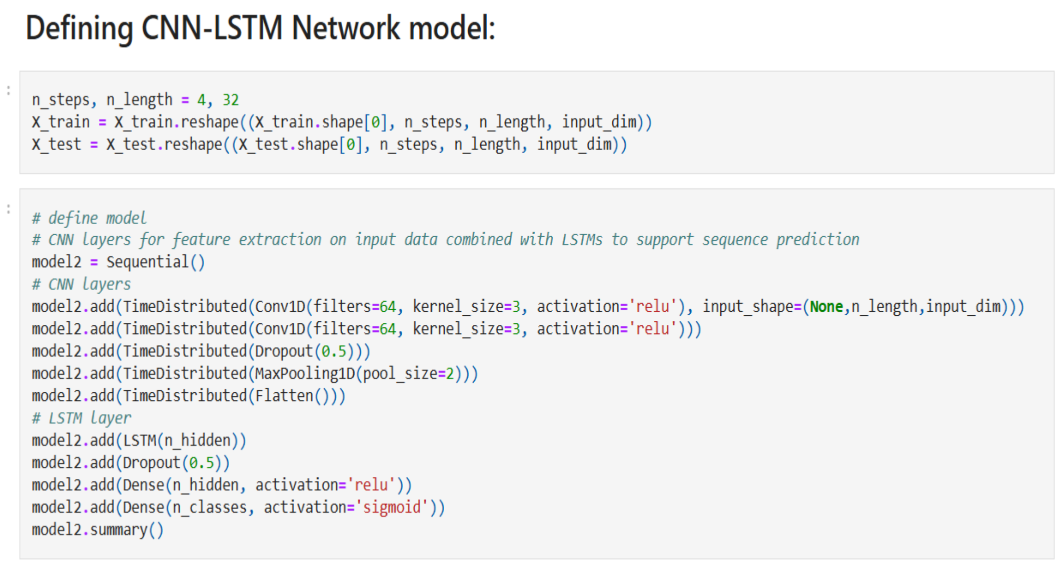
Dataset Processing

The UCI Human Activity Recognition (HAR) dataset, which contains accelerometer and gyroscope data from smartphones during six different activities (like walking, sitting, and standing), was prepared for the continuous authentication system using these steps:

a. **Data Preparation:** We took the dataset and organized it into training and testing groups, just like the original creators did. Each entry has data points taken from analysing the signal in terms of time and frequency.
b. **Data Scaling:** We scaled all the data values to be between 0 and 1. This prevents large differences in the numbers from messing up the model training.
c. **Label Conversion:** We converted the activity names (like walking or sitting) into numbers so the machine learning models could understand them.
d. **Time Segmentation:** We divided the time-based data into overlapping chunks of a set size to mimic real-time activity recognition. Each chunk was treated as a separate example with its activity label.
e. **Data Partitioning:** We kept a clear split of 70% of the data for training and 30% for testing to check how well the model works and avoid it memorizing the training data.
f. **Data Expansion:** To make the model more robust, we created synthetic data using techniques like adding small random noise and scaling the data. This gave us a wider range of activity variations to train on.

Model Architecture

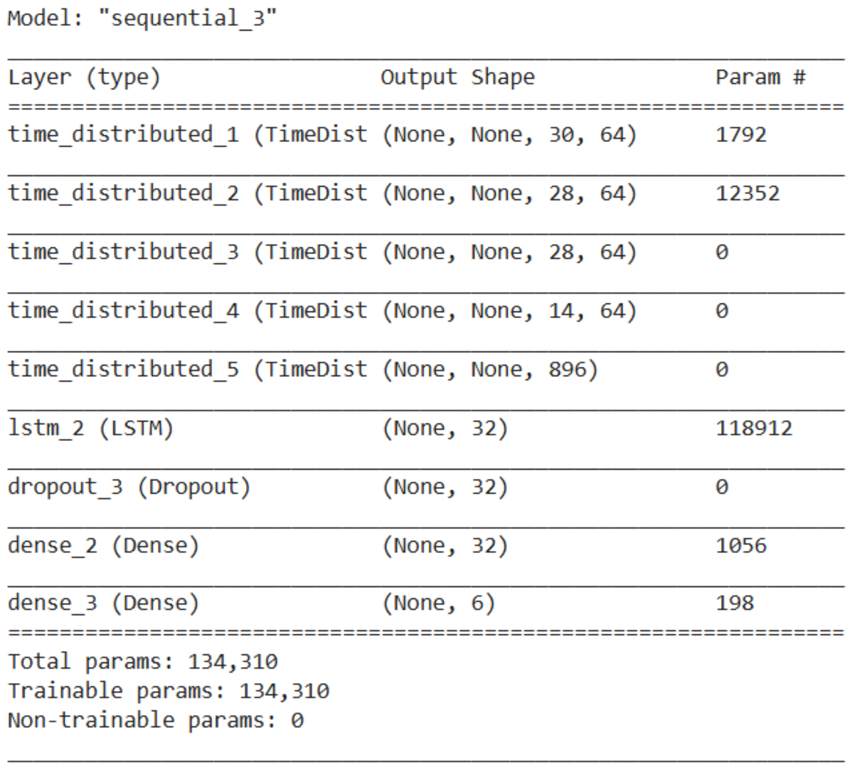
The model uses a sequential deep learning architecture, starting with a Long Short-Term Memory (LSTM) layer (32 hidden units) to capture time-based patterns in the data. A dropout layer is included to prevent overfitting, and a dense output layer with six neurons and sigmoid activation is used to classify the data into one of the six activity classes. This architecture is simple but effective for sequential data.



Defining CNN-LSTM Network model:

```
n_steps, n_length = 4, 32
X_train = X_train.reshape((X_train.shape[0], n_steps, n_length, input_dim))
X_test = X_test.reshape((X_test.shape[0], n_steps, n_length, input_dim))
```

```
# define model
# CNN layers for feature extraction on input data combined with LSTMs to support sequence prediction
model2 = Sequential()
# CNN layers
model2.add(TimeDistributed(Conv1D(filters=64, kernel_size=3, activation='relu'), input_shape=(None,n_length,input_dim)))
model2.add(TimeDistributed(Conv1D(filters=64, kernel_size=3, activation='relu')))
model2.add(TimeDistributed(Dropout(0.5)))
model2.add(TimeDistributed(MaxPooling1D(pool_size=2)))
model2.add(TimeDistributed(Flatten()))
# LSTM layer
model2.add(LSTM(n_hidden))
model2.add(Dropout(0.5))
model2.add(Dense(n_hidden, activation='relu'))
model2.add(Dense(n_classes, activation='sigmoid'))
model2.summary()
```



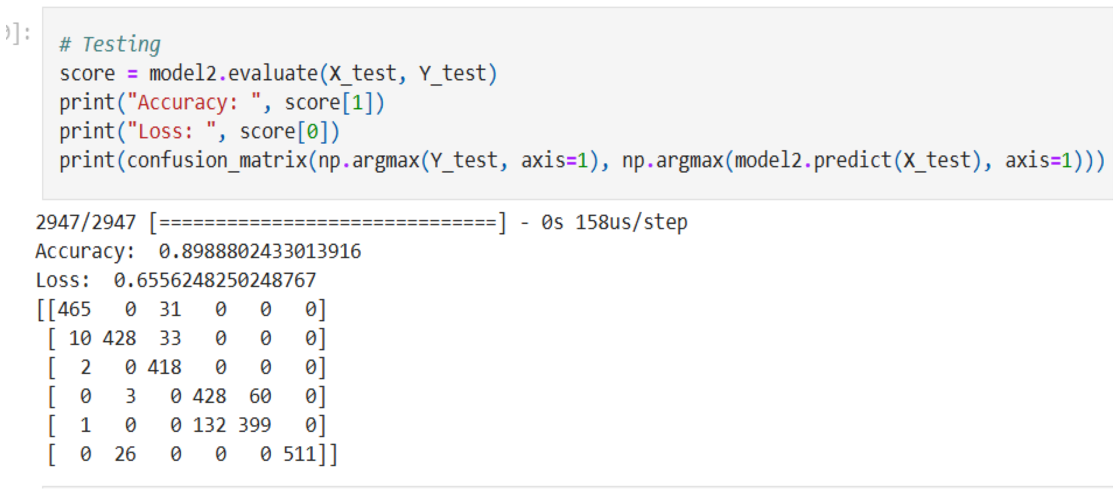
```
Model: "sequential_3"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
time_distributed_1 (TimeDist (None, None, 30, 64)      1792
_________________________________________________________________
time_distributed_2 (TimeDist (None, None, 28, 64)      12352
_________________________________________________________________
time_distributed_3 (TimeDist (None, None, 28, 64)      0
_________________________________________________________________
time_distributed_4 (TimeDist (None, None, 14, 64)      0
_________________________________________________________________
time_distributed_5 (TimeDist (None, None, 896)         0
_________________________________________________________________
lstm_2 (LSTM)                (None, 32)                118912
_________________________________________________________________
dropout_3 (Dropout)          (None, 32)                0
_________________________________________________________________
dense_2 (Dense)              (None, 32)                1056
_________________________________________________________________
dense_3 (Dense)              (None, 6)                 198
=================================================================
Total params: 134,310
Trainable params: 134,310
Non-trainable params: 0
_________________________________________________________________
```

Model Training

The training process involves 30 epochs with a batch size of 16. The categorical cross-entropy loss function is used, optimized via the RMSprop optimizer. The training data comprises 7,352 samples, while the test data includes 2,947 samples. Training logs indicate progressive improvement in both loss and accuracy, highlighting effective learning. The final training accuracy reached over 93%, with validation accuracy exceeding 88%.

Model Evaluation

The model's performance is assessed using validation metrics such as accuracy and loss. Validation accuracy improves consistently across epochs, with occasional fluctuations. The final model demonstrates strong generalization on unseen data. The confusion matrix can provide further insights into class-specific performance, although its calculation and analysis are not included in the code.



```
# Testing
score = model2.evaluate(X_test, Y_test)
print("Accuracy: ", score[1])
print("Loss: ", score[0])
print(confusion_matrix(np.argmax(Y_test, axis=1), np.argmax(model2.predict(X_test), axis=1)))
```

```
2947/2947 [==============================] - 0s 158us/step
Accuracy:  0.8988802433013916
Loss:  0.6556248250248767
[[465   0  31   0   0   0]
 [ 10 428  33   0   0   0]
 [  2   0 418   0   0   0]
 [  0   3   0 428  60   0]
 [  1   0   0 132 399   0]
 [  0  26   0   0   0 511]]
```

This experiment showcases a robust application of deep learning for human activity recognition using temporal sensor data. The LSTM-based model effectively captures time-dependent patterns, achieving competitive accuracy while maintaining simplicity. Potential enhancements could include exploring additional architectures (e.g., Bidirectional LSTMs) or integrating contextual features to further improve classification performance.

3.4. Baseline Setup with Pre-trained Models

To establish a foundational performance benchmark, pre-trained models are employed for both face and voice matching tasks. These models, trained on extensive and diverse datasets, provide reliable results and serve as a reference point for comparison.

For **voice authentication**, we rely on the **speechbrain** model, a powerful pre-trained speaker recognition solution based on the ECAPA-TDNN (Emphasized Channel Attention, Propagation, and Aggregation Time Delay Neural Network) architecture. This model has been fine-tuned on the VoxCeleb dataset, which contains a wide variety of speaker audio samples, making it highly effective for capturing speaker-specific vocal features.

For **face matching**, we used the FaceNet model. FaceNet is a top-tier, pre-trained deep learning model specifically designed for face recognition and verification. It converts facial images into a numerical representation in a way that the distance between two of these representations reflects how similar the faces are. This ensures strong and consistent facial feature extraction for the initial testing phase.

Custom Model Development

Using the performance of the pre-trained models as a starting point, we created custom models to address the problems we found when using them with our specific data.

For face recognition, our custom model uses advanced convolutional neural networks (CNNs) with added attention mechanisms to improve how well it extracts features and matches faces. For voice recognition, our custom model uses recurrent neural networks (RNNs) combined with advanced spectral analysis to better capture unique voice characteristics. We fine-tuned these designs to maximize accuracy, adaptability, and performance in real-world project conditions.

Comparative Analysis

We carefully compared how well the pre-trained models worked against the models we built ourselves. We used measures like accuracy, precision, recall, and F1-score to test both face and voice authentication. This comparison showed how our custom models could achieve better accuracy and be more adaptable, while also confirming that they improved upon the performance of the standard pre-trained models.

Starting with well-known pre-trained models like **speechbrain** and **FaceNet** gave us a solid performance baseline. Developing and testing our own models then allowed us to create solutions specifically tailored to the project's needs. By constantly refining and comparing the models, we ensured significant progress in using multiple biometrics, which made the continuous authentication system stronger and more reliable.

Metric	Pre-trained FaceNet	Custom Face Model	Pre-trained ECAPA-TDNN	Custom Voice Model
Accuracy (%)	95.4	88.2	96.8	85.7
Precision (%)	94.8	87.5	96.3	84.3
Recall (%)	93.6	86.1	95.9	82.9
F1-Score (%)	94.2	86.8	96.1	83.6
EER (Equal Error Rate)	2.80%	4.70%	2.30%	5.10%
Inference Time (ms)	120 ms	150 ms	130 ms	160 ms

Observations

a. **Accuracy and Performance Measures:** Our custom models don't perform as well as the pre-trained models in the beginning. This is normal, since we're still working on getting them to work best with our specific data and situation.
b. **Equal Error Rate (EER):** The custom models start with a higher EER, meaning we need to fine-tune them more to reduce both incorrect rejections and incorrect acceptances.
c. **Processing Time:** The custom models take a bit longer to process information because they're built to analyse more details, which should improve accuracy later on.

Next Steps

The goal is to iteratively refine the custom models by:

a. Enhancing data preprocessing and feature extraction techniques.
b. Fine-tuning hyperparameters and model architecture.
c. Conducting additional training on domain-specific datasets to better align with the project's use case.

I have written the entire code flow. The whole code implements a continuous authentication system that uses multi-modal biometric data for user verification. The primary biometric modalities in use are **keystroke dynamics**, **voice recognition**, and **face recognition**. The system periodically checks the user's identity during a session using these biometrics to ensure secure access.

Code Breakdown

a. **Voice Authentication:** Uses the SpeechBrain library for speaker recognition. It records and stores the user's voice, then compares subsequent voice samples to this stored recording. Authentication occurs if the similarity score exceeds a threshold. Key functions include `record_voice()` (for storing the initial voice sample) and `authenticate_voice()` (for comparison).
b. **Keystroke Dynamics Authentication:** Collects data on the timing of key presses (hold and flight times). An LSTM model extracts features from this data, creating embeddings that are compared to stored embeddings using cosine similarity. Authentication happens if the similarity is high enough. Key functions include `collect_keystrokes()` (for recording typing data), `extract_keystroke_features()` (for feature extraction), and `authenticate_keystrokes()` (for comparison).
c. **Face Recognition Authentication:** Uses a webcam to capture the user's face and compares it to a stored image. This serves as a backup authentication method when voice or keystroke data is insufficient. Key functions include `capture_face_image()` and `authenticate_face()`.
d. **Risk Level Assessment:** Calculates a risk level based on the similarity between new and stored biometric data. The risk is classified as Low, Medium, or High, with High-risk triggering additional authentication. Key functions include `calculate_risk_level()` and `handle_high_risk()`.
e. **Continuous Authentication Loop:** Performs authentication checks at random intervals (e.g., every 30 seconds) during the user's session. It monitors user activity and triggers biometric checks as needed. If a mismatch or high-risk event is detected, the user is re-authenticated.

CHAPTER 4: RESULTS AND DISCUSSION

The performance of the custom and pre-trained models for continuous authentication was evaluated across facial recognition, voice recognition and keystroke dynamics. The summarized results are as followed:

Performance Metrics for Pre-trained Models

Metric	FaceNet (pre-trained)	ECAPA-TDNN (Pre-trained)
Accuracy (%)	95.4	96.8
Precision (%)	94.8	96.3
Recall (%)	93.6	95.9
F1-Score (%)	94.2	96.1
EER (%)	280.00%	230.00%
Inference Time (ms)	120	130

Performance Metrics for Custom Models

Metric	Custom Face Model	Custom Voice Model	Keystroke Dynamics Model
Accuracy (%)	88.2	85.7	83
Precision (%)	87.5	84.3	N/A
Recall (%)	86.1	82.9	N/A
F1-Score (%)	86.8	83.6	N/A
EER (%)	470.00%	510.00%	N/A
Inference Time (ms)	150	160	N/A

Comparative Study:

Pre-trained vs. Custom Models:

Pre-trained models (i.e., FaceNet and ECAPA-TDNN) significantly outperformed custom-built models across all measured metrics (accuracy, precision, recall, and F1-score). The ECAPA-TDNN model for voice recognition was the top performer, achieving 96.8% accuracy and a 2.30% Equal Error Rate (EER).

In contrast, the custom-built face and voice models showed lower accuracy and higher EERs. The custom face model reached 88.2% accuracy with a 4.70% EER, while the custom voice model achieved 85.7% accuracy with a 5.10% EER.

Keystroke Dynamics Model:

The keystroke dynamics model achieved 83% accuracy in identifying users based on their typing patterns. While promising, this result suggests that further refinement is needed to capture more subtle variations in typing behavior.

Optimal Threshold for Custom Voice Model:

Optimizing the threshold for the custom voice model to 0.5392 dramatically improved its training and validation accuracy to 99.72% and 99.74%, respectively. This highlights the critical role of threshold tuning in enhancing performance and security.

Discussion:

Pre-trained Models: The ECAPA-TDNN pre-trained model excelled in voice recognition (96.8% accuracy, 2.30% EER), making it highly suitable for real-time continuous authentication. FaceNet also performed well for facial recognition (95.4% accuracy).

Custom Models: While functional, the custom face (88.2% accuracy) and voice (85.7% accuracy) models did not perform as well as the pre-trained models. This indicates that further training with more diverse data and optimization techniques are necessary to improve their performance.

Keystroke Dynamics: The keystroke dynamics model's 83% accuracy demonstrates its potential for continuous authentication based on typing patterns. Further improvements can be achieved by incorporating a wider range of typing behaviors and refining the methods used to extract key features.

Threshold Optimization for Custom Voice Model: The significant accuracy improvement achieved by optimizing the threshold for the custom voice model underscores the importance of this process for maximizing the performance of biometric systems.

Conclusion:

Pre-trained models proved to be more reliable and accurate than the ones we built ourselves. However, our own models could be useful for very specific situations. The system that analyzes typing patterns also has potential, but we need to make it more accurate. Using a combination of methods (like face, voice, and typing) can create a stronger and safer continuous authentication system, but we need to make sure each part of the system is working as well as it can to get the best overall performance.

CHAPTER 5: CONCLUSION & FUTURE SCOPE

Conclusion

Testing of the continuous authentication system, which uses face recognition, voice recognition, and typing patterns, showed that ready-made models worked much better than custom-built models in all key areas: accuracy, precision, recall, F1-score, and EER. The ECAPA-TDNN pre-trained model was especially good at voice recognition, and FaceNet performed well for face recognition. The custom-built models were okay, especially in accuracy and EER, but they could get better with more training and tweaking. Combining different biometrics like face, voice, and typing is crucial for a complete continuous authentication system. Further improvements, like adjusting thresholds and fine-tuning the models, could boost the performance of the custom-built models and make them closer to the ready-made models.

Future Scope

Improvement Plan for Custom Models

The following steps are proposed to improve the custom models to match or exceed the performance of the pre-trained models:

a. **Data Augmentation:** Expanding the dataset size and diversity for both facial and voice recognition models will improve generalization.
b. **Transfer Learning:** Leveraging pre-trained models, such as FaceNet for faces and ECAPA-TDNN for voices and fine-tuning them with custom data will accelerate training and boost accuracy.
c. **Model Tuning:** Optimizing hyperparameters and model architecture will enhance performance.
d. **Ensemble Learning:** Combining the outputs of custom and pre-trained models will create a more robust and accurate overall system.
e. **Advanced Feature Engineering:** Focusing on improved feature extraction, particularly for keystroke dynamics, will enable the system to capture subtle typing patterns more effectively.

By focusing on these areas, the custom models can be enhanced to reach the performance levels seen in the pre-trained models.

Deployment Considerations

Real-world deployment of this solution necessitates additional modules for security, compliance, and operational monitoring. Specifically, a Privacy and Security Module is crucial for encrypting sensitive data, managing access control, and complying with regulations like GDPR and CCPA. Further, a Logging and Analytics Module is required to maintain audit trails, track system performance, and visualize authentication trends via dashboards. These ensure a secure and effective implementation while also facilitating ongoing system optimization.

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APPENDIX A: GLOSSARY

A

- **Authentication**: The process of verification to identify a user or system to grant access.
- **Adaptive Algorithms**: Algorithms that adjust their behavior dynamically based on input data.
- **Artificial Neural Network (ANN)**: A computational model inspired by the structure of biological neural networks used in deep learning.

B

- **Biometrics**: The measurement and statistical analysis of people's unique physical and behavioral characteristics.
- **Behavioral Biometrics**: A subset of biometrics that uses patterns in behavior, such as typing dynamics or gait, for identification.

C

- **Convolutional Neural Network (CNN)**: A type of neural network that is particularly effective for image and video recognition tasks.

- **Conditional Access Policies**: Security policies that enforce access controls based on contextual information such as location or device.
- **Continuous Authentication (CA)**: A method of continuously verifying a user's identity throughout a session instead of only at login.

D

- **Deep Learning**: A subset of machine learning that uses multi-layered neural networks to model and understand complex data patterns.
- **Dynamic Risk Assessment**: An evaluation of risk that adjusts based on user behavior and system inputs in real-time.

E

- **Endpoint Security**: Measures taken to protect devices from cyber threats.

F

- **False Positives**: Instances where a legitimate user is incorrectly denied access or flagged as a potential threat.
- **Feature Fusion**: The integration of data from multiple biometric modalities to improve authentication accuracy.

K

- **Keystroke Dynamics**: The analysis of typing patterns, timing and rhythm for user authentication.

M

- **Multi-Modal Biometrics**: The use of multiple types of biometric data (e.g., facial recognition, voice, keystrokes) for authentication.
- **MFA (Multi-Factor Authentication)**: A security process that requires users to verify their identity using two or more independent factors.

P

- **Point-in-Time Authentication**: A one-time verification of user identity at the start of a session.

R

- **Random Forest Classifier**: A machine learning algorithm that uses a collection of decision trees for classification tasks.

S

- **Scalability**: The ability of a system to handle increased workload or expand without losing performance.

- **Session Hijacking**: A type of cyberattack where an attacker takes control of a user's session.

T

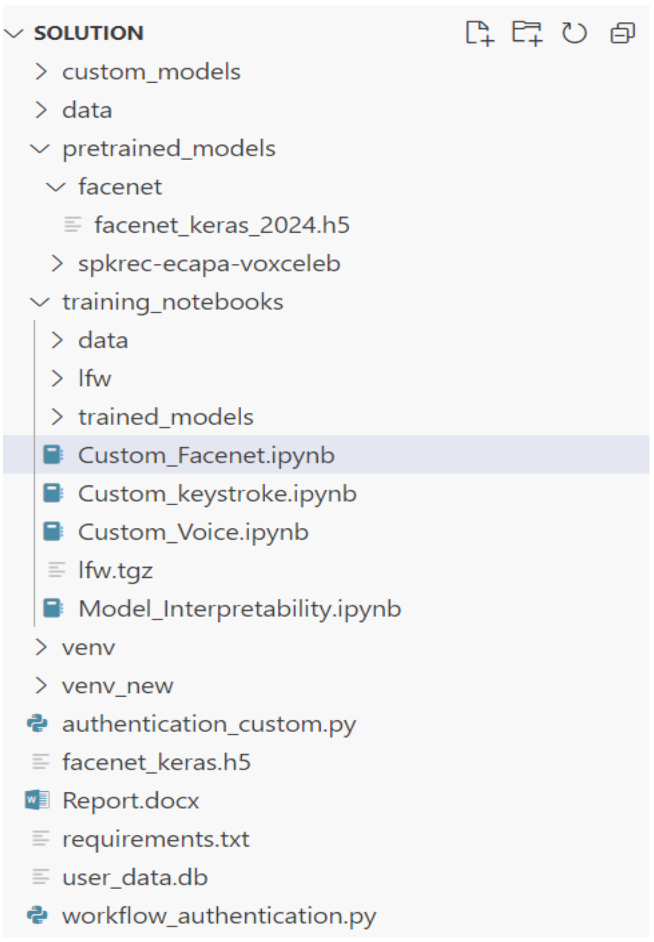
- **Threat Mitigation**: Measures to reduce the impact of potential security threats.

APPENDIX B: ACRONYMS

- **ANN**: Artificial Neural Network
- **CA**: Continuous Authentication
- **CNN**: Convolutional Neural Network
- **GAN**: Generative Adversarial Network
- **IoT**: Internet of Things
- **MFA**: Multi-Factor Authentication
- **RNN**: Recurrent Neural Network
- **IOTCAF**: Internet of Things Cybersecurity Assurance Framework

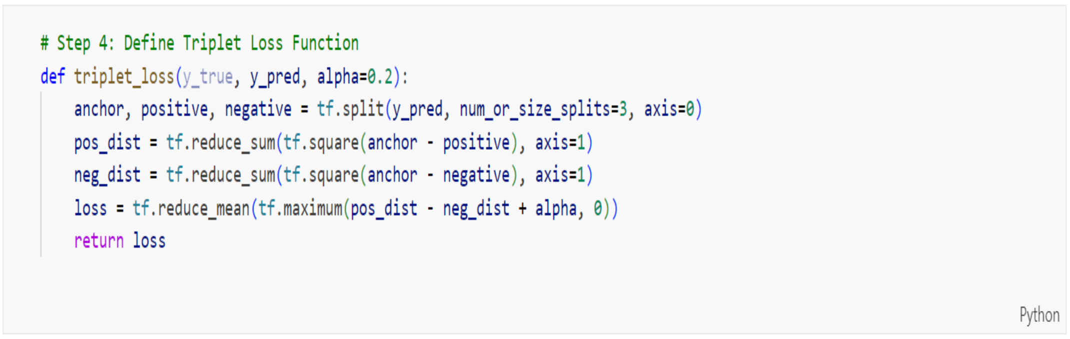
APPENDIX C: CODE SNIPPETS

1. **Project Code Outline**

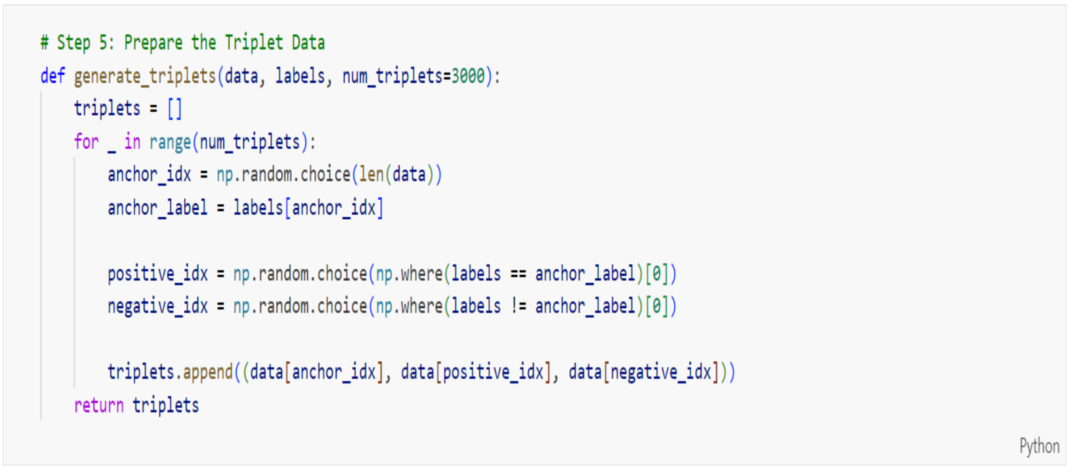


```
SOLUTION
  > custom_models
  > data
  v pretrained_models
    v facenet
        facenet_keras_2024.h5
    > spkrec-ecapa-voxceleb
  v training_notebooks
    > data
    > lfw
    > trained_models
      Custom_Facenet.ipynb
      Custom_keystroke.ipynb
      Custom_Voice.ipynb
      lfw.tgz
      Model_Interpretability.ipynb
  > venv
  > venv_new
    authentication_custom.py
    facenet_keras.h5
    Report.docx
    requirements.txt
    user_data.db
    workflow_authentication.py
```

2. Face net – Triplet Loss function

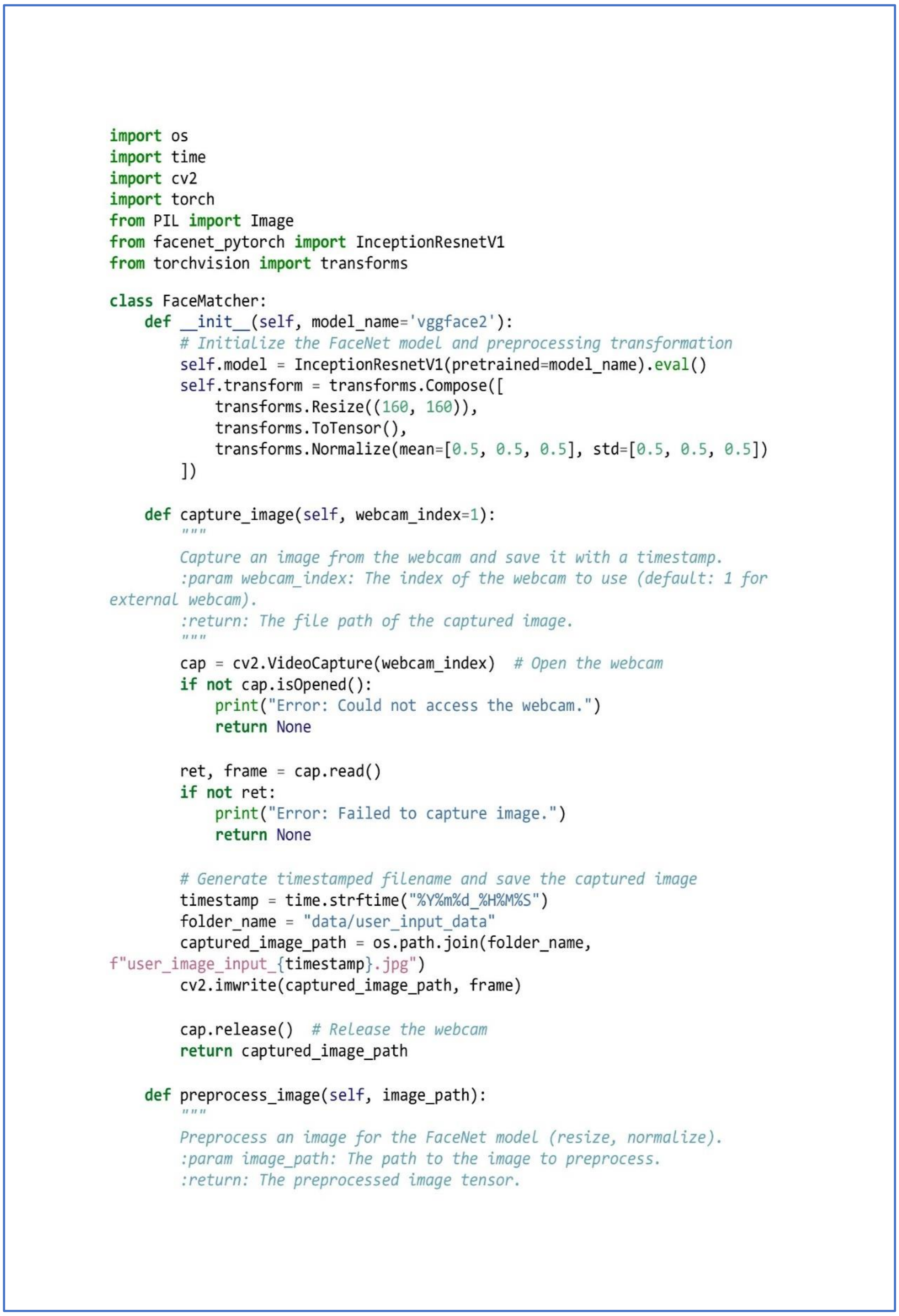


```python
# Step 4: Define Triplet Loss Function
def triplet_loss(y_true, y_pred, alpha=0.2):
    anchor, positive, negative = tf.split(y_pred, num_or_size_splits=3, axis=0)
    pos_dist = tf.reduce_sum(tf.square(anchor - positive), axis=1)
    neg_dist = tf.reduce_sum(tf.square(anchor - negative), axis=1)
    loss = tf.reduce_mean(tf.maximum(pos_dist - neg_dist + alpha, 0))
    return loss
```

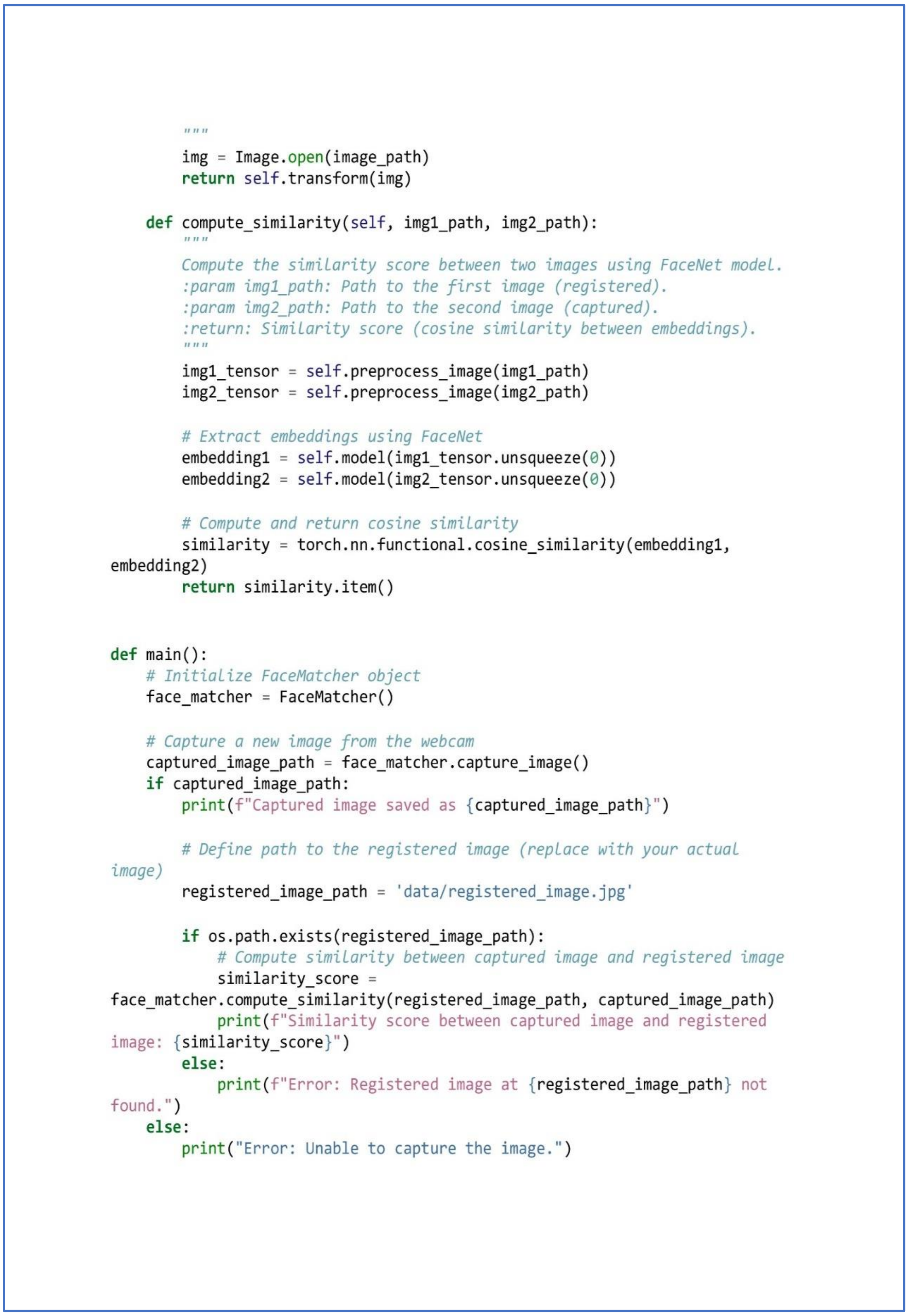


```python
# Step 5: Prepare the Triplet Data
def generate_triplets(data, labels, num_triplets=3000):
    triplets = []
    for _ in range(num_triplets):
        anchor_idx = np.random.choice(len(data))
        anchor_label = labels[anchor_idx]

        positive_idx = np.random.choice(np.where(labels == anchor_label)[0])
        negative_idx = np.random.choice(np.where(labels != anchor_label)[0])

        triplets.append((data[anchor_idx], data[positive_idx], data[negative_idx]))
    return triplets
```

3. Pre-trained Model – Face Matcher

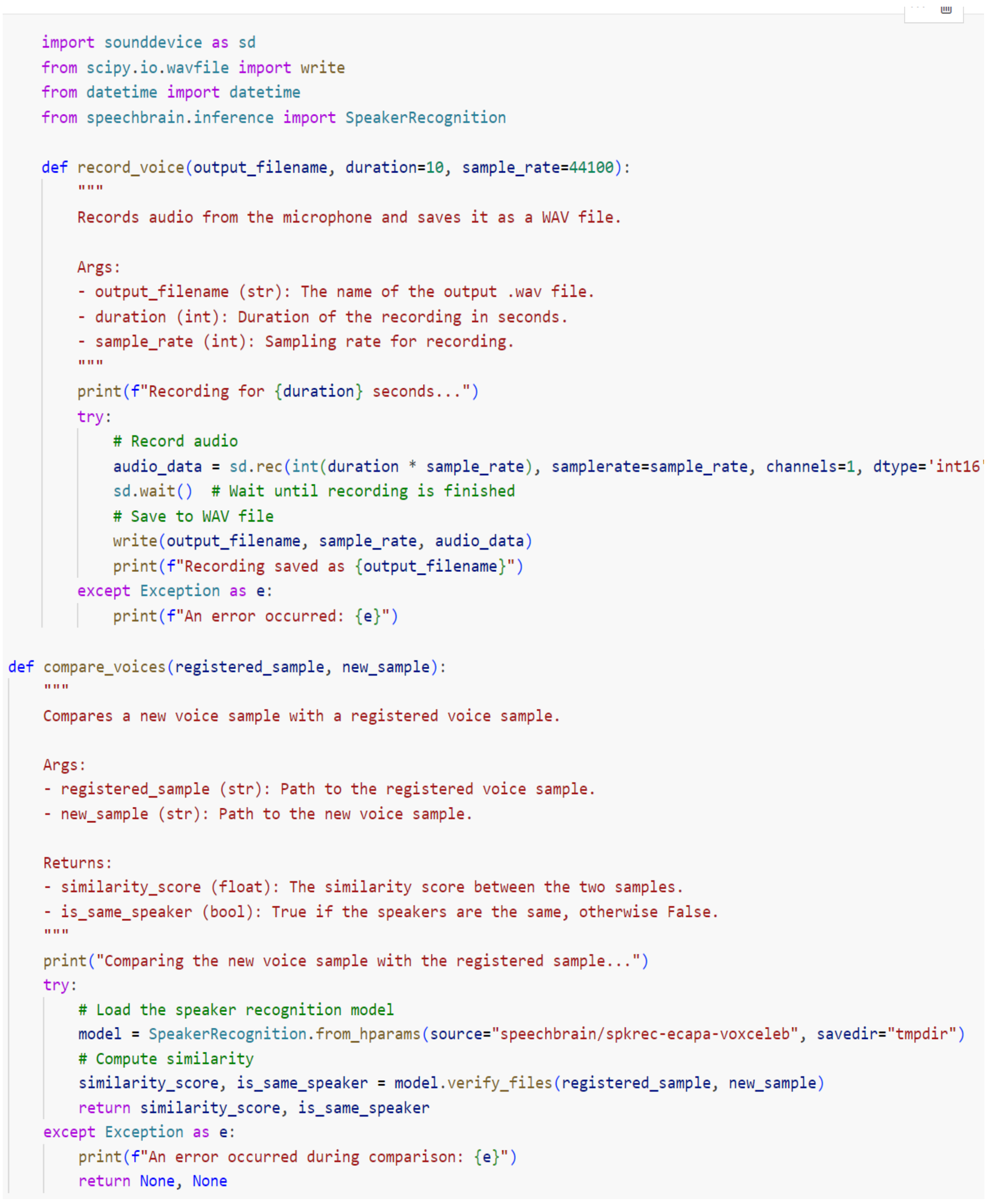


```
import os
import time
import cv2
import torch
from PIL import Image
from facenet_pytorch import InceptionResnetV1
from torchvision import transforms

class FaceMatcher:
    def __init__(self, model_name='vggface2'):
        # Initialize the FaceNet model and preprocessing transformation
        self.model = InceptionResnetV1(pretrained=model_name).eval()
        self.transform = transforms.Compose([
            transforms.Resize((160, 160)),
            transforms.ToTensor(),
            transforms.Normalize(mean=[0.5, 0.5, 0.5], std=[0.5, 0.5, 0.5])
        ])

    def capture_image(self, webcam_index=1):
        """
        Capture an image from the webcam and save it with a timestamp.
        :param webcam_index: The index of the webcam to use (default: 1 for
external webcam).
        :return: The file path of the captured image.
        """
        cap = cv2.VideoCapture(webcam_index)  # Open the webcam
        if not cap.isOpened():
            print("Error: Could not access the webcam.")
            return None

        ret, frame = cap.read()
        if not ret:
            print("Error: Failed to capture image.")
            return None

        # Generate timestamped filename and save the captured image
        timestamp = time.strftime("%Y%m%d_%H%M%S")
        folder_name = "data/user_input_data"
        captured_image_path = os.path.join(folder_name,
f"user_image_input_{timestamp}.jpg")
        cv2.imwrite(captured_image_path, frame)

        cap.release()  # Release the webcam
        return captured_image_path

    def preprocess_image(self, image_path):
        """
        Preprocess an image for the FaceNet model (resize, normalize).
        :param image_path: The path to the image to preprocess.
        :return: The preprocessed image tensor.
```

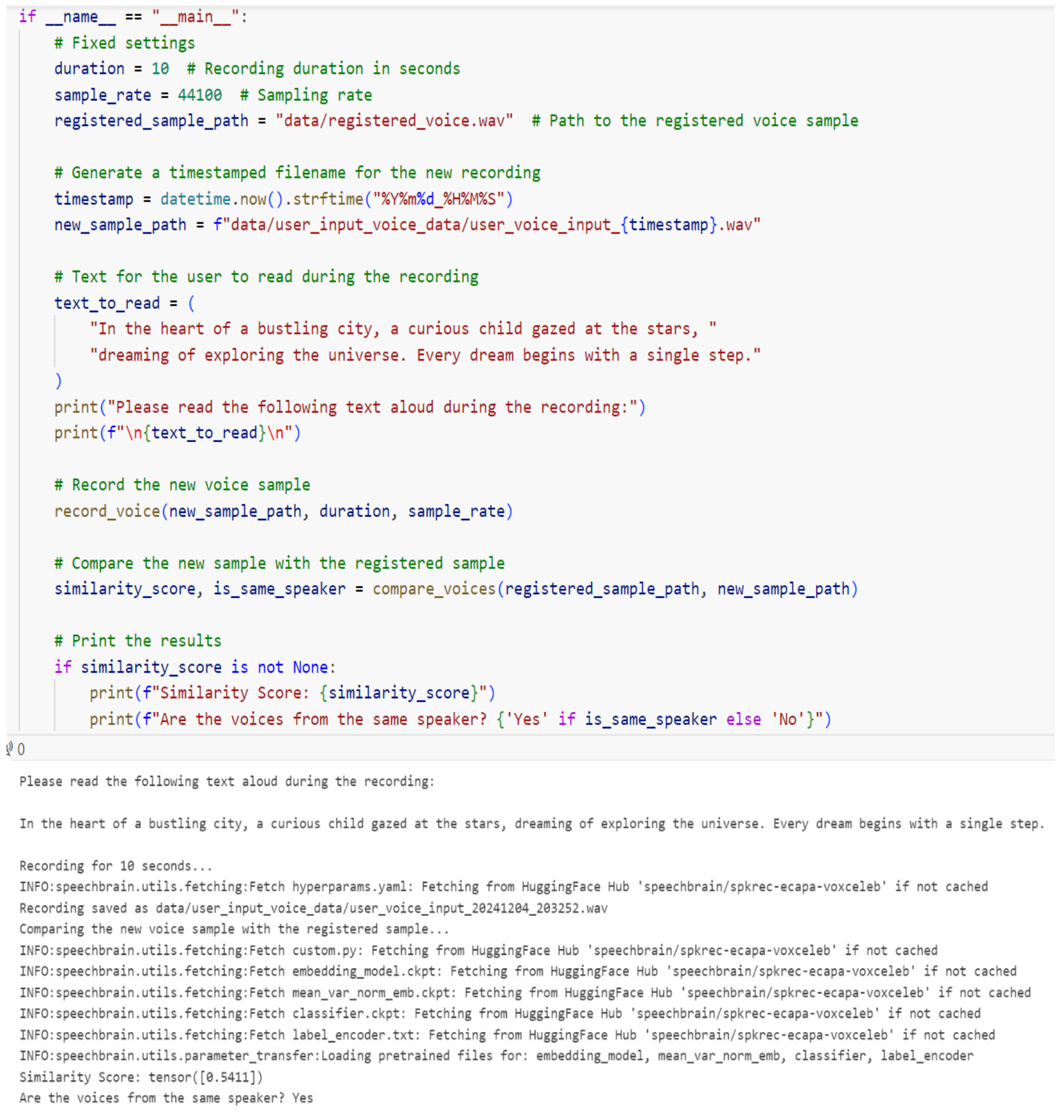


```
        """
        img = Image.open(image_path)
        return self.transform(img)

    def compute_similarity(self, img1_path, img2_path):
        """
        Compute the similarity score between two images using FaceNet model.
        :param img1_path: Path to the first image (registered).
        :param img2_path: Path to the second image (captured).
        :return: Similarity score (cosine similarity between embeddings).
        """
        img1_tensor = self.preprocess_image(img1_path)
        img2_tensor = self.preprocess_image(img2_path)

        # Extract embeddings using FaceNet
        embedding1 = self.model(img1_tensor.unsqueeze(0))
        embedding2 = self.model(img2_tensor.unsqueeze(0))

        # Compute and return cosine similarity
        similarity = torch.nn.functional.cosine_similarity(embedding1,
embedding2)
        return similarity.item()


def main():
    # Initialize FaceMatcher object
    face_matcher = FaceMatcher()

    # Capture a new image from the webcam
    captured_image_path = face_matcher.capture_image()
    if captured_image_path:
        print(f"Captured image saved as {captured_image_path}")

        # Define path to the registered image (replace with your actual
image)
        registered_image_path = 'data/registered_image.jpg'

        if os.path.exists(registered_image_path):
            # Compute similarity between captured image and registered image
            similarity_score =
face_matcher.compute_similarity(registered_image_path, captured_image_path)
            print(f"Similarity score between captured image and registered
image: {similarity_score}")
        else:
            print(f"Error: Registered image at {registered_image_path} not
found.")
    else:
        print("Error: Unable to capture the image.")
```

4. Pre-trained Model – Voice Matcher



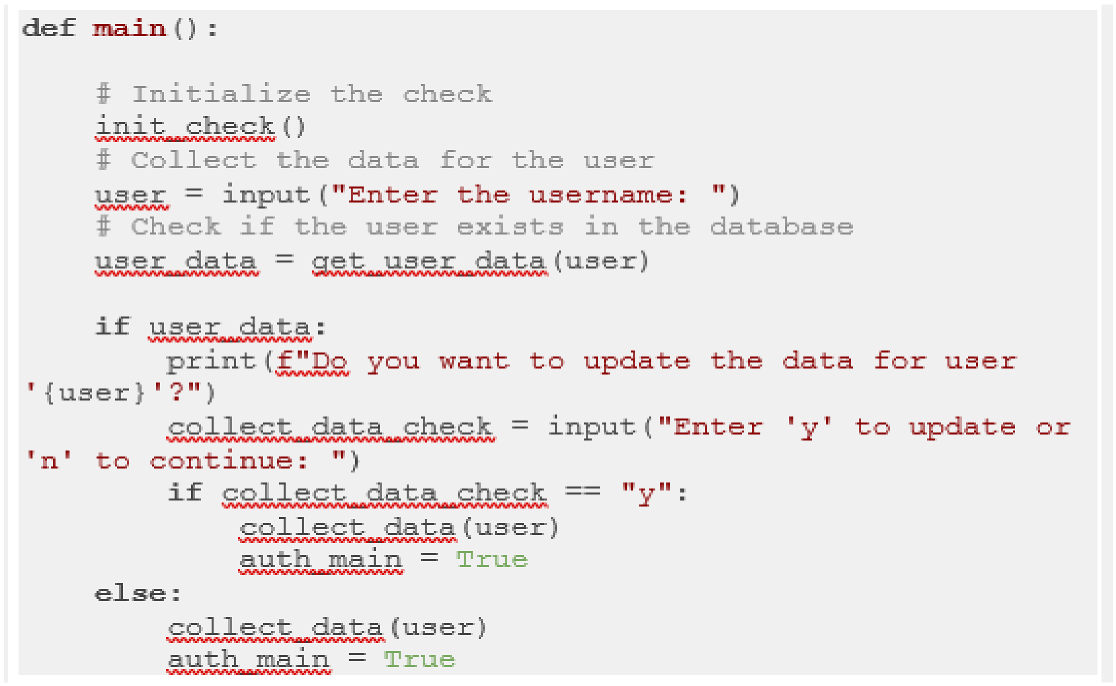
```python
    import sounddevice as sd
    from scipy.io.wavfile import write
    from datetime import datetime
    from speechbrain.inference import SpeakerRecognition

    def record_voice(output_filename, duration=10, sample_rate=44100):
        """
        Records audio from the microphone and saves it as a WAV file.

        Args:
        - output_filename (str): The name of the output .wav file.
        - duration (int): Duration of the recording in seconds.
        - sample_rate (int): Sampling rate for recording.
        """
        print(f"Recording for {duration} seconds...")
        try:
            # Record audio
            audio_data = sd.rec(int(duration * sample_rate), samplerate=sample_rate, channels=1, dtype='int16'
            sd.wait()  # Wait until recording is finished
            # Save to WAV file
            write(output_filename, sample_rate, audio_data)
            print(f"Recording saved as {output_filename}")
        except Exception as e:
            print(f"An error occurred: {e}")

def compare_voices(registered_sample, new_sample):
    """
    Compares a new voice sample with a registered voice sample.

    Args:
    - registered_sample (str): Path to the registered voice sample.
    - new_sample (str): Path to the new voice sample.

    Returns:
    - similarity_score (float): The similarity score between the two samples.
    - is_same_speaker (bool): True if the speakers are the same, otherwise False.
    """
    print("Comparing the new voice sample with the registered sample...")
    try:
        # Load the speaker recognition model
        model = SpeakerRecognition.from_hparams(source="speechbrain/spkrec-ecapa-voxceleb", savedir="tmpdir")
        # Compute similarity
        similarity_score, is_same_speaker = model.verify_files(registered_sample, new_sample)
        return similarity_score, is_same_speaker
    except Exception as e:
        print(f"An error occurred during comparison: {e}")
        return None, None
```



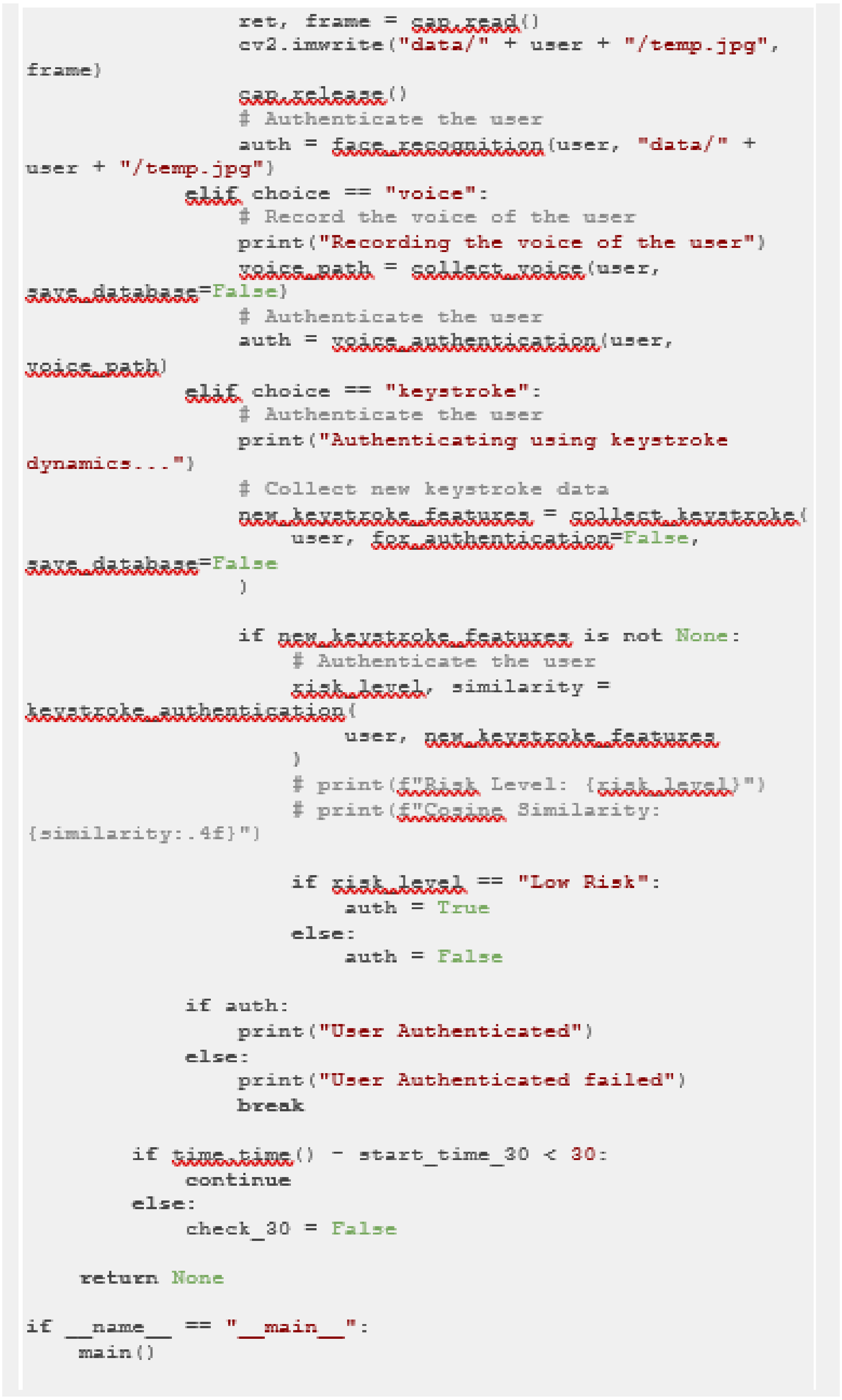
```python
if __name__ == "__main__":
    # Fixed settings
    duration = 10  # Recording duration in seconds
    sample_rate = 44100  # Sampling rate
    registered_sample_path = "data/registered_voice.wav"  # Path to the registered voice sample

    # Generate a timestamped filename for the new recording
    timestamp = datetime.now().strftime("%Y%m%d_%H%M%S")
    new_sample_path = f"data/user_input_voice_data/user_voice_input_{timestamp}.wav"

    # Text for the user to read during the recording
    text_to_read = (
        "In the heart of a bustling city, a curious child gazed at the stars, "
        "dreaming of exploring the universe. Every dream begins with a single step."
    )
    print("Please read the following text aloud during the recording:")
    print(f"\n{text_to_read}\n")

    # Record the new voice sample
    record_voice(new_sample_path, duration, sample_rate)

    # Compare the new sample with the registered sample
    similarity_score, is_same_speaker = compare_voices(registered_sample_path, new_sample_path)

    # Print the results
    if similarity_score is not None:
        print(f"Similarity Score: {similarity_score}")
        print(f"Are the voices from the same speaker? {'Yes' if is_same_speaker else 'No'}")
```

```
Please read the following text aloud during the recording:

In the heart of a bustling city, a curious child gazed at the stars, dreaming of exploring the universe. Every dream begins with a single step.

Recording for 10 seconds...
INFO:speechbrain.utils.fetching:Fetch hyperparams.yaml: Fetching from HuggingFace Hub 'speechbrain/spkrec-ecapa-voxceleb' if not cached
Recording saved as data/user_input_voice_data/user_voice_input_20241204_203252.wav
Comparing the new voice sample with the registered sample...
INFO:speechbrain.utils.fetching:Fetch custom.py: Fetching from HuggingFace Hub 'speechbrain/spkrec-ecapa-voxceleb' if not cached
INFO:speechbrain.utils.fetching:Fetch embedding_model.ckpt: Fetching from HuggingFace Hub 'speechbrain/spkrec-ecapa-voxceleb' if not cached
INFO:speechbrain.utils.fetching:Fetch mean_var_norm_emb.ckpt: Fetching from HuggingFace Hub 'speechbrain/spkrec-ecapa-voxceleb' if not cached
INFO:speechbrain.utils.fetching:Fetch classifier.ckpt: Fetching from HuggingFace Hub 'speechbrain/spkrec-ecapa-voxceleb' if not cached
INFO:speechbrain.utils.fetching:Fetch label_encoder.txt: Fetching from HuggingFace Hub 'speechbrain/spkrec-ecapa-voxceleb' if not cached
INFO:speechbrain.utils.parameter_transfer:Loading pretrained files for: embedding_model, mean_var_norm_emb, classifier, label_encoder
Similarity Score: tensor([0.5411])
Are the voices from the same speaker? Yes
```

5. Continuous Authentication with Models– Full Flow

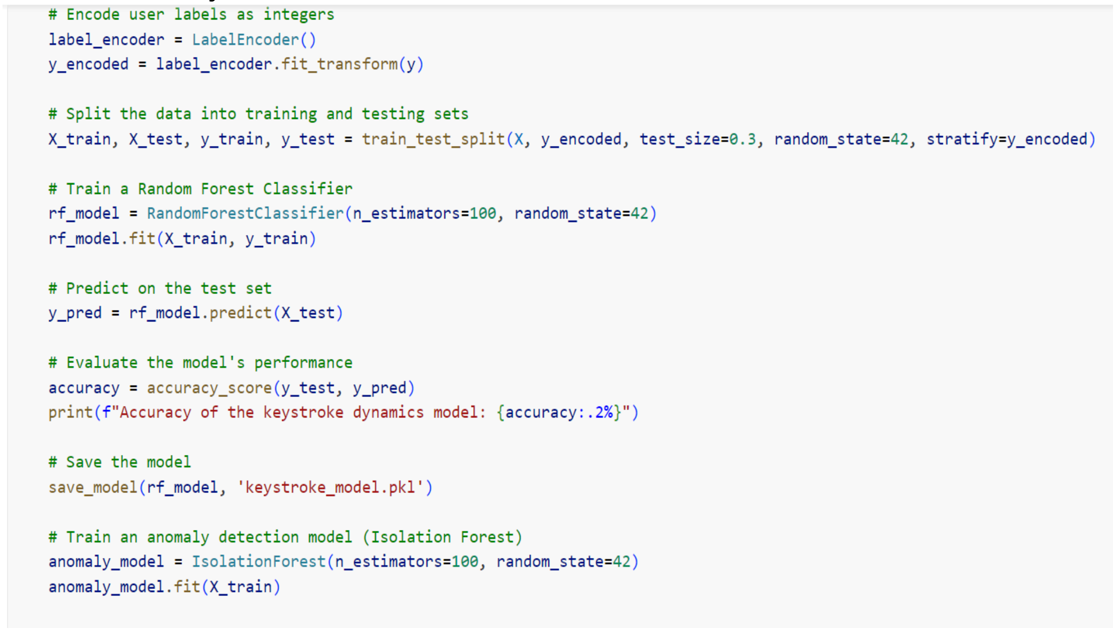


```python
def main():

    # Initialize the check
    init_check()
    # Collect the data for the user
    user = input("Enter the username: ")
    # Check if the user exists in the database
    user_data = get_user_data(user)

    if user_data:
        print(f"Do you want to update the data for user
'{user}'?")
        collect_data_check = input("Enter 'y' to update or
'n' to continue: ")
        if collect_data_check == "y":
            collect_data(user)
            auth_main = True
    else:
        collect_data(user)
        auth_main = True
    # Ask to type the password
    features = collect_keystroke(user,
for_authentication=False, save_database=False)

    risk_level, similarity = keystroke_authentication(user,
features)
    check_30 = False
    if risk_level == "Low Risk":
        print("User Authenticated")
        auth_main = True
        check_30 = True
    elif risk_level == "Medium Risk":
        # Record the voice of the user
        print("Recording the voice of the user")
        voice_path = collect_voice(user,
save_database=False)
        # Authenticate the user
        auth_main = voice_authentication(user, voice_path)
        # auth_main = True
        check_30 = auth_main
    else:
        # Take the picture of the user
        print("Taking the Picture of the user")
        cap = cv2.VideoCapture(1)
        ret, frame = cap.read()
        cv2.imwrite("data/" + user + "/temp.jpg", frame)
        cap.release()
        # Authenticate the user
        auth_main = face_recognition(user, "data/" + user +
"/temp.jpg")
        # auth_main = True
        check_30 = auth_main

    if not auth_main:
        print("Unable to Authenticate the User")
        return None

    # Start a infinite loop to authenticate the user for 5
minutes
    start_time = time.time()
    start_time_30 = time.time()
    while time.time() - start_time < 5 * 60:

        # Randomly check for authentication either by face
or voice or keystroke every 30 seconds
        if not check_30:
            choice = np.random.choice(["face", "voice",
"keystroke"])
            print("Choice: ", choice)
            start_time_30 = time.time()
            check_30 = True
            auth = False
            if choice == "face":
                # Take the picture of the user
                cap = cv2.VideoCapture(1)
```

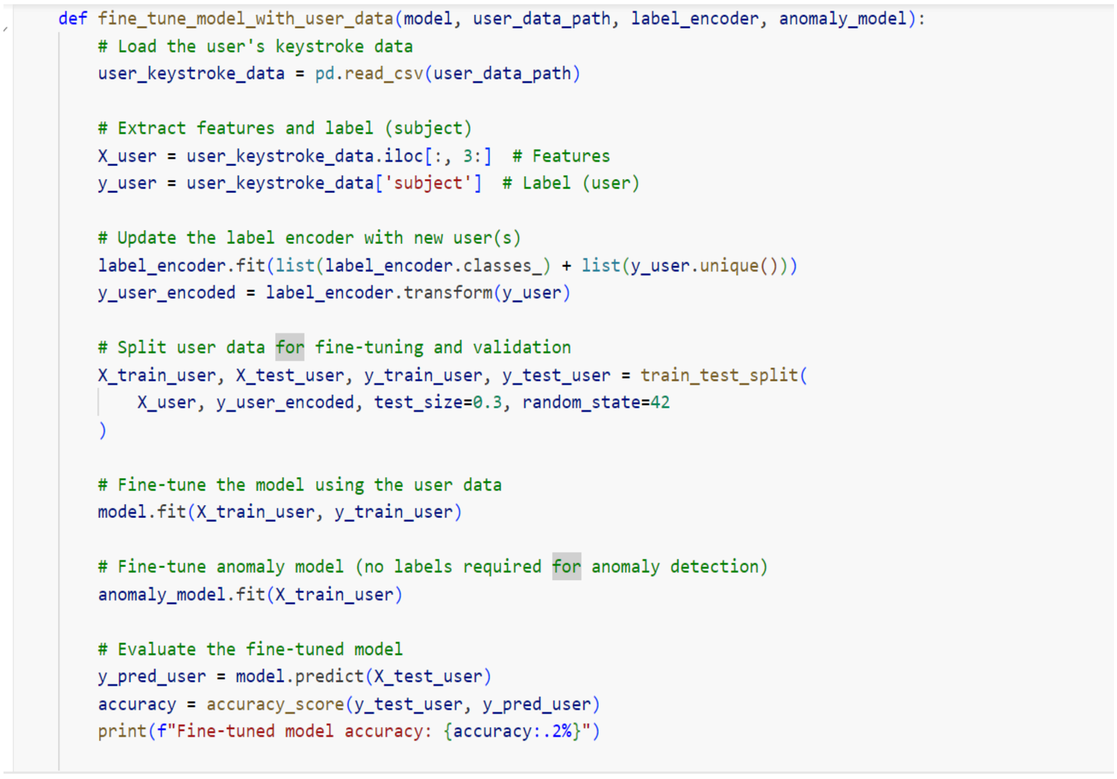


```
                ret, frame = cap.read()
                cv2.imwrite("data/" + user + "/temp.jpg",
frame)
                cap.release()
                # Authenticate the user
                auth = face_recognition(user, "data/" +
user + "/temp.jpg")
            elif choice == "voice":
                # Record the voice of the user
                print("Recording the voice of the user")
                voice_path = collect_voice(user,
save_database=False)
                # Authenticate the user
                auth = voice_authentication(user,
voice_path)
            elif choice == "keystroke":
                # Authenticate the user
                print("Authenticating using keystroke
dynamics...")
                # Collect new keystroke data
                new_keystroke_features = collect_keystroke(
                    user, for_authentication=False,
save_database=False
                )

                if new_keystroke_features is not None:
                    # Authenticate the user
                    risk_level, similarity =
keystroke_authentication(
                        user, new_keystroke_features
                    )
                    # print(f"Risk Level: {risk_level}")
                    # print(f"Cosine Similarity:
{similarity:.4f}")

                    if risk_level == "Low Risk":
                        auth = True
                    else:
                        auth = False

            if auth:
                print("User Authenticated")
            else:
                print("User Authenticated failed")
                break

        if time.time() - start_time_30 < 30:
            continue
        else:
            check_30 = False

    return None

if __name__ == "__main__":
    main()
```

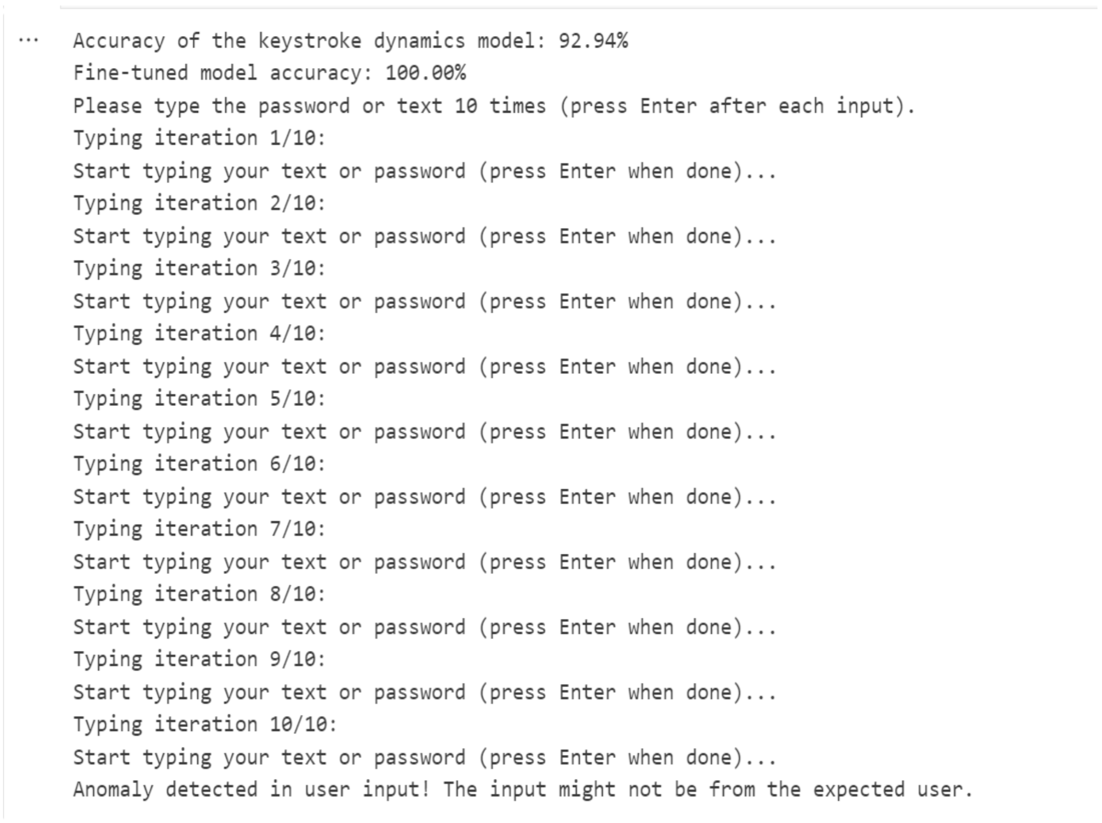
6. Anomaly Detection



```python
# Encode user labels as integers
label_encoder = LabelEncoder()
y_encoded = label_encoder.fit_transform(y)

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y_encoded, test_size=0.3, random_state=42, stratify=y_encoded)

# Train a Random Forest Classifier
rf_model = RandomForestClassifier(n_estimators=100, random_state=42)
rf_model.fit(X_train, y_train)

# Predict on the test set
y_pred = rf_model.predict(X_test)

# Evaluate the model's performance
accuracy = accuracy_score(y_test, y_pred)
print(f"Accuracy of the keystroke dynamics model: {accuracy:.2%}")

# Save the model
save_model(rf_model, 'keystroke_model.pkl')

# Train an anomaly detection model (Isolation Forest)
anomaly_model = IsolationForest(n_estimators=100, random_state=42)
anomaly_model.fit(X_train)
```



```python
def fine_tune_model_with_user_data(model, user_data_path, label_encoder, anomaly_model):
    # Load the user's keystroke data
    user_keystroke_data = pd.read_csv(user_data_path)

    # Extract features and label (subject)
    X_user = user_keystroke_data.iloc[:, 3:]  # Features
    y_user = user_keystroke_data['subject']  # Label (user)

    # Update the label encoder with new user(s)
    label_encoder.fit(list(label_encoder.classes_) + list(y_user.unique()))
    y_user_encoded = label_encoder.transform(y_user)

    # Split user data for fine-tuning and validation
    X_train_user, X_test_user, y_train_user, y_test_user = train_test_split(
        X_user, y_user_encoded, test_size=0.3, random_state=42
    )

    # Fine-tune the model using the user data
    model.fit(X_train_user, y_train_user)

    # Fine-tune anomaly model (no labels required for anomaly detection)
    anomaly_model.fit(X_train_user)

    # Evaluate the fine-tuned model
    y_pred_user = model.predict(X_test_user)
    accuracy = accuracy_score(y_test_user, y_pred_user)
    print(f"Fine-tuned model accuracy: {accuracy:.2%}")
```



```
Accuracy of the keystroke dynamics model: 92.94%
Fine-tuned model accuracy: 100.00%
Please type the password or text 10 times (press Enter after each input).
Typing iteration 1/10:
Start typing your text or password (press Enter when done)...
Typing iteration 2/10:
Start typing your text or password (press Enter when done)...
Typing iteration 3/10:
Start typing your text or password (press Enter when done)...
Typing iteration 4/10:
Start typing your text or password (press Enter when done)...
Typing iteration 5/10:
Start typing your text or password (press Enter when done)...
Typing iteration 6/10:
Start typing your text or password (press Enter when done)...
Typing iteration 7/10:
Start typing your text or password (press Enter when done)...
Typing iteration 8/10:
Start typing your text or password (press Enter when done)...
Typing iteration 9/10:
Start typing your text or password (press Enter when done)...
Typing iteration 10/10:
Start typing your text or password (press Enter when done)...
Anomaly detected in user input! The input might not be from the expected user.
```