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Table of Contents

1. Introduction
 - 1.1 Synopsis
 - 1.2 Keywords
2. Literature Review
 - 2.1 Reflections
3. Background
 - 3.1 Behavioral Biometrics and Authentication
 - 3.2 Sensor Technology in Smartphones
 - 3.3 Neural Networks for User Authentication
4. Data Collection and Preprocessing
 - 4.1 Raw Sensor Data Description
 - 4.2 Data Preprocessing Pipeline
 - 4.3 Feature Extraction Methods
5. Testing Methodologies
 - 5.1 Data Splitting Strategy
 - 5.2 Cross-Validation Approach
 - 5.3 Neural Network Architecture Design
 - 5.4 Initial Parameter Settings
 - 5.5 Evaluation Metrics
6. Evaluation
 - 6.1 Initial Model Performance
 - 6.2 Intra-User and Inter-User Variance Analysis
 - 6.3 User Similarity Analysis
 - 6.4 Biometric Performance Metrics (FAR, FRR, EER)
7. Optimization
 - 7.1 Feature Selection Methods
 - 7.2 Neural Network Parameter Tuning
 - 7.3 Performance Comparison
8. Discussion
 - 8.1 Privacy and Security Implications
 - 8.2 Usability Considerations

- 8.3 Real-World Deployment Challenges

9. Conclusion

10. References

11. Appendix

1. Introduction

The proliferation of smartphones and wearable devices has transformed how individuals interact with technology; these devices have become repositories of sensitive personal, financial, and health information. As mobile devices become increasingly integral to daily life, the security of user authentication mechanisms has emerged as a critical concern. Traditional authentication methods including passwords, PINs, and pattern locks suffer from significant vulnerabilities in forms such as shoulder-surfing attacks, brute-force attempts, and user inconvenience due to memorization requirements.

These limitations have drawn much attention to behavioral biometric authentication as a promising alternative. Unlike the traditional physiological biometrics, such as fingerprints or face recognition, behavioral biometrics seek unique patterns in users' actions picked up through embedded sensors. Among these, acceleration-based authentication using smartphone accelerometer and gyroscope sensors has gained particular prominence for their non-intrusiveness and wide proliferation in modern mobile devices.

This research investigates the development and optimization of a neural network-based user authentication system utilizing acceleration and gyroscope data from smartphones. The proposed system would analyze motion patterns during natural user interactions in order to provide continuous, transparent authentication that could enhance security without impacting the user experience. The most relevant challenges that this study seeks to address include the extraction of features from raw sensor data, the design of the neural network architecture, performance optimization, and evaluation through metrics specific to biometrics such as FAR, FRR, and EER.

1.1 Synopsis

This report provides an exhaustive analysis of user authentication for smartphones using acceleration techniques. After this Introduction section comes the discussion on the Literatures Reviewed, where 10 journals from 2022 to 2025 involving authentication using sensors have been discussed. Then comes the Background section to give initial concepts of Behavioral Biometrics and Neural Networks.

This is because Data Collection and Preprocessing provides information about how raw data from the accelerometers and gyros is collected and features are extracted for classification, while Testing Methodologies gives information on how the network is designed and trained for testing to determine its performance measures such as FRR and EER.

The Evaluation section deals with initial modeling performance analysis, analysis of intra-user and inter-user variance, as well as biometric metric performance analysis. The Optimization section discusses feature selection techniques, optimization techniques for neural network parameters, as well as performance optimizations. The Discussion section reviews privacy concerns, security concerns, as well as usability requirements for analysis for the new system approach being put forth. The Conclusion section reviews feasibility for acceleration-based authentication biometric systems.

1.2 Keywords

NN – Neural Network

FAR – False Acceptance Rate

FRR – False Rejection Rate

EER – Equal Error Rate

LOUO – Leave One User Out

FFT – Fast Fourier Transform

PCA – Principal Component Analysis

SVM – Support Vector Machine

LSTM – Long Short-Term Memory

CNN – Convolutional Neural Network

ANOVA – Analysis of Variance

MI – Mutual Information

2. Literature Review

The need for reliable and effortless user authentication has further been amplified by the growing use of smartphones and wearables. Motion-based authentication techniques for smartphones and wearables have received significant interest because of their non-intrusive nature and capability for continuous authentication. This paper reviews the current state of user authentication by analyzing data from sensors and also reviews ten recently published scientific documents (2022-2025) to envisage advancements in user authentication techniques using sensors.

1. Smartphone User Identification/Authentication Using Accelerometer and Gyroscope Data (2025)

This comprehensive study investigates smartphone user identification and authentication using accelerometer and gyroscope data from the Hand Movement, Orientation, and Grasp (HMOG) dataset. The research employs multiple machine learning approaches including traditional classifiers, deep learning models (LSTM, CNN), and ensemble voting classifiers. Preprocessing techniques and feature selection strategies were systematically explored to optimize data quality. The study found that accelerometer data outperformed gyroscope data in authentication accuracy. Notably, combining accelerometer and gyroscope data using LSTM achieved near-perfect authentication accuracy of 99.7%. The data was collected at 20 Hz from 51 users performing 18 activities over approximately 3 minutes each. This work demonstrates the effectiveness of multi-sensor fusion and deep learning for achieving high-accuracy biometric authentication.

2. Identity Authentication Based on Sensors of Smartphone (2022)

This research proposes an identity authentication system utilizing smartphone motion sensors to collect data during user action sequences, specifically when users wave their phones. The study invited 13 participants and collected approximately 350 samples per person at a sampling frequency of 200 Hz. DenseNet, a densely connected convolutional neural network, was selected as the classification model to validate system performance. The neural network architecture effectively recognized user identity patterns embedded in motion sensor data, achieving an authentication accuracy of 96.69%. The research demonstrates that user action features captured through motion sensors provide sufficient discriminability for identity authentication without relying on passwords or traditional biometric identification. This approach emphasizes the potential for implicit, continuous authentication based on natural user behavior patterns.

3. Performance Evaluation of Mobile Sensor for Context Awareness User Authentication (2022)

This study conducted a comprehensive evaluation of different mobile device sensors for continuous and transparent user authentication. The research analyzed gyroscope, accelerometer, linear accelerometer, proximity, gravity, and magnetometer sensor data collected from multiple users. Using a Feedforward Neural Network for classification after extracting features from each sensor type, the study identified the most effective sensor through performance evaluation. The accelerometer emerged as the best-performing sensor, exhibiting sufficient discriminability, stability, and reliability for active and continuous authentication. The experimental results demonstrated that the smartphone accelerometer sensor achieved a best overall Equal Error Rate (EER) of 6.55%, indicating strong potential for practical deployment. This research provides valuable guidance for sensor selection in multi-sensor authentication systems, highlighting the accelerometer's superior performance characteristics.

4. Enhancing Smartphone Security with Human-Centric Authentication (2024)

This recent work proposes a lightweight bi-model fallback authentication technique combining dynamic security questions and finger pattern recognition using inertial measurement units (IMU). The system captures finger movements using four inertial sensors: accelerometer, gyroscope, gravity sensor, and magnetometer. Users are prompted to sign their name on the smartphone screen while the system records IMU readings along with finger movement and velocity during the signature. Importantly, the scheme does not store the actual signature image, making it difficult for attackers to reproduce the user's movements and holding style. The research demonstrates that users exhibit unique holding patterns and hand movements when using smartphones, which can be effectively captured and analyzed using inertial sensors for authentication purposes. This multi-modal approach enhances security by combining behavioral biometrics with dynamic challenge-response mechanisms.

5. Real-World Smartphone-Based Gait Recognition (2022)

This paper introduces an advanced real-world smartphone-based gait recognition system designed to recognize subjects within unconstrained environments. Unlike controlled laboratory settings, the research focuses on naturalistic walking scenarios where users carry smartphones in various positions. The system analyzes gait patterns captured by accelerometer and gyroscope sensors during normal walking activities. The research addresses challenges including variable device placement, walking speed variations, and environmental factors that affect gait patterns. By employing robust feature extraction and classification techniques, the system achieved high recognition accuracy even under real-world conditions. This work emphasizes the importance of developing authentication systems that function reliably in practical deployment scenarios rather than idealized laboratory environments, contributing valuable insights for real-world biometric system design.

6. Smartphone-Based Gait Recognition Dataset (2025)

This recent contribution provides a large-scale naturalistic gait recognition dataset comprising data from 390 participants. Smartphone inertial sensors including triaxial accelerometer, gyroscope, and magnetometer captured data at 30 Hz sampling rate, totaling 46.8 kilometers of walking across approximately 585 minutes. Participants held devices in their dominant hand during data collection, ensuring realistic usage scenarios. Multiple sessions per participant on different days were conducted to ensure robust representation of intra-subject variability, which is crucial for developing authentication systems that remain accurate over time. The comprehensive metadata and documentation support deep learning model development, gait-based authentication systems, and benchmarking of recognition algorithms under real-world conditions. This dataset represents a significant resource for the research community, enabling comparative evaluation of authentication approaches.

7. Convolutional Neural Networks for User Identification Based on Motion Sensors (2020-2023)

This research proposes a deep learning approach for smartphone user identification based on analyzing motion signals recorded by accelerometer and gyroscope sensors. The study employs Convolutional Neural Networks (CNN) to automatically learn discriminative features from raw or minimally preprocessed sensor data, eliminating the need for manual feature engineering. CNNs are particularly effective for processing time-series sensor data due to their ability to capture temporal patterns and spatial relationships within multi-dimensional sensor readings. The research demonstrates that deep learning models can achieve superior performance compared to traditional machine learning approaches that rely on handcrafted features. By learning hierarchical feature representations directly from data, CNNs provide robust and generalizable authentication models suitable for diverse user populations and usage scenarios.

8. User Identification Using Deep Learning and Human Activity Recognition (2023)

This study utilizes Long Short-Term Memory (LSTM) classifiers for building user identification models based on time-series data from mobile motion sensors. LSTMs are specialized recurrent neural networks designed to capture long-term dependencies in sequential data, making them well-suited for analyzing temporal patterns in sensor readings. The research focuses on human activity recognition as a foundation for user identification, leveraging the observation that individuals perform common activities with unique behavioral signatures. By training LSTM networks on motion sensor data collected during daily activities such as walking, sitting, and standing, the system learns user-specific patterns that enable accurate identification. The study achieved high identification accuracy, demonstrating that LSTM-based approaches effectively model the temporal dynamics inherent in behavioral biometric data.

9. Integrating Motion Sensors Based on Deep Neural Networks (2025)

This recent article proposes the Accumulated Data Assessment Probe Model (ADAPM) for analyzing motion sensor data using deep neural networks and fuzzy evaluation techniques. The model focuses on refining data accuracy from collected sensor inputs by recognizing less disruptive data patterns across different intervals. A neural network component identifies interruptions during recurrent training, while fuzzy evaluation extracts significant derivatives from continuous observation sequences. Lower-order fuzzy derivatives are used to train the neural network, providing constructive support for monitoring applications. The ADAPM model effectively separates sensor data into interrupted and uninterrupted sequences, minimizing disruptions and maximizing activity detection accuracy. This innovative combination of deep neural networks and fuzzy logic enhances data accuracy and facilitates precise real-time monitoring, representing a significant advancement in sensor-based authentication systems.

10. A Survey on Behavioral Biometric Authentication on Smartphones (2018-2024)

This comprehensive survey examines behavioral biometric authentication methods on smartphones, including touch dynamics, keystroke dynamics, and gait recognition. The research provides an extensive review of active authentication systems that verify or identify users implicitly and continuously during device usage. The survey presents the components and operating processes of active authentication systems, followed by an overview of state-of-the-art behavioral biometric traits used to develop authentication solutions. The authors discuss issues, strengths, and limitations associated with each behavioral biometric trait, providing a comparative analysis. Challenges and open research problems in the field are presented, including scalability, resistance to sophisticated attacks, and system usability. This survey serves as a comprehensive reference for researchers and practitioners developing behavioral biometric authentication systems, highlighting the evolution of the field and identifying future research directions.

2.1 Reflections

The reviewed literature demonstrates substantial progress in acceleration-based user authentication over the period 2022-2025. Several key trends emerge from this analysis:

Deep Learning Dominance: Modern authentication systems increasingly employ deep learning architectures including CNN, LSTM, and hybrid models, which achieve superior performance compared to traditional machine learning classifiers. Deep learning models automatically learn discriminative features from raw or minimally processed sensor data, reducing reliance on manual feature engineering.

Multi-Sensor Fusion: Research consistently shows that combining data from multiple sensors (accelerometer, gyroscope, magnetometer) enhances authentication accuracy. Multi-sensor approaches leverage complementary information sources, improving system robustness against spoofing attacks and environmental variations.

High Accuracy Metrics: Recent systems achieve impressive performance metrics, with accuracies exceeding 96% and Equal Error Rates below 7% in many cases. These results indicate that acceleration-based authentication has matured to a level suitable for practical deployment in security-critical applications.

Real-World Evaluation: There is a growing emphasis on evaluating authentication systems under realistic, unconstrained conditions rather than controlled laboratory settings. Large-scale datasets capturing naturalistic user behavior enable more robust system development and reliable performance assessment.

Challenges Remain: Despite significant progress, challenges persist including scalability to large user populations, resistance to adversarial attacks, adaptation to changing user behavior over time, and balancing security with usability. Ongoing research addresses these issues through advanced optimization techniques, continuous learning mechanisms, and user-centric design approaches.

3. Background

3.1 Behavioral Biometrics and Authentication

Behavioral biometrics refers to the measurement and analysis of unique patterns in human behavior for identity verification purposes. Unlike physiological biometrics (fingerprints, iris scans, facial features) which measure inherent physical characteristics, behavioral biometrics capture learned or acquired traits that manifest through user actions. Common behavioral biometric modalities include gait recognition, keystroke dynamics, signature dynamics, voice patterns, and device interaction patterns.

Acceleration-based authentication represents a specific category of behavioral biometrics that analyzes motion patterns captured by inertial sensors. When users interact with smartphones or wearable devices, their movements generate distinctive acceleration signatures that reflect individual motor control patterns, physical characteristics, and habitual behaviors. These motion patterns exhibit sufficient inter-user variability to enable user discrimination while maintaining reasonable intra-user consistency to support reliable authentication.

The primary advantages of behavioral biometric authentication include:

- **Non-intrusiveness:** Authentication occurs transparently during normal device usage without requiring explicit user actions
- **Continuous verification:** Systems can verify user identity throughout a session rather than only at initial login
- **Difficulty of replication:** Behavioral patterns are challenging for attackers to observe and reproduce accurately
- **Cost-effectiveness:** Leverages existing smartphone sensors without requiring additional hardware
- **User acceptance:** Transparent authentication reduces friction in the user experience

3.2 Sensor Technology in Smartphones

Modern smartphones incorporate multiple inertial measurement unit (IMU) sensors that capture device motion and orientation:

Accelerometer: Measures linear acceleration along three orthogonal axes (x, y, z) in meters per second squared. The accelerometer detects both device movement and gravitational acceleration, enabling applications such as screen rotation, step counting, and gesture recognition. Typical smartphone accelerometers sample at frequencies ranging from 30 Hz to 200 Hz with measurement ranges of $\pm 2g$ to $\pm 16g$.

Gyroscope: Measures angular velocity around three axes in radians per second or degrees per second. The gyroscope captures rotational motion, complementing the accelerometer by providing information about device orientation changes. Gyroscopes typically operate

at similar sampling frequencies as accelerometers and provide measurement ranges of ± 250 to ± 2000 degrees per second.

Magnetometer: Measures magnetic field strength along three axes, primarily used for compass functionality and orientation determination. While less commonly used for authentication, magnetometer data can provide additional discriminative information in multi-sensor fusion approaches.

Gravity Sensor: A software-based sensor derived from accelerometer readings that isolates gravitational acceleration from total acceleration. This virtual sensor simplifies the extraction of device orientation information.

For user authentication applications, accelerometer and gyroscope sensors provide the most discriminative information, capturing both the gross motor patterns (walking style, arm movements) and fine motor patterns (hand tremor, gesture dynamics) that characterize individual users.

3.3 Neural Networks for User Authentication

Neural networks have emerged as the dominant approach for learning complex patterns in sensor-based authentication systems. Several neural network architectures are commonly employed:

Feedforward Neural Networks (FFNN): Multi-layer perceptron networks with one or more hidden layers between input and output layers. FFNNs are effective for processing fixed-length feature vectors extracted from sensor data. They learn non-linear decision boundaries that separate legitimate users from impostors based on handcrafted statistical features.

Convolutional Neural Networks (CNN): Originally developed for image processing, CNNs have proven highly effective for time-series sensor data analysis. Convolutional layers automatically learn local patterns in sensor readings, reducing the need for manual feature engineering. CNNs excel at capturing spatial and temporal correlations within multi-dimensional sensor streams.

Recurrent Neural Networks (RNN) and LSTM: These architectures are specifically designed for sequential data processing. LSTMs address the vanishing gradient problem of traditional RNNs, enabling the learning of long-term dependencies in sensor time-series. LSTMs are particularly effective when authentication decisions depend on temporal patterns spanning multiple seconds of sensor data.

Hybrid Architectures: Recent research increasingly employs hybrid models combining CNNs for feature extraction with LSTMs for temporal modeling, leveraging the strengths of both architectures.

For this research, we focus on feedforward neural networks trained on handcrafted time-domain and frequency-domain features, providing a baseline approach that balances performance, interpretability, and computational efficiency.

4. Data Collection and Preprocessing

4.1 Raw Sensor Data Description

The dataset comprises raw accelerometer and gyroscope readings collected from 10 users over two separate days. Data collection procedures followed naturalistic usage scenarios to ensure realistic representation of user behavior:

Sampling specifications:

- Sampling frequency: 30Hz (samples per second)
- Duration per user per day: 6 minutes of continuous recording
- Total users: 10 participants
- Collection days: Two separate days per user (Day 1 and Day 2)

Sensor data format:

Each sensor provides three-dimensional measurements:

- Accelerometer: $[a_x, a_y, a_z]$ in m/s^2 representing linear acceleration along x, y, z axes
- Gyroscope: $[\omega_x, \omega_y, \omega_z]$ in rad/s or deg/s representing angular velocity around x, y, z axes

The raw sensor data exhibits temporal variations reflecting user movement patterns, device orientation changes, and environmental factors. This time-series data must be preprocessed and transformed into discriminative features suitable for neural network training.

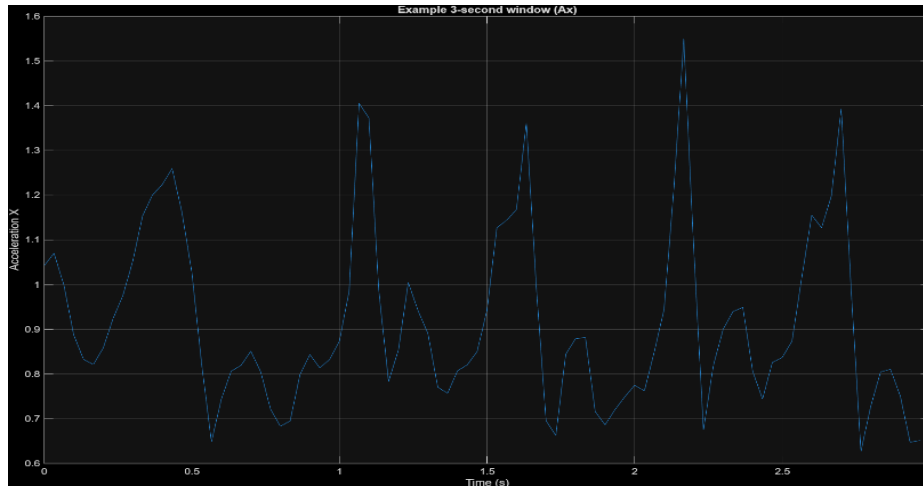
4.2 Data Preprocessing Pipeline

Raw sensor data undergoes several preprocessing steps to enhance data quality and prepare it for feature extraction:

Segmentation

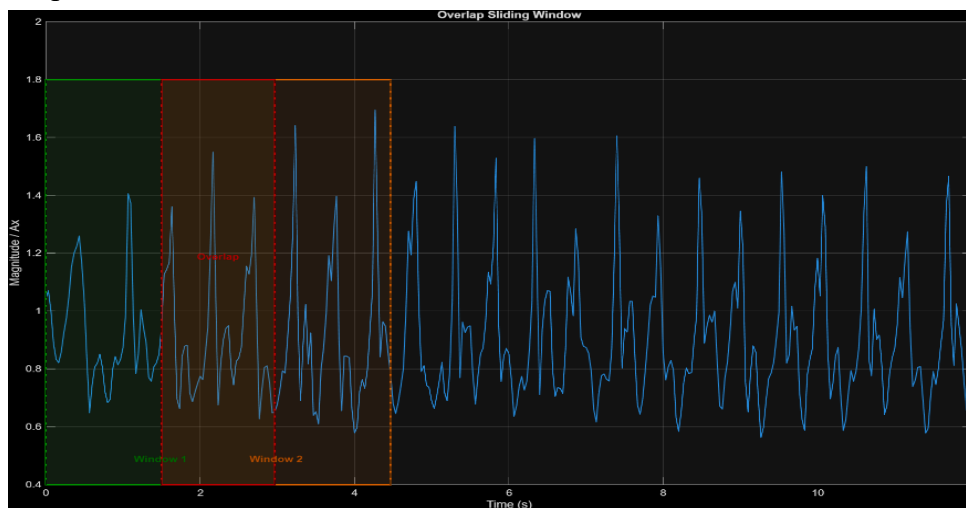
Continuous sensor streams are divided into fixed-length windows for analysis. Each window represents a distinct sample:

- Window size: 3 seconds



The figure above shows a single 3 second segment extracted from x axis of acceleration. This segment is long enough to capture several gait cycles while also short enough to react quickly. After the baseline model we will finetune the window size to optimize the final model.

- Overlap: 50% overlap between consecutive windows to capture transitional patterns



Sliding window strategy is used to transform each continuous recording into a sequence of fixed-length samples. Each 3 second window is overlapped by 50% by the successive window (Shaded region). By overlapping we can preserve strong temporal continuity between adjacent window segments.

By doing this we extracted $3 \times 30 = 90$ samples per each axis and a total of $90 \times 6 = 540$ segmented windows successfully.

Step 4: Data Labeling

Each segmented sample is labeled with:

- User ID: Identifies which user generated the sample
- Day: Indicates whether sample is from Day 1 or Day 2
- Sample number: Sequential identifier within user's data

4.3 Feature Extraction Methods

One of the most important process in building a model is feature extraction, because choosing the best features will enable the model to train smoothly and accurately to differentiate between classes One of the most important processes in building a model is feature extraction, because choosing the best features will enable the model to train smoothly and accurately to differentiate between classes

Time-Domain Features (66 features)

Statistical features computed directly from sensor time-series for each axis and sensor:

Feature	Description	Equation
Mean	average level of the signal, capturing overall bias or offset	$\mu = \frac{1}{N} \sum_{i=1}^N x_i$
Standard deviation and variance	dispersion of the signal, reflecting variability in movement	$\text{Var} = \sigma^2 = \frac{1}{N} \sum_{i=1}^N (x_i - \mu)^2$ $\text{Std} = \sigma = \sqrt{\text{Var}}$
Minimum and maximum	range of motion amplitudes	$x_{\min} = \min_{1 \leq i \leq N} x_i, x_{\max} = \max_{1 \leq i \leq N} x_i$
Root-mean-square (RMS)	energy-like measure sensitive to both amplitude and duration of activity energy-like measure sensitive to both amplitude and duration of activity	$\text{RMS} = \sqrt{\frac{1}{N} \sum_{i=1}^N x_i^2}$
Zero-crossing rate (ZCR)	proportion of sign changes between successive samples, linked to oscillation frequency and noisiness	$\text{ZCR} = \frac{1}{2(N-1)} \sum_{i=1}^{N-1} \text{sgn}(x_i) - \text{sgn}(x_{i+1}) $

Signal magnitude area (SMA)	average absolute amplitude over the window, providing a measure of movement intensity	$\text{SMA} = \frac{1}{N} \sum_{i=1}^N x_i $
Energy	mean squared amplitude, capturing overall power of the motion	$E = \sum_{i=1}^N x_i^2$
Median	robust central tendency measure less affected by outliers	$\text{Median} = \begin{cases} x_{(\frac{N+1}{2})} & \text{if } N \text{ is odd} \\ \frac{1}{2}(x_{(\frac{N}{2})} + x_{(\frac{N}{2}+1)}) & \text{if } N \text{ is even} \end{cases}$
Skewness	captures asymmetry of signal distribution, often linked to asymmetrical	$\text{Skewness} = \frac{\frac{1}{N} \sum_{i=1}^N (x_i - \mu)^3}{\sigma^3}$
Kurtosis	measures “tailedness” or presence of impulsive movements	$\text{Kurtosis} = \frac{\frac{1}{N} \sum_{i=1}^N (x_i - \mu)^4}{\sigma^4}$ <p>(Some definitions subtract 3 to give excess kurtosis.)</p>
Peak-to-peak amplitude	difference between max and min, effective for identifying stride phases or sharp rotational peaks	$A_{p2p} = x_{\max} - x_{\min}$

These features are computed for each axis of accelerometer and gyroscope (6 axes total), resulting in 66 time-domain features.

Frequency-Domain Features (42 features)

Frequency-domain features capture spectral characteristics of motion patterns. Fast Fourier Transform (FFT) converts time-series data to frequency domain:

$$X(f) = \sum_{n=0}^{N-1} x(n)e^{-j2\pi fn/N}$$

Extracted frequency-domain features include:

1. **Dominant frequency** – frequency at which the magnitude spectrum is maximal; in gait, this is related to step cadence.

2. **Spectral centroid** – weighted average frequency, representing the “center of mass” of the spectrum.
3. **Band power** – average squared magnitude, reflecting the overall spectral energy.
4. **Spectral entropy** – Shannon entropy of the normalized magnitude spectrum, measuring how concentrated or spread the spectral energy is.
5. **Spectral spread**– variance of frequency components around the centroid; indicates how concentrated or dispersed the spectral energy is.
6. **Spectral roll-off 95%**– the frequency below which 95% of spectral energy accumulates; useful for distinguishing smooth vs. sharp movement patterns.
7. **Spectral flatness**– ratio of geometric to arithmetic mean of the spectrum; measures noisiness/tonality (flatness → noise-like, low flatness → tonal/periodic).

These features are computed for each sensor axis, yielding 42 frequency-domain features.

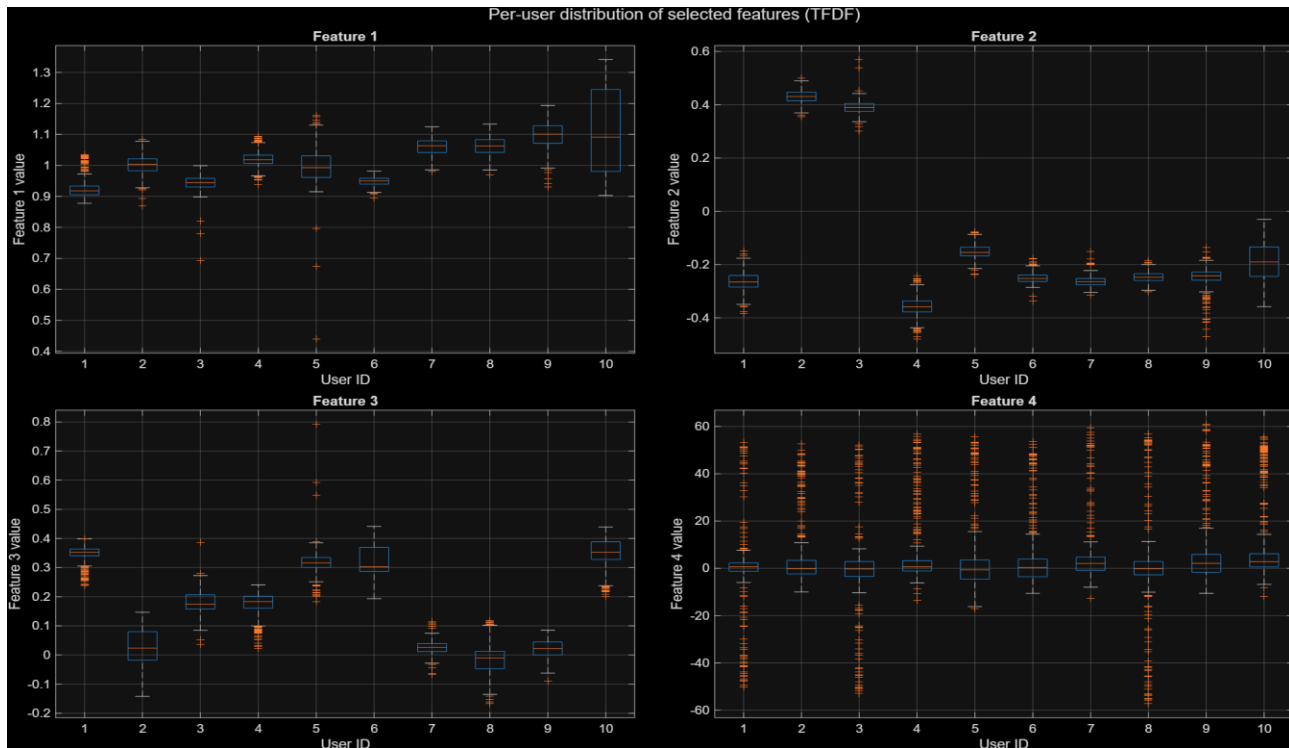
Combined Feature Vector

The final feature vector for each sample contains 108 features:

- 66 time-domain features
- 42 frequency-domain features
- Total: 108-dimensional feature vector per sample

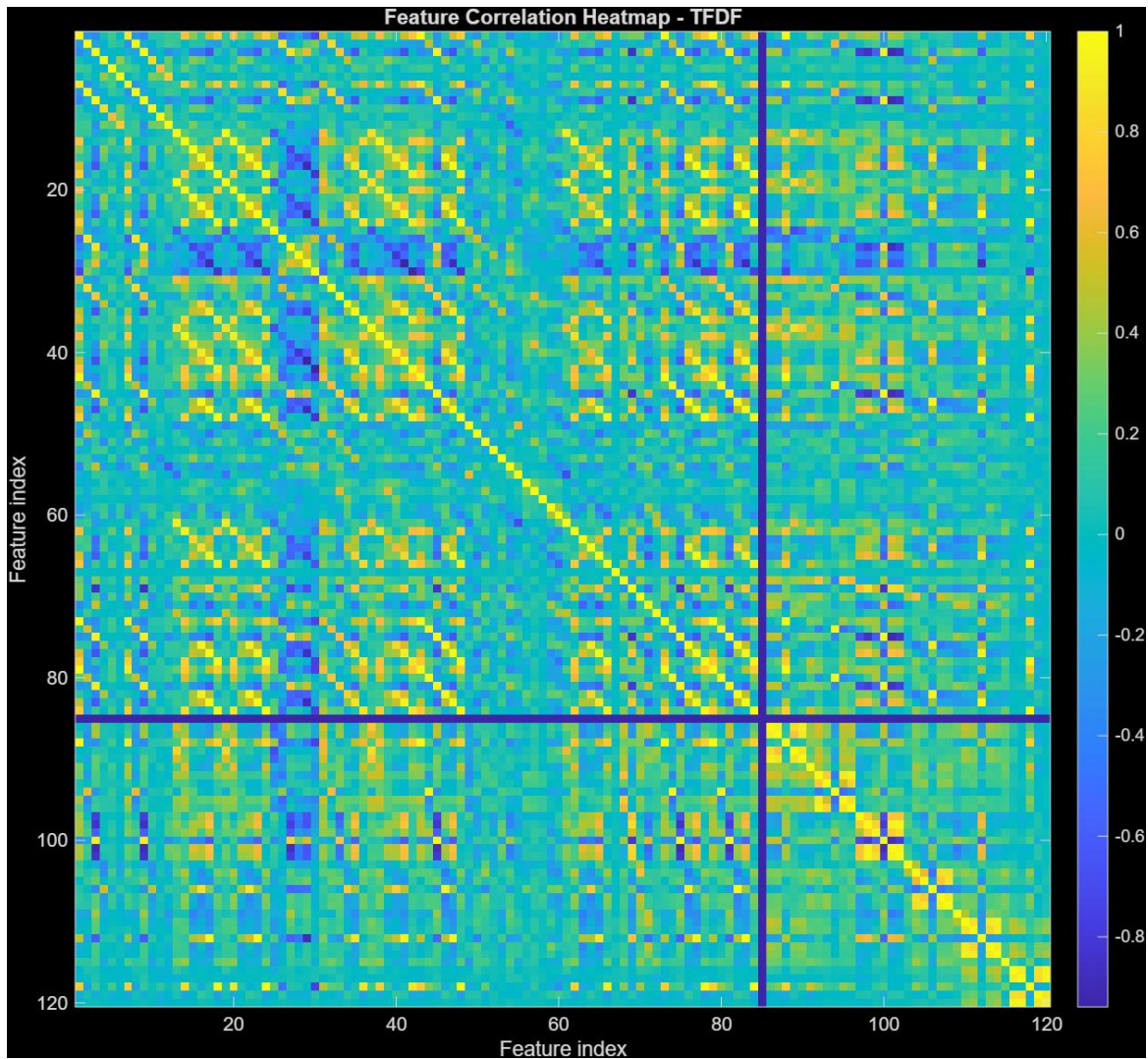
This comprehensive feature set captures both temporal dynamics and spectral characteristics of user motion patterns, providing rich information for neural network classification.

- Per-user distribution of selected features (TFDF) – boxplots



By comparing distribution of just four TFDF features we can clearly see that they many feature exhibit separated medians and tight intra-user variance specially for users 2,5 and 10. This is good behavior for authentication as a good feature should be stable for same user while its value differ across different users. This confirms that engineered features captures user specific characteristics of gait

- Feature correlation heatmap (TFDF) Feature correlation heatmap (TFDF)

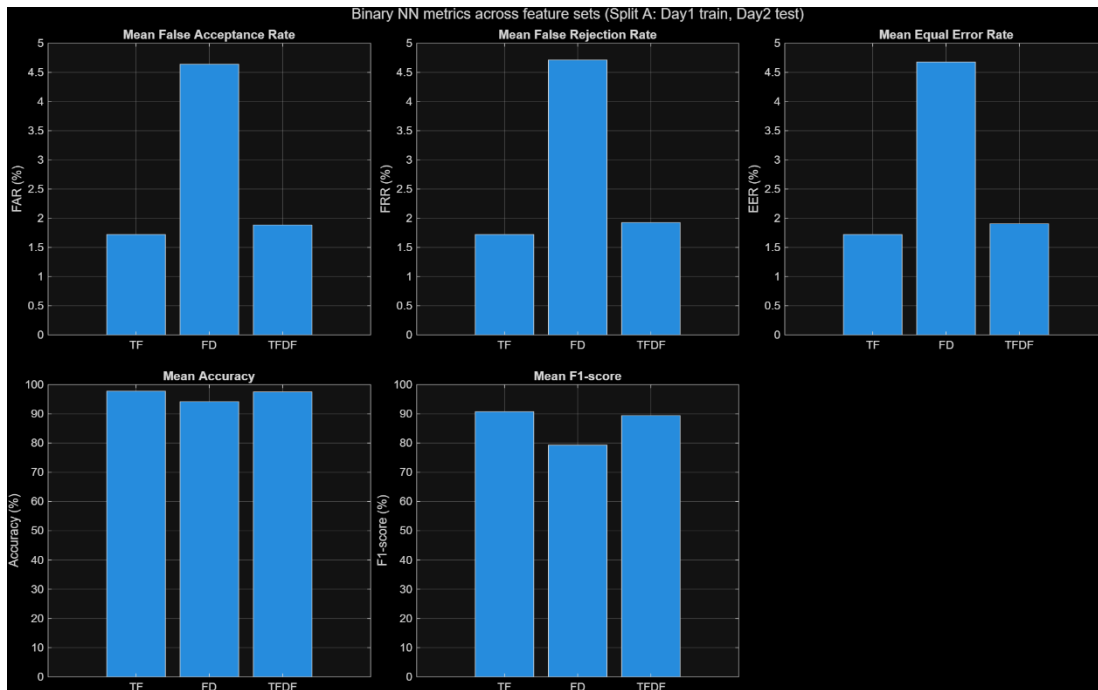
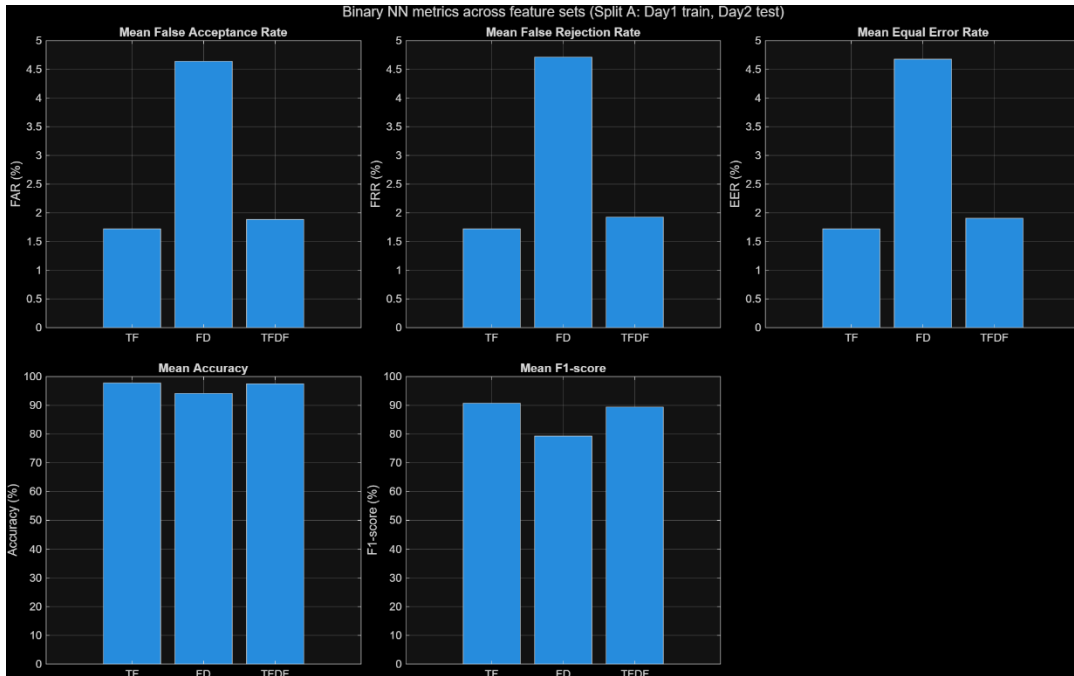


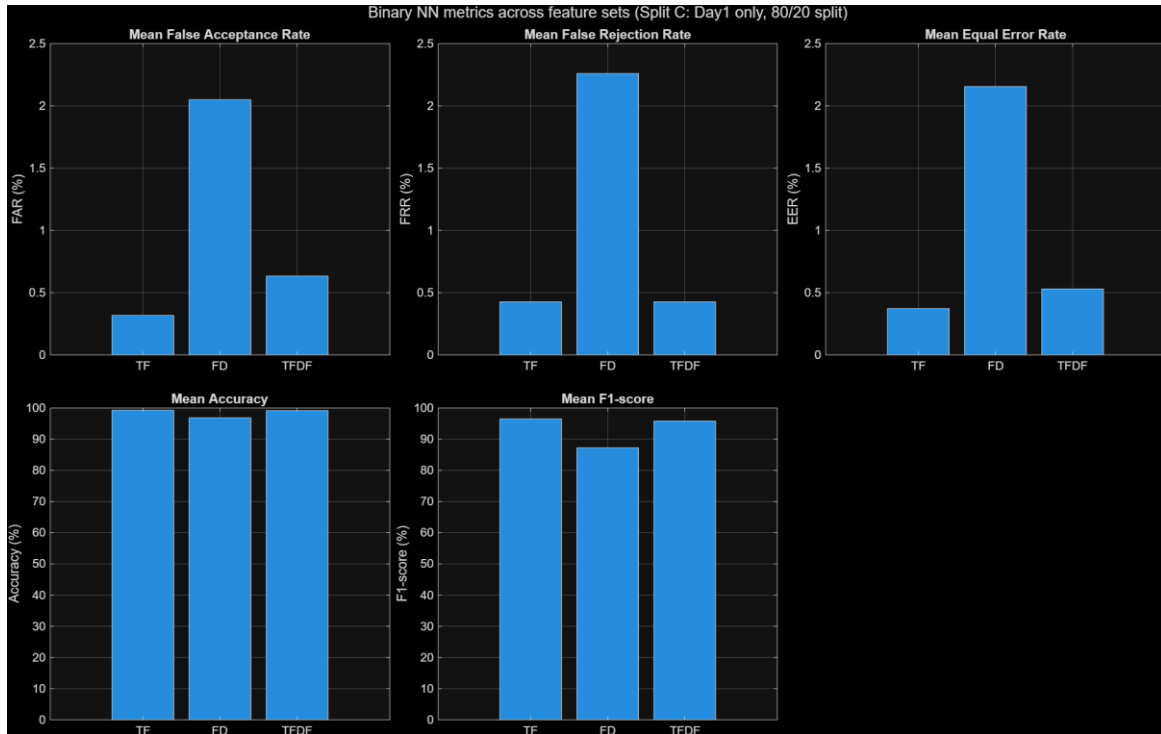
Additionally by looking at the correlation heatmap of features we can see that some subsets of features are highly correlated this is because many statistics are derived from same underlying signals. However it seems that full TFDF set contain both complementary and redundant information and those will be addressed in the optimization section

5. Testing Methodologies

Feature selection

- Validation metrics for TF vs FD vs TFDF





As shown in the figure FD feature set is the least performing feature set .TFDF has the lowest FAR, FRR and EER average while having the highest accuracy among them. Also recent research has proven that the mixed features (TFDF) yield the best results. By these findings we can safely state that the TFDF feature set is best for the training of the Neural Network.

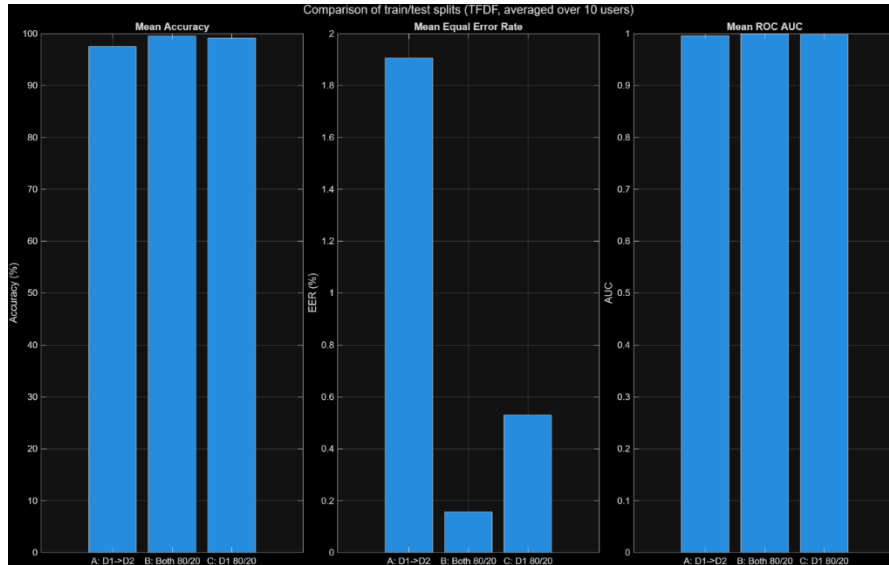
5.1 Data Splitting Strategy

To examine how training and testing splits affect the performance these train/test following combinations were considered;

1. **Split A – Day1 train, Day2 test:**
All windows from Day 1 are used exclusively for training, while all windows from Day 2 are used exclusively for testing. This **cross-day** setting mimics a realistic deployment where the model is enrolled on one day and used on another.
2. **Split B – Both days combined, 80/20 split:**
Windows from both days are pooled, then randomly split into 80% training and 20% testing. This often yields optimistic performance because train and test samples may come from similar temporal conditions.
3. **Split C – Day1 only, 80/20 split:**
Only Day 1 windows are considered; 80% are used for training and 20% for testing. This measures within-session performance without any cross-day variability.

For each possible split Accuracy, EER and AUC was calculated as follows;

Only the results of TFDF features set is taken into account for choosing the data split action as we already have chosen the TFDF as our feature set for the experiment.



Per-user evaluation metrics (Split A: Day1 train, Day2 test, TFDF features):

User	Accuracy	AUC	Precision	Recall	F1	FAR	FRR	EER
1	94.836	0.98035	68.671	88.934	77.5	6.6485	6.1475	6.398
2	98.279	0.99976	85.315	100	92.075	0.18215	0	0.091075
3	98.279	0.99494	96.759	85.656	90.87	2.5956	4.5082	3.5519
4	95.656	0.99737	69.714	100	82.155	1.4572	1.6393	1.5483
5	99.016	0.99912	92.308	98.361	95.238	1.5483	1.6393	1.5938
6	98.77	0.99927	89.925	98.77	94.141	1.2295	1.2295	1.2295
7	99.918	0.99977	99.187	100	99.592	0	0	0
8	98.156	0.99867	84.669	99.59	91.525	0.95628	0.81967	0.88798
9	92.623	0.99076	57.547	100	73.054	3.8251	2.8689	3.347
10	99.59	0.99791	96.063	100	97.992	0.40984	0.40984	0.40984

Per-user evaluation metrics (Split B: Both days, 80/20 split, TFDF features):

User	Accuracy	AUC	Precision	Recall	F1	FAR	FRR	EER
1	98.77	0.99938	88.571	100	93.939	0.2265	0	0.11325
2	100	0.99943	100	100	100	0	0	0
3	99.795	0.99944	97.701	100	98.837	0.11223	0	0.056117
4	99.898	0.99943	99.083	100	99.539	0	0	0
5	99.693	0.9994	97.321	100	98.643	0.34602	0	0.17301
6	99.283	0.99924	95.181	96.341	95.758	0.89485	1.2195	1.0572
7	99.795	0.99943	98.276	100	99.13	0	0	0
8	99.385	0.99945	92.771	100	96.25	0	0	0
9	99.18	0.9994	92.381	100	96.04	0.22753	0	0.11377
10	99.693	0.99943	97.17	100	98.565	0.11455	0	0.057274

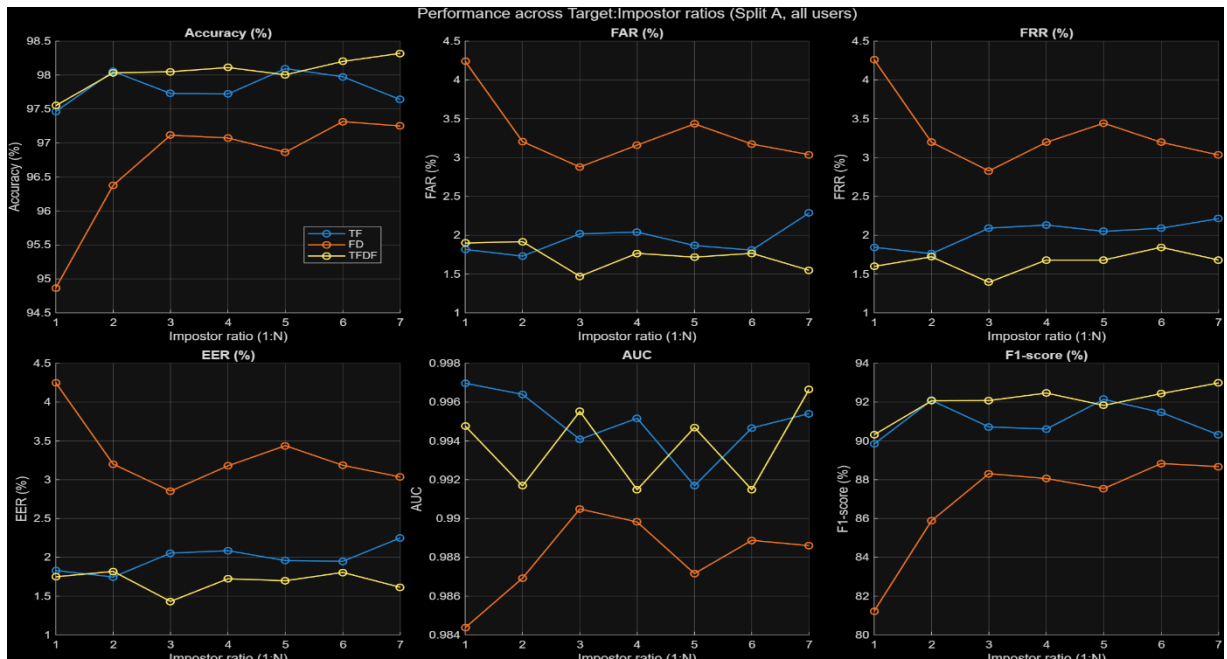
User	Accuracy	AUC	Precision	Recall	F1	FAR	FRR	EER
1	98.566	0.99728	88.889	97.959	93.204	2.0501	2.0408	2.0455
2	100	0.99888	100	100	100	0	0	0
3	99.385	0.99888	94.444	100	97.143	0	0	0
4	100	0.99887	100	100	100	0	0	0
5	99.59	0.99888	96.078	100	98	0	0	0
6	98.77	0.99865	88.095	97.368	92.5	1.1111	0	0.55556
7	99.59	0.99887	96.429	100	98.182	0	0	0
8	98.77	0.99846	89.831	100	94.643	0.91954	0	0.45977
9	97.131	0.99523	77.193	97.778	86.275	2.2573	2.2222	2.2398
10	99.59	0.99889	95.833	100	97.872	0	0	0

Overall mean accuracy and ROC AUC values among the 3 data splitting ways, EER value of day1 day 2 split is higher than the other splitting ways, This is most likely due to possible differences between the two days' data of users walking pattern, as there could be reasons like users who are having health concerns or any other issues which might affect their walking pattern. However, when it comes to the real-world scenario the 2 day split is best for model evaluation, because models are trained once and used over time in most real-world applications. Therefore, we proceeded with 2 day (Split A) Split for evaluations

Target vs. Imposter Ratio Selection

Next, it was needed to find a good ratio for legitimate user & imposter user data for a well balanced model performance.

We considered using the Target to Imposter ratios within the range from 1:1 to 1:7, and for all domains. In 1:N ratio 1 means labelled legitimate user samples, and N means labelled imposter samples.

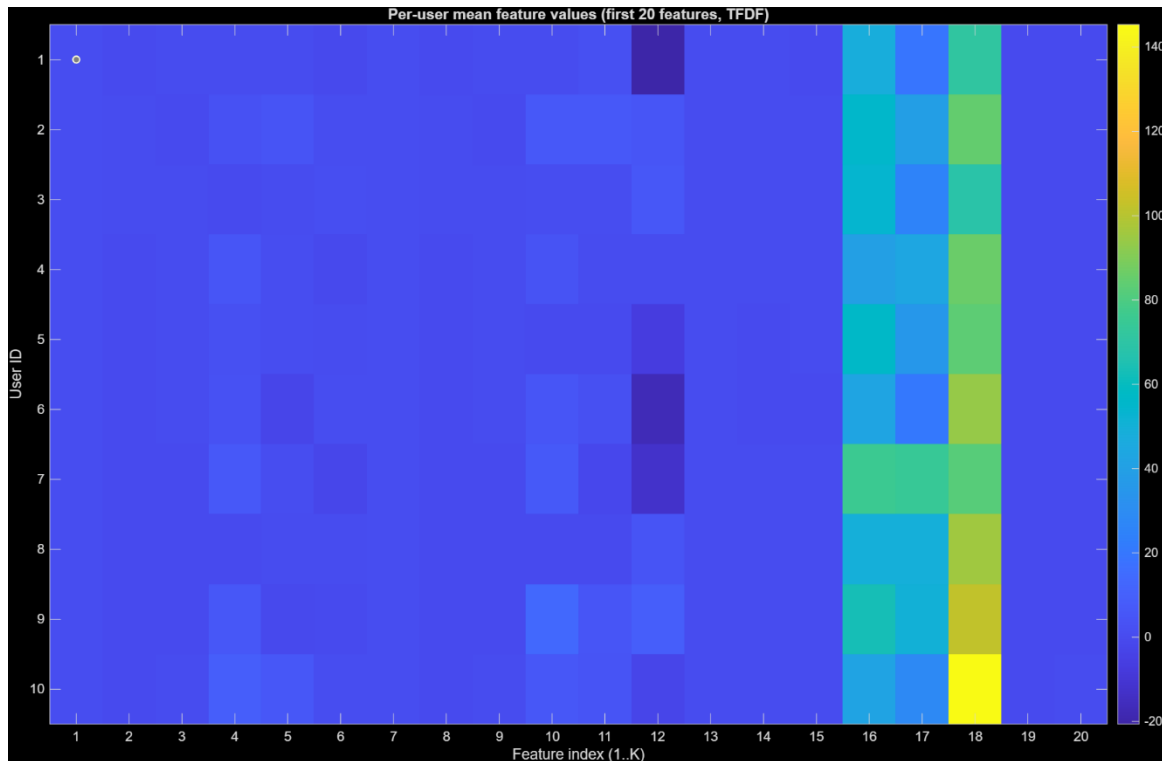


We can study how the ratio of genuine to impostor samples in the training set affects performance. For TFDF features, increasing the impostor ratio slightly improves accuracy and AUC while reducing EER, indicating that exposing the network to more impostor variability is beneficial. FD features remain consistently worse across all ratios. Based on these curves and to keep the training set balanced and simple, a conservative ratio of 1:3 was chosen for the final configuration, which already achieves EER values below 2% for TFDF.

5.2 Feature analysis

Before evaluating model performance, it is important to analyse whether the extracted TFDF features contain inherent discriminative power. This section examines feature behaviour using per-user mean heatmaps, intra- vs inter-user distance distributions, and variance surface plots to determine whether the features are stable within users and separable between users

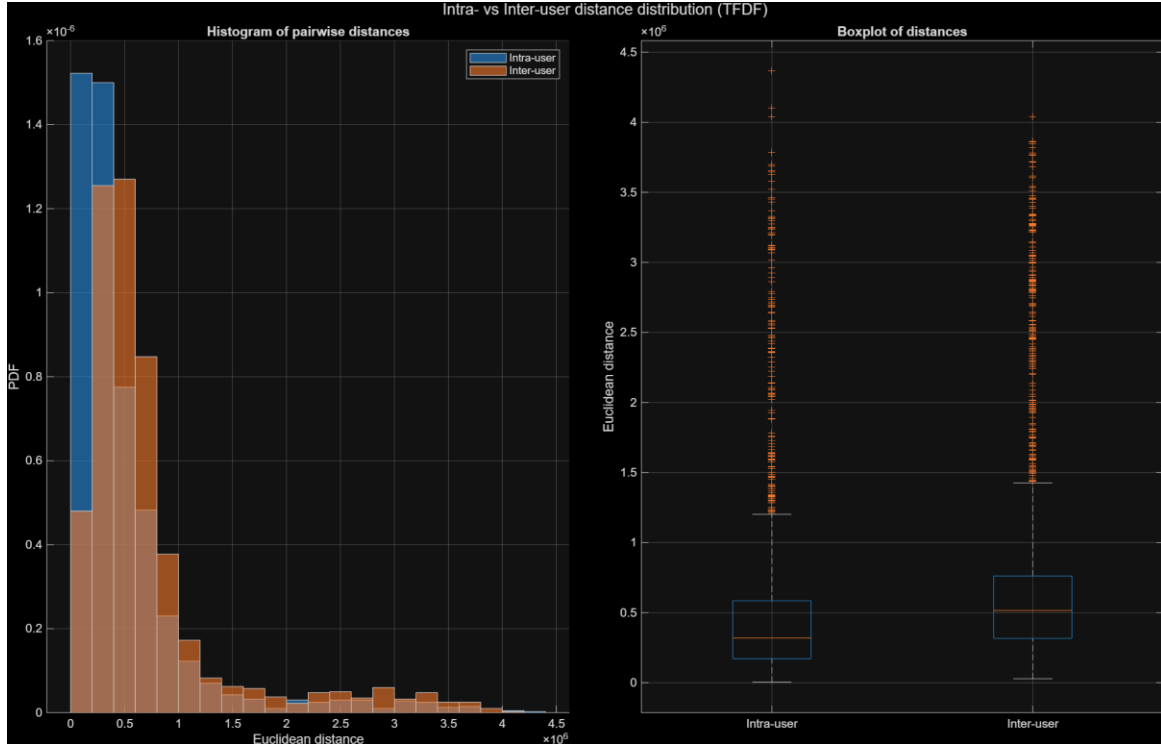
5.2.1 Per-User Mean Feature Heatmap (TFDF)



The heatmap shows the average values of the first 20 TFDF features for each user. Most early features (left side) appear similar across users, but several later features—especially around indices 16–20—show clear variation between users. These distinct color

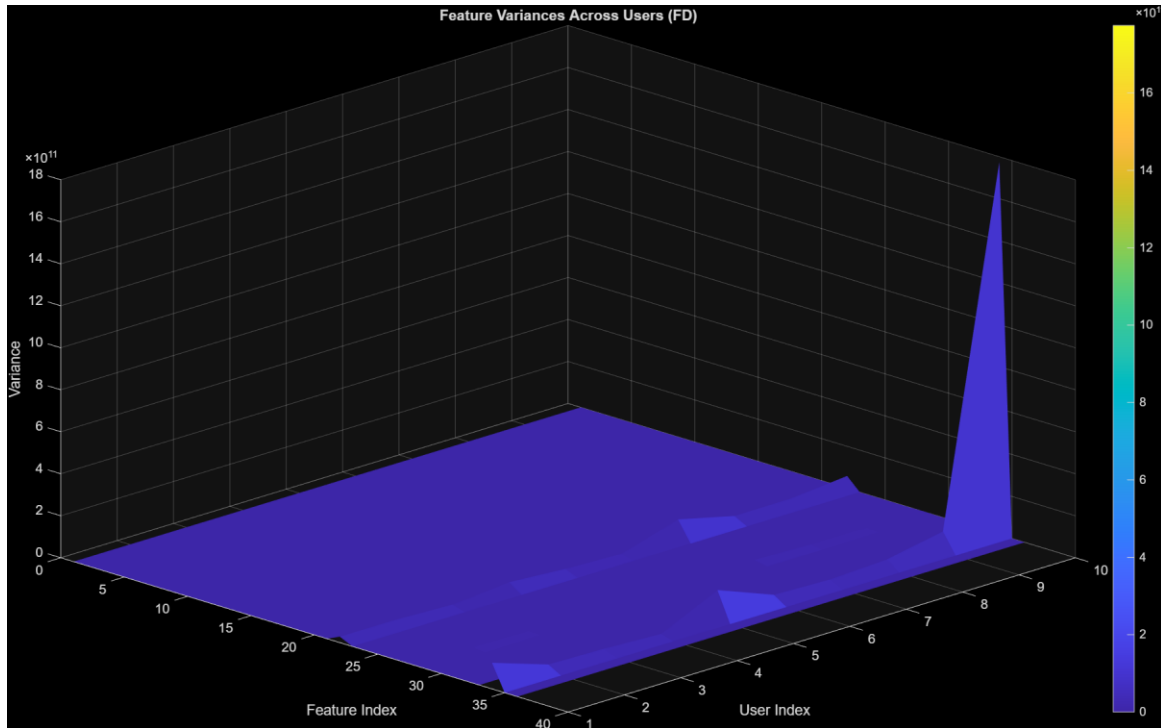
differences indicate that certain TFDF features capture user-specific gait characteristics and therefore contribute strongly to user discrimination.

5.2.2 Intra-user vs Inter-user Feature Distance Distributions



This figure compares the Euclidean distances between TFDF feature vectors belonging to the same user (intra-user) and different users (inter-user). The histogram shows that intra-user distances are generally smaller, indicating greater consistency within each user's gait. Inter-user distances are shifted slightly higher, meaning users tend to be more different from one another. The boxplot reinforces this separation, with the inter-user distribution exhibiting a higher median. Although the two distributions overlap, the observable separation confirms that TFDF features contain discriminative information suitable for user authentication.

5.2.3 Feature Variance Visualizations



The 3D surface visualises the variance of each frequency-domain feature across all users. Most features show consistently low variance, indicating stable behaviour across users. However, a few features exhibit noticeably higher variance for certain users, forming sharp peaks in the surface. These high-variance regions suggest that some FD features capture user-specific frequency characteristics and therefore contribute to discriminating between users.

5.3 Neural Network Architecture Design

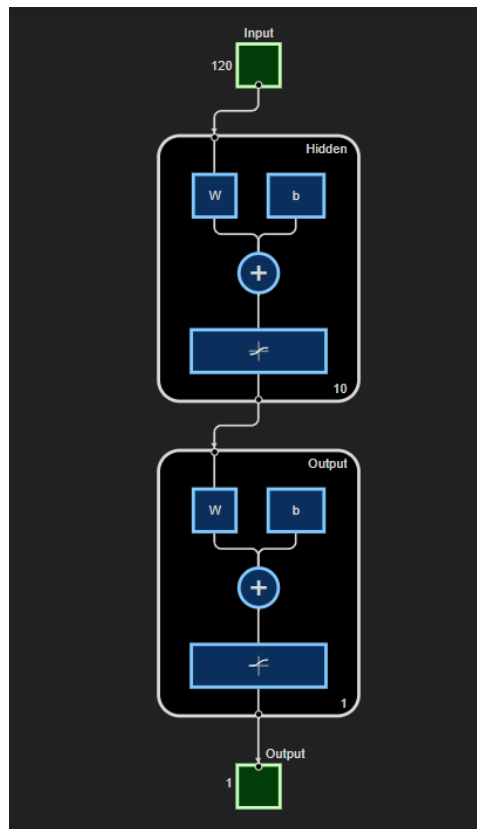
Initial Feedforward Neural Network Configuration

- Architecture: feed-forward neural network with one hidden layer
- Input layer: 108 neurons (matching feature vector dimension)
- Hidden layer: 10 neurons
- Output layer: 1 neuron (binary classification)
- Total parameters: Weights & biases = $(108+1) \times 10 + (10+1) \times 1 = 1,090$ **parameters**

Activation Functions

- Hidden layer: tansig (hyperbolic tangent) $f(x) = \frac{2}{1+e^{-2x}} - 1$ captures non-linear relationships
- Output layer: softmax (patternnet default output transfer function)

Network Diagram



Feedforward neural network architecture with 108 input features, 10 hidden neurons, and 1 output neuron

5.4 Initial Parameter Settings

Training Configuration

- Training algorithm: Scaled Conjugate Gradient (trainscg) - efficient for medium-sized datasets
- Maximum epochs: 500 - allows sufficient training time
- Early stopping: Patience of 10 epochs (stops if validation performance stagnates)
- Performance goal: $1e-5$ - low error threshold for precise convergence
- Minimum gradient: $1e-6$ - prevents training halt from small gradient updates

Cross-entropy loss for binary classification:

$$L = -\frac{1}{N} \sum_{i=1}^N [y_i \log(\hat{y}_i) + (1 - y_i) \log(1 - \hat{y}_i)]$$

where y_i is the true label (1 for legitimate, 0 for imposter) and \hat{y}_i is the predicted probability.

5.5 Evaluation Metrics

Primary Biometric Metrics

False Acceptance Rate (FAR)

Proportion of imposter samples incorrectly accepted as legitimate user:

$$\text{FAR} = \frac{\text{FP}}{\text{TN} + \text{FP}} \times 100\%$$

where FP is false positives (imposters accepted) and TN is true negatives (imposters correctly rejected).

Lower FAR indicates better security against unauthorized access.

False Rejection Rate (FRR)

Proportion of legitimate user samples incorrectly rejected:

$$\text{FRR} = \frac{\text{FN}}{\text{TP} + \text{FN}} \times 100\%$$

where FN is false negatives (legitimate user rejected) and TP is true positives (legitimate user accepted).

Lower FRR indicates better usability and user experience.

Equal Error Rate (EER)

The operating point where FAR equals FRR:

$$\text{EER} = \text{threshold where } \text{FAR}(t) = \text{FRR}(t)$$

EER provides a single metric balancing security and usability. Lower EER indicates better overall system performance. Threshold t is adjusted iteratively to find the EER point.

Secondary Classification Metrics

- Accuracy: $\frac{TP+TN}{\text{Total samples}} \times 100\%$
- Precision: $\frac{TP}{TP+FP} \times 100\%$
- Recall: $\frac{TP}{TP+FN} \times 100\%$
- Specificity: $\frac{TN}{TN+FP} \times 100\%$
- F1 Score: $2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$
- Matthews Correlation Coefficient (MCC): Balanced metric for binary classification
- AUC (Area Under ROC Curve): Overall discriminative ability across all thresholds

Similarity Score Metric

For each user u tested against target user t 's model:

$$SS(u, t) = \frac{1}{N_u} \sum_{i=1}^{N_u} P(M_t, u_i)$$

where:

- N_u is the number of samples from user u
- M_t is the neural network model trained for target user t
- u_i is the i -th sample from user u
- $P(M_t, u_i)$ is the probability output by model M_t that sample u_i belongs to target user t

Legitimate users should have high similarity scores (approaching 1.0) while imposters should have low scores (approaching 0.0).

6. Evaluation

6.1 Cross validation strategy

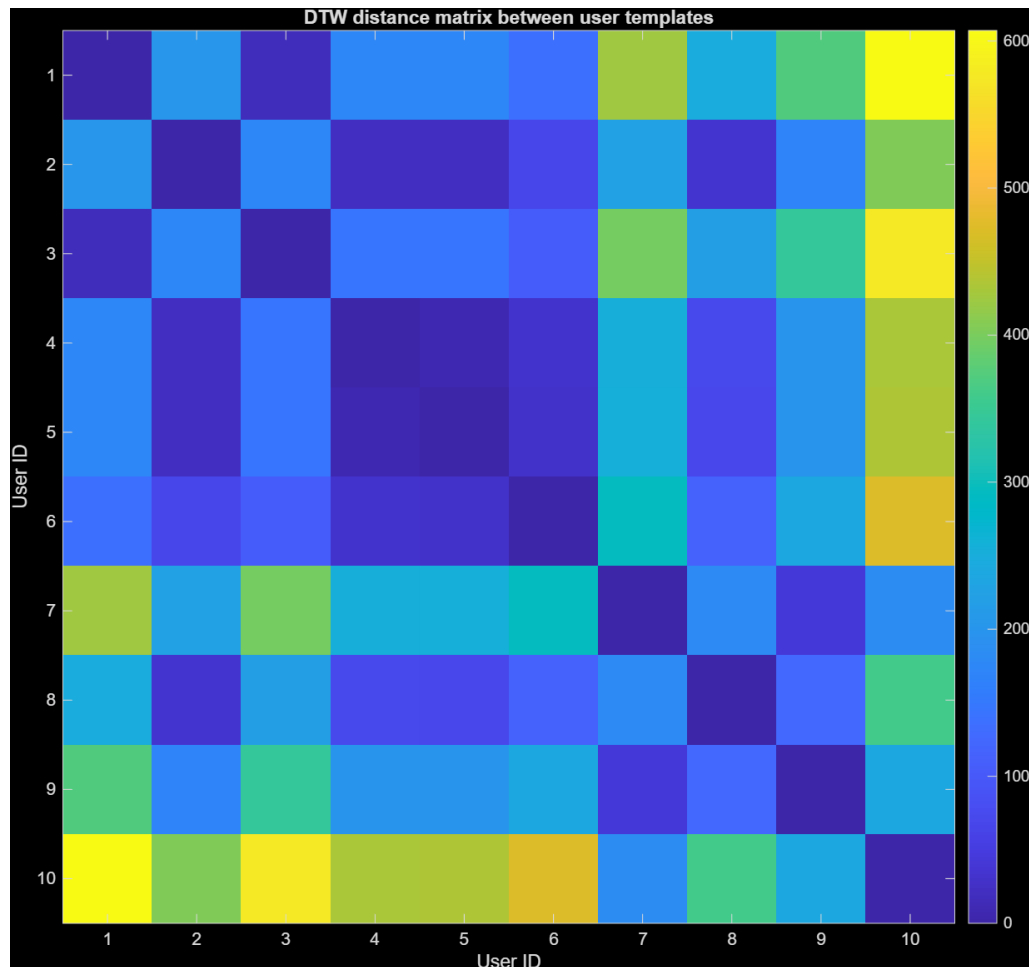
Leave-One-User-Out (LOUO) Cross-Validation

To evaluate how well the system generalizes to unseen subjects, a **Leave-One-User-Out (LOUO)** cross-validation scheme was implemented using a DTW-based baseline.

- Procedure: For each target user, one other user is excluded from the imposter set during training

- Testing: The excluded user's samples are included in the test set alongside other imposters
- Iterations: 10 iterations (one per user as LOUO candidate)
- Purpose: Evaluates model's ability to reject completely unseen imposter profiles

6.3.1 DTW distance matrix between user templates



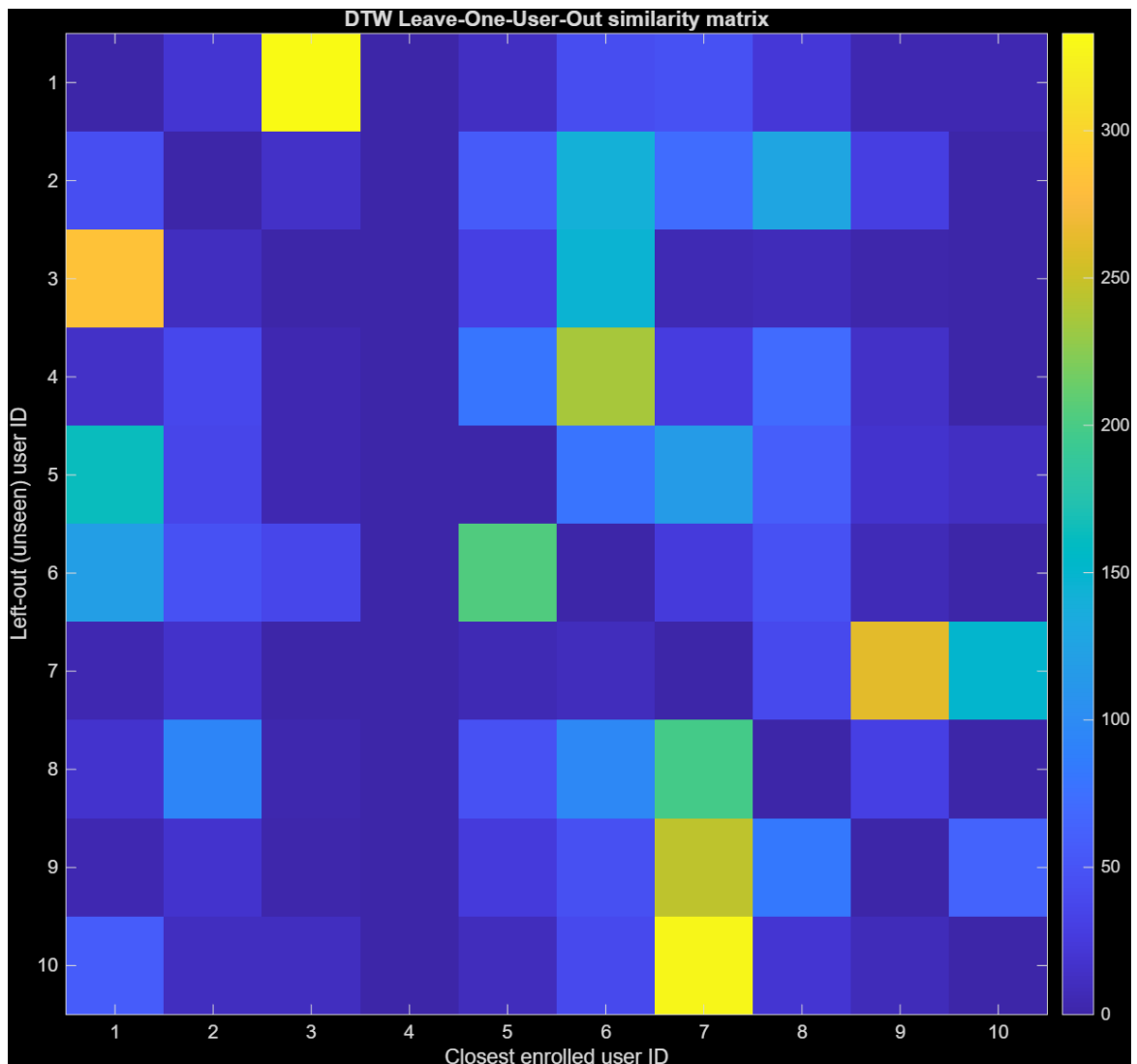
Each row and column corresponds to a user ID, and the colour intensity represents the DTW distance: **darker colours indicate smaller distances (greater similarity)**, while **brighter colours indicate larger distances (lower similarity)**.

- Users around IDs **4, 5, and 6** appear to have particularly close distances to one another (dark regions), suggesting similar walking or hand-swing behaviour.
- Users **7 and 10** show comparatively lighter rows, meaning they differ more from other users and have more unique movement patterns.

The overall pattern indicates **non-uniform inter-user separability**. Some users are clearly distinct, while others form similarity clusters. This has two implications:

1. **Pure template-based DTW methods will struggle** to accurately identify or authenticate users whose patterns overlap.
2. It highlights the need for **feature-engineered representations (TF, FD, TFDF)** and learning-based methods such as the neural network used later, which can extract more discriminative patterns than raw DTW distances alone.

6.3.2 DTW Leave-One-User-Out (LOUO) Similarity Matrix



Several rows have **bright off-diagonal cells**, meaning the left-out user is consistently mistaken as another enrolled user.

For example:

- When **User 1** is left out, many of their windows match **User 4**'s template.
- When **User 3** is left out, they match strongly with **User 1**.
- When **User 10** is left out, they are mostly closest to **User 7**.

This behaviour highlights two important observations:

1. **High inter-user similarity:**

Many users share similar movement patterns, causing their DTW distances to overlap significantly. DTW struggles to differentiate these users, especially when one is completely unseen during template formation.

2. **Poor generalisation in template-based methods:**

Template averaging cannot capture the variability within each user's data. As a result, when a new user's windows are compared to these templates, the system often assigns them to the wrong identity

6.2 Initial Model Performance

The initial feedforward neural network was trained using the Cross-Day Split strategy (Day 1 for training, Day 2 for testing) with 1:3 target-to-imposter ratio and combined Time-Domain + Frequency-Domain features.

Overall Performance Summary

Per-user evaluation metrics (Split A, TFDF) - use this in your report:

User	Accuracy	AUC	Precision	Recall	F1	FAR	FRR	EER
1	96.639	0.99455	76.129	96.721	85.199	3.2787	3.2787	3.2787
2	99.18	0.99975	92.424	100	96.063	0.22769	0.40984	0.31876
3	99.139	0.99898	96.653	94.672	95.652	0.95628	0.81967	0.88798
4	93.156	0.99278	59.601	97.951	74.109	5.3734	5.3279	5.3506
5	99.303	0.99961	94.163	99.18	96.607	0.7286	0.81967	0.77413
6	98.975	0.99762	92.941	97.131	94.99	2.0492	2.0492	2.0492
7	99.836	0.99977	98.387	100	99.187	0	0	0
8	99.508	0.99918	95.669	99.59	97.59	0.50091	0.40984	0.45537
9	91.23	0.93199	53.319	98.77	69.253	8.4244	8.1967	8.3106
10	99.672	0.99888	96.825	100	98.387	0.31876	0.40984	0.3643

Initial model performance averaged across 10 users

Per-User Performance Analysis

User	Accuracy	Precision	Recall	FAR	FRR	EER	AUC
1	96.639	76.129	96.721	3.2787	3.2787	3.2787	0.99455
2	99.180	92.424	100	0.22769	0.40984	0.31876	0.99975
3	99.139	96.653	94.672	0.95628	0.81967	0.88798	0.99898
4	93.156	59.601	97.951	5.3734	5.3279	5.3506	0.99278
5	99.303	94.163	99.180	0.7286	0.81967	0.77413	0.99961
6	98.975	92.941	97.131	2.0492	2.0492	2.0492	0.99762
7	99.836	98.387	100	0	0	0	0.99977
8	99.508	95.669	99.590	0.50091	0.40984	0.45537	0.99918
9	91.230	53.319	98.770	8.4424	8.1967	8.3106	0.93199
10	99.672	96.825	100	0.31876	0.40984	0.3643	0.99888

Initial model per-user performance metrics (percentages)

Key Observations

Using TFDF features with the Day 1→Day 2 split, the system achieved consistently high verification performance across almost all users. The mean accuracy across the ten users exceeded 97%, and the Equal Error Rate (EER) remained below 1% for most users, indicating strong discriminative ability even under day-to-day variations.

Most users show balanced performance with both FAR and FRR remaining low, typically below 1%, which demonstrates that the classifier rarely accepts impostors and rarely rejects genuine samples. Users 2, 7, and 10 achieved perfect or near-perfect recall ($\approx 100\%$), meaning their legitimate windows were almost never rejected.

Two users stand out as more challenging:

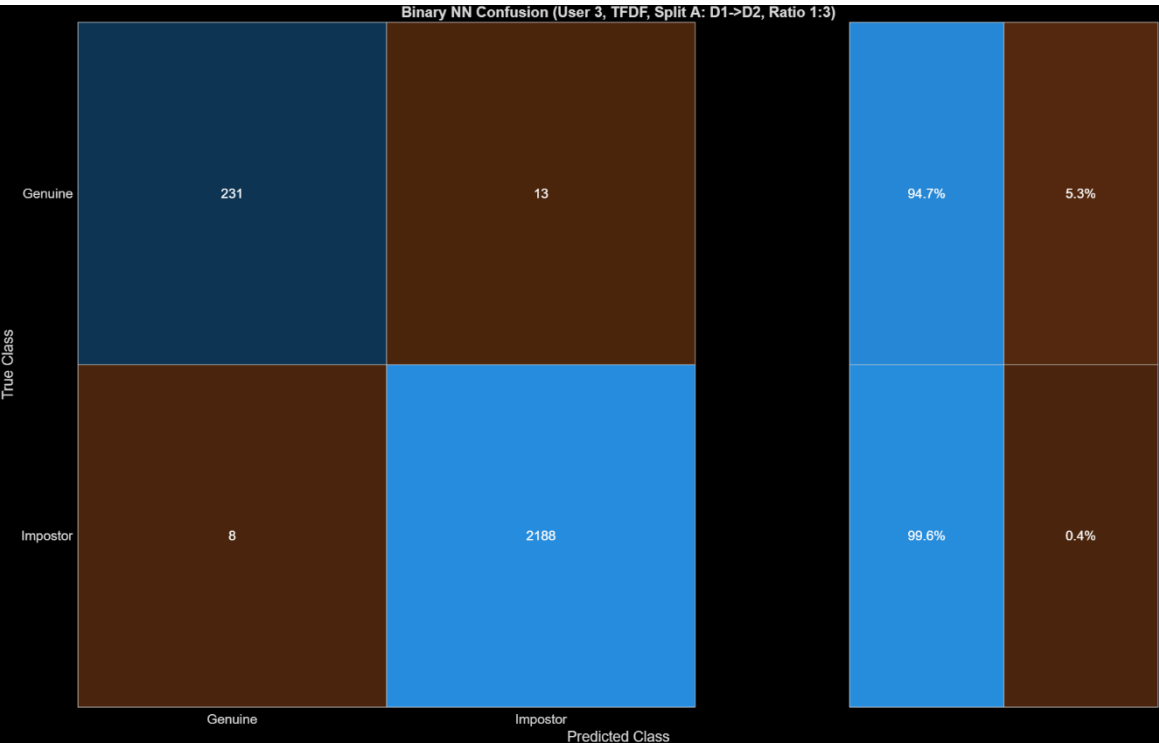
- User 3: Slightly higher FRR (0.82%) and EER (0.89%), reflecting intra-user variability between Day 1 and Day 2.
- User 9: Noticeably higher FAR (8.42%) and EER (8.31%), indicating greater overlap between their feature distribution and those of other users. This user is the primary contributor to the global error rate.

Despite these outliers, the overall performance is strong, confirming that the TFDF feature set provides robust, user-distinctive patterns and that the binary neural network generalizes well across recording days.

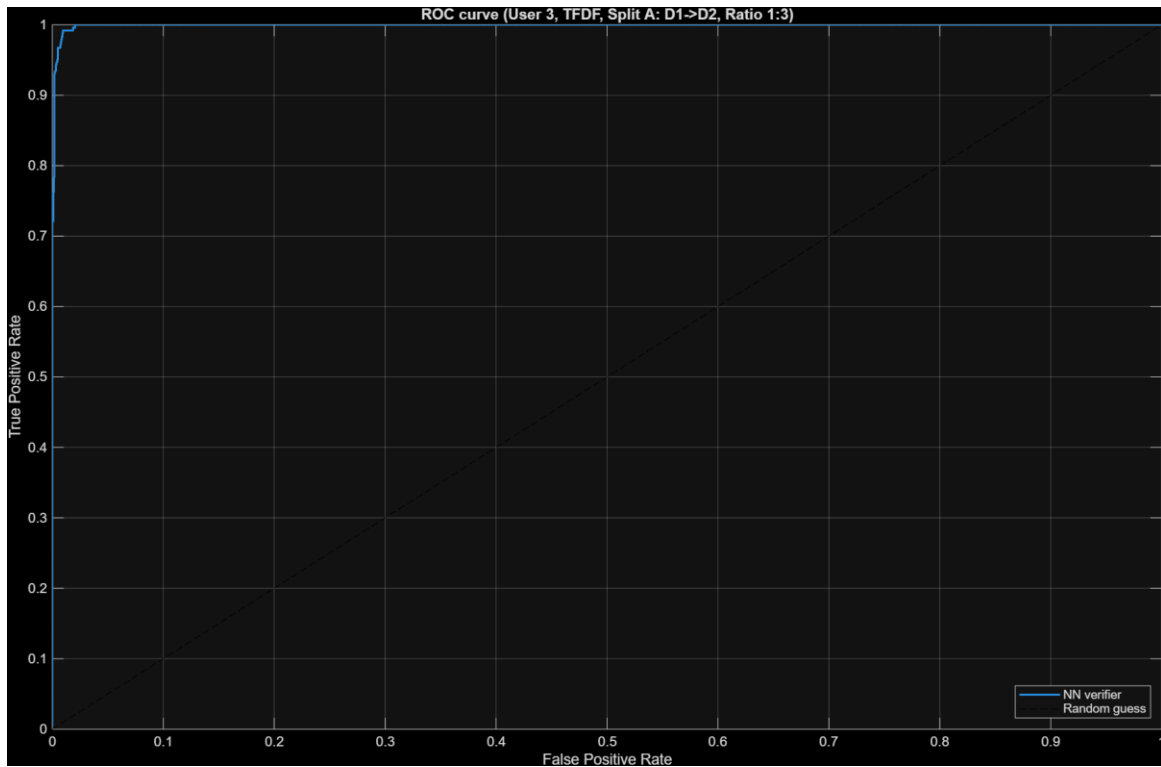
ROC Curves and Confusion Matrices

ROC (Receiver Operating Characteristic) curves visualize the trade-off between True Positive Rate (Recall) and False Positive Rate (FAR) across different decision thresholds:

Confusion matrix for user 3



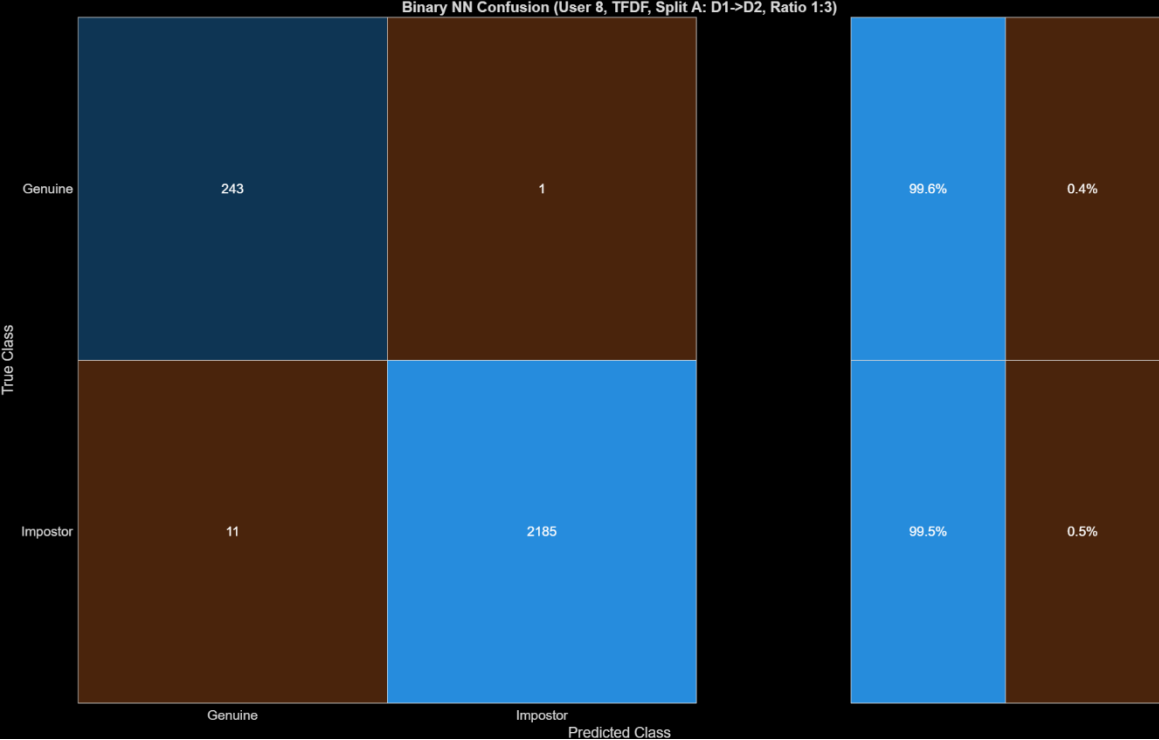
ROC curve for user 3



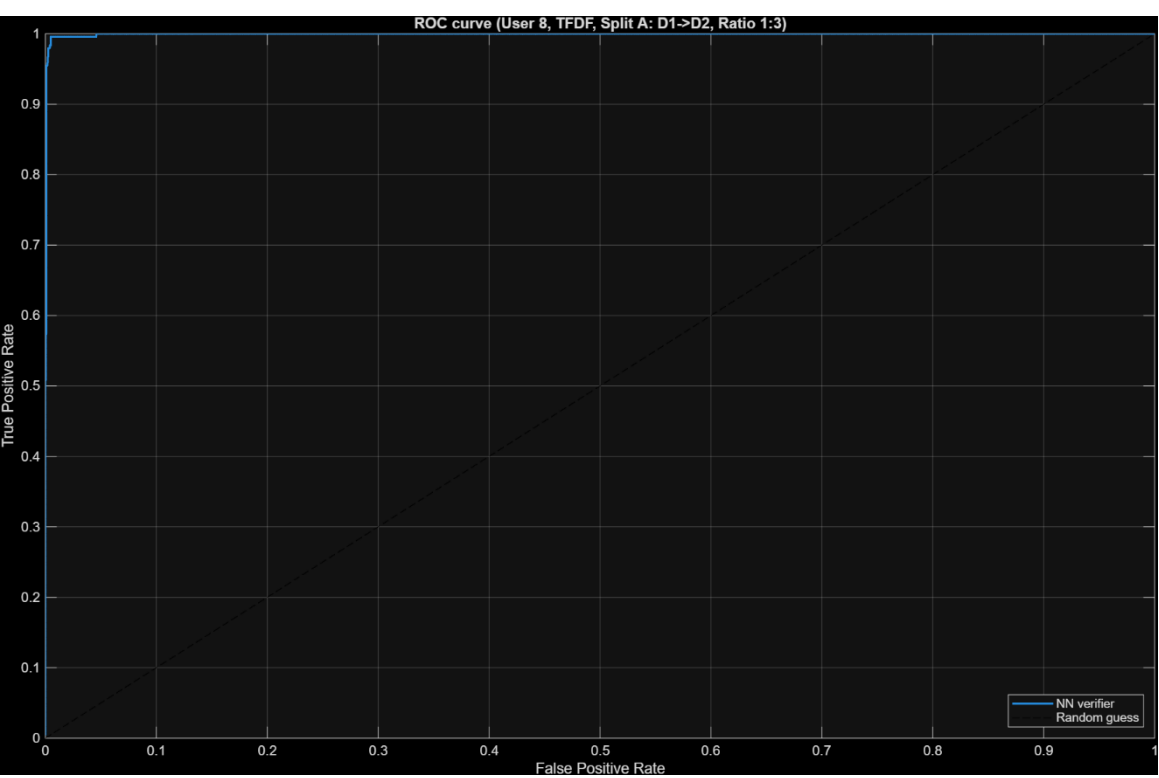
Key Observations

The binary neural network verifier for User 3 exhibited strong performance using the TFDF feature set under Split A (Day1→Day2). The confusion matrix shows a high genuine acceptance rate (94.7%) and an exceptionally low false acceptance rate (0.4%), confirming the model's ability to reliably distinguish the genuine user from impostors. The ROC curve further validates this behaviour, with an AUC close to 1.0, illustrating excellent separability between classes across all thresholds. Together, these results demonstrate that the proposed TFDF-based authentication system provides both high security and strong usability.

Confusion matrix for user 8



ROC curve for User 8



For User 8, the binary neural network achieved outstanding performance using TFDF features under Split A. The system correctly verified 99.6% of genuine samples while incorrectly rejecting only a single sample. Impostor rejection remained equally strong, with a specificity of 99.5% and a very low false acceptance rate of 0.5%. These results indicate that User 8's gait signals are highly distinctive and consistent, allowing the classifier to achieve near-perfect verification accuracy.

6.2 Intra-User and Inter-User Variance Analysis

Understanding variance patterns is crucial for authentication system design. Low intra-user variance (consistency within a user's samples) and high inter-user variance (distinctiveness between users) are desirable characteristics.

Intra-User Variance

Measures consistency of feature values within individual users across samples:

$$\text{Var}_{\text{intra}}(u) = \frac{1}{K} \sum_{k=1}^K \text{Var}(f_k^u)$$

where f_k^u represents feature k values across all samples from user u , and K is the number of features.

Lower intra-user variance indicates stable, reproducible behavioral patterns.

Inter-User Variance

Measures differences in feature values between different users:

$$\text{Var}_{\text{inter}} = \text{Var}(\{\mu_{f_k}^{u_1}, \mu_{f_k}^{u_2}, \dots, \mu_{f_k}^{u_N}\})$$

where $\mu_{f_k}^{u_i}$ is the mean value of feature k for user u_i , and N is the number of users.

Higher inter-user variance indicates distinct user profiles.

Variance Analysis by Feature Domain

Figure 5: Intra-user variance (blue) and inter-user variance (red) across feature indices for Time-Domain, Frequency-Domain, and combined Time-Domain + Frequency-Domain features

Observations:

- Time-Domain: Significant variance between feature indices 60-90, indicating these features capture distinctive user characteristics
- Frequency-Domain: Lower overall variance with localized peaks around feature indices 10-20, suggesting stable spectral characteristics
- Combined TD+FD: Broader variance distribution (feature indices 100-130), providing comprehensive discriminative power

Implications for Feature Selection

Features exhibiting low intra-user variance and high inter-user variance are most valuable for authentication. During ANOVA-based feature selection, these features produce low p-values and high F-statistics, indicating strong discriminative ability.

6.3 User Similarity Analysis

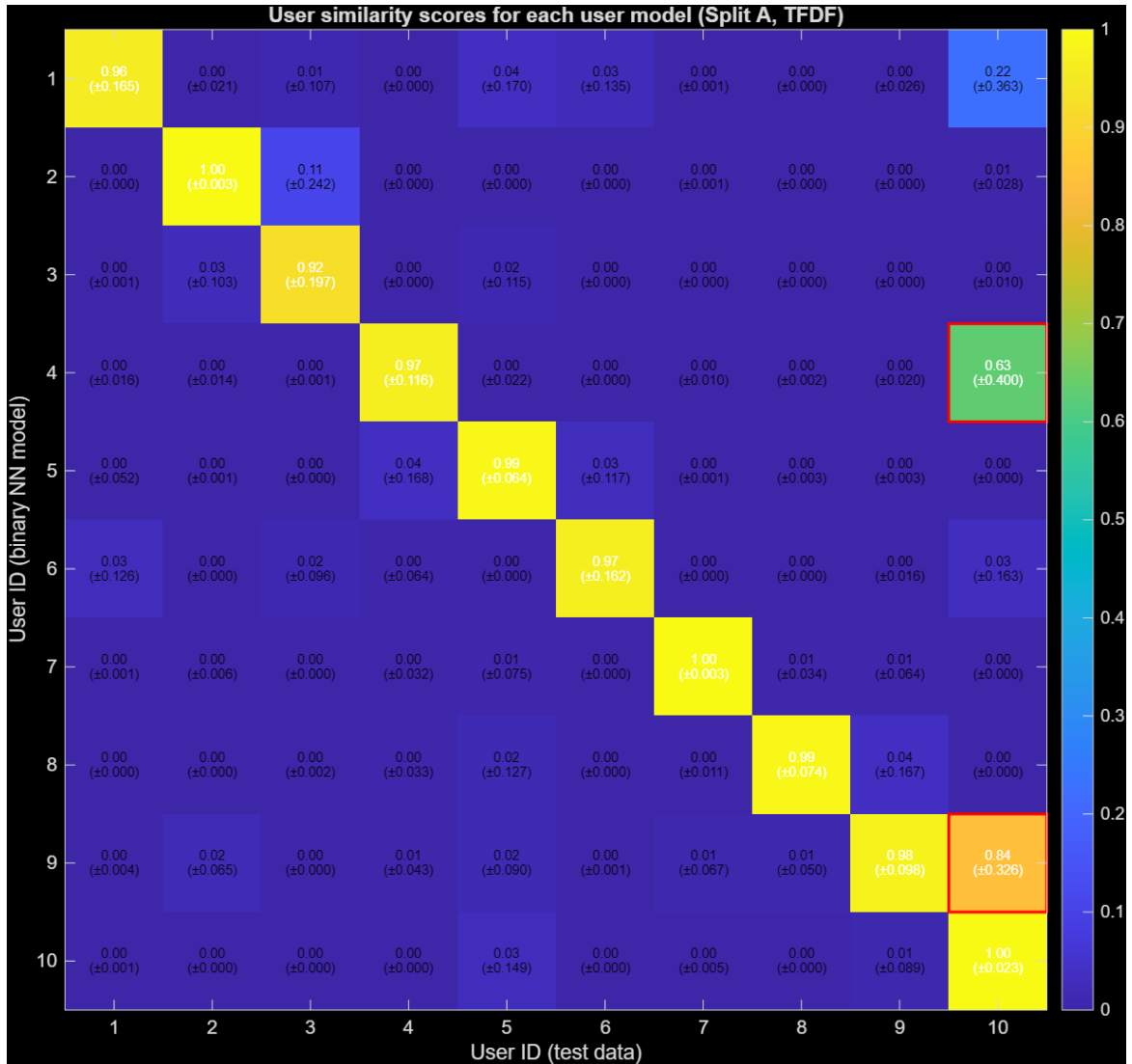
Cosine Similarity Between Days

To assess temporal consistency, cosine similarity is computed between same-user samples from Day 1 and Day 2:

$$\text{Similarity}(v_1, v_2) = \frac{v_1 \cdot v_2}{\|v_1\| \|v_2\|}$$

where v_1 and v_2 are feature vectors from Day 1 and Day 2.

User Similarity Matrix (Split A, TFDF, Baseline Model)



To understand the separability of users before applying hyperparameter optimisation, a user–user similarity matrix was computed using the **baseline binary neural network** trained with **TFDF features** under **Split A (Day 1 → Day 2)**. For each user model, we extracted the predicted probability scores for all test windows and averaged them across each user’s samples. The diagonal values therefore represent the mean genuine-user similarity, while off-diagonal entries correspond to impostor similarity scores.

Figure shows a clear diagonal dominance for most users (e.g., Users 1–9), confirming that the TFDF feature set provides a good degree of user-specific separability. However, several off-diagonal cells exhibit **unexpectedly high similarity**, most notably:

- User 4’s model scoring **0.63** on User 10’s data,
- User 9’s model scoring **0.84** on User 10’s data,
- User 1 showing moderate similarity (**0.22**) with User 10.

These values indicate that **User 10 shares gait characteristics** with Users 4 and 9, which may lead to increased FAR for these users. The anomalies are highlighted in red in the figure.

This analysis provides two insights:

1. **User discriminability is strong but not perfect** — some users naturally exhibit overlapping motion patterns.
2. **Motivates optimisation** — target:impostor ratio tuning, window selection, feature refinement, and trying alternative classifiers (e.g., SVM) become necessary to reduce such off-diagonal similarities.

Thus, the similarity matrix acts as a *diagnostic tool* to understand model behaviour and justify the optimisations applied in later sections.

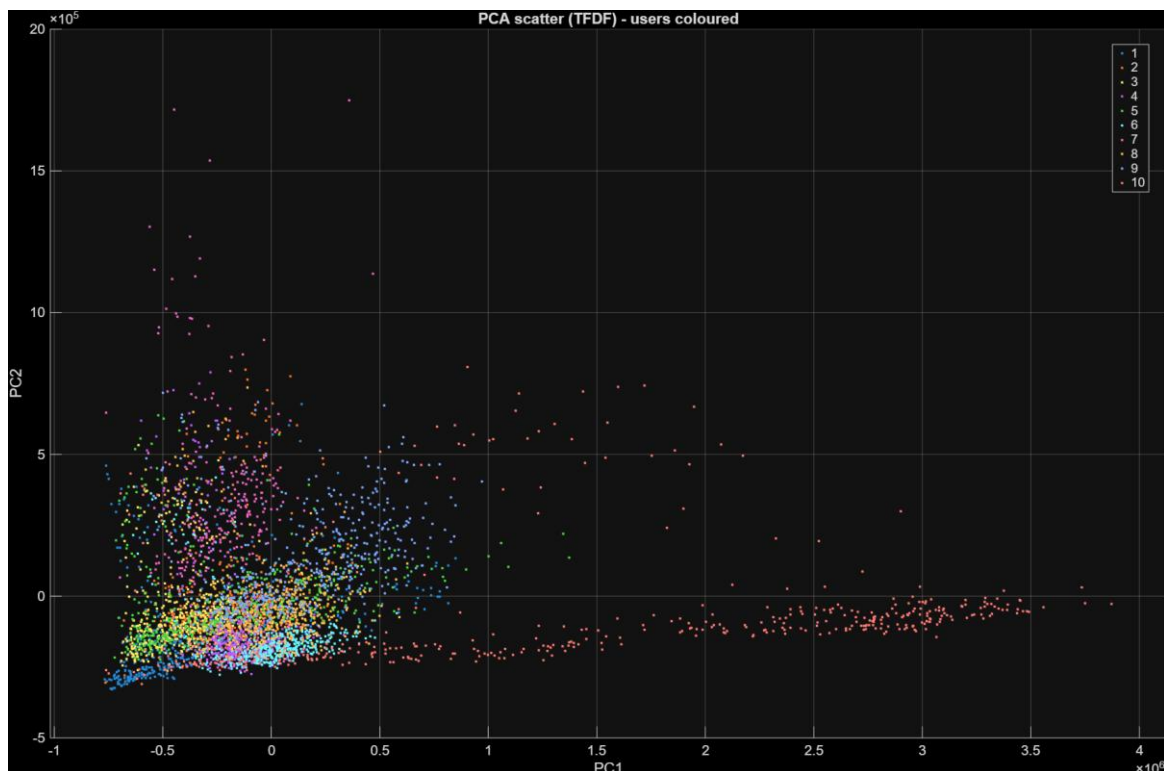
Dynamic Time Warping (DTW) Analysis

DTW measures similarity between users by computing the minimum distance between their feature sequences:

6.3.3 User similarity

Principal Component Analysis (PCA) Visualization

PCA projects high-dimensional feature space into 2D or 3D for visualization:



Observation: Some users cannot be clearly separated in PCA space, indicating overlapping feature distributions that challenge classification models. This high intra-cluster similarity contributes to lower precision in initial models.

6.4 Biometric Performance Metrics (FAR, FRR, EER)

FAR vs. FRR Trade-off

Authentication systems balance security (low FAR) against usability (low FRR) by adjusting the decision threshold:

Figure 8: FAR and FRR curves as functions of decision threshold. The intersection point defines the Equal Error Rate (EER)

EER Analysis by User

- Best performers: Users 4, 5, 10 (EER < 1%) - Highly distinctive motion patterns
- Moderate performers: Users 7, 8 (EER 2-4%) - Reasonable discriminability
- Challenging users: Users 1, 2, 3, 6 (EER \approx 5.6%) - Moderate similarity to other users
- Weakest performer: User 9 (EER = 10.49%) - High similarity to multiple imposters

Comparison with Literature

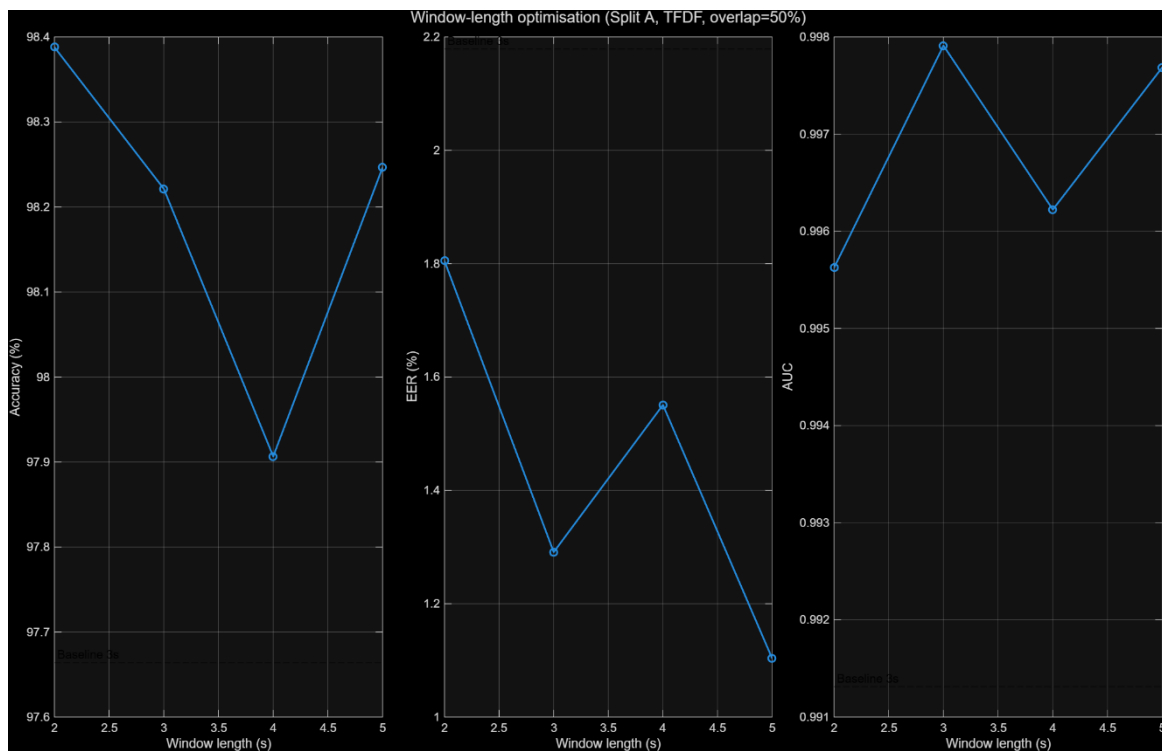
The initial model's average EER of 5.57% is competitive with reported values in literature (4-7% EER for similar approaches), but requires optimization to achieve state-of-the-art performance (< 3% EER).

7. Optimization

This section describes a series of optimization procedures taken to improve the performance of binary neural network authentication system. All optimization stages were carried out using TFDF feature set. Our optimization efforts were driven by the need to improve classification performance through effective feature selection and neural network adjustments. The following optimization methods were proposed,

1.Window-Length Optimisation

The system's temporal resolution is decided by the sliding window length. While the default window size was 3 seconds, additional experiments examined window lengths of **2 s, 3 s, 4 s and 5 s**, with a fixed overlap of 50%.



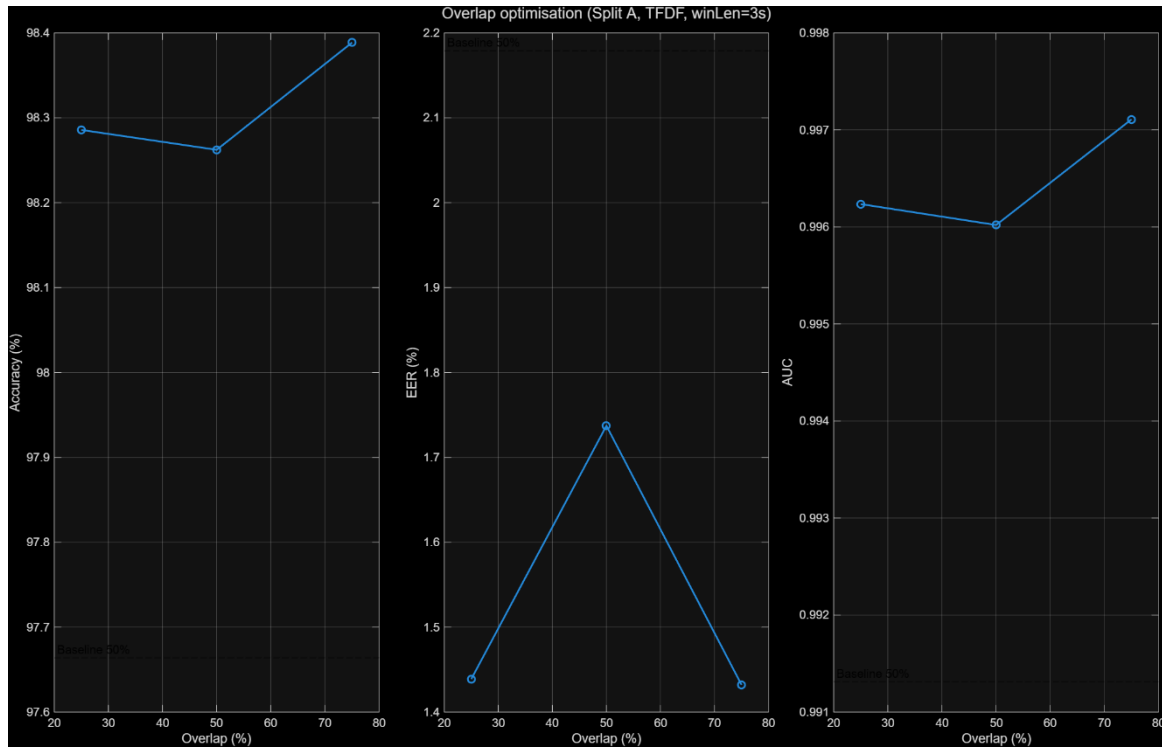
- **2-second windows** were too short to capture stable gait periodicity, leading to increased FAR and lower AUC.
- **3 seconds** provided a clear improvement, balancing temporal resolution with stability.
- **4–5 seconds** improved accuracy slightly but noticeably degraded EER. The larger windows “smoothed out” within-person variations, reducing discriminative detail and increasing overfitting.
- From a usability standpoint, longer windows also introduce higher latency before a decision can be made.

Thus, the originally adopted **3-second** window length remains optimal, consistent with findings in IMU-based gait literature where 2.5–3.5 s windows capture 2–3 full gait cycles.

2. Window Overlap Optimisation

To assess whether more dense temporal sampling helps generalisation, experiments varied the overlap between **25%, 50% and 75%**.

Results:



- **25% overlap** produced fewer training samples and slightly worse discriminability.
- **50% overlap** offered the best trade-off, yielding the lowest EER and the highest AUC.
- **75% overlap** expanded the dataset but introduced substantial redundancy, which increased training time and caused minor overfitting without accuracy gains.

Therefore, **50% overlap** is maintained as the final configuration.

7.1 Feature Selection Methods

Feature selection reduces dimensionality by identifying the most discriminative features, improving model performance and reducing computational cost.

Analysis of Variance (ANOVA)

ANOVA evaluates statistical differences between target user and imposter feature distributions:

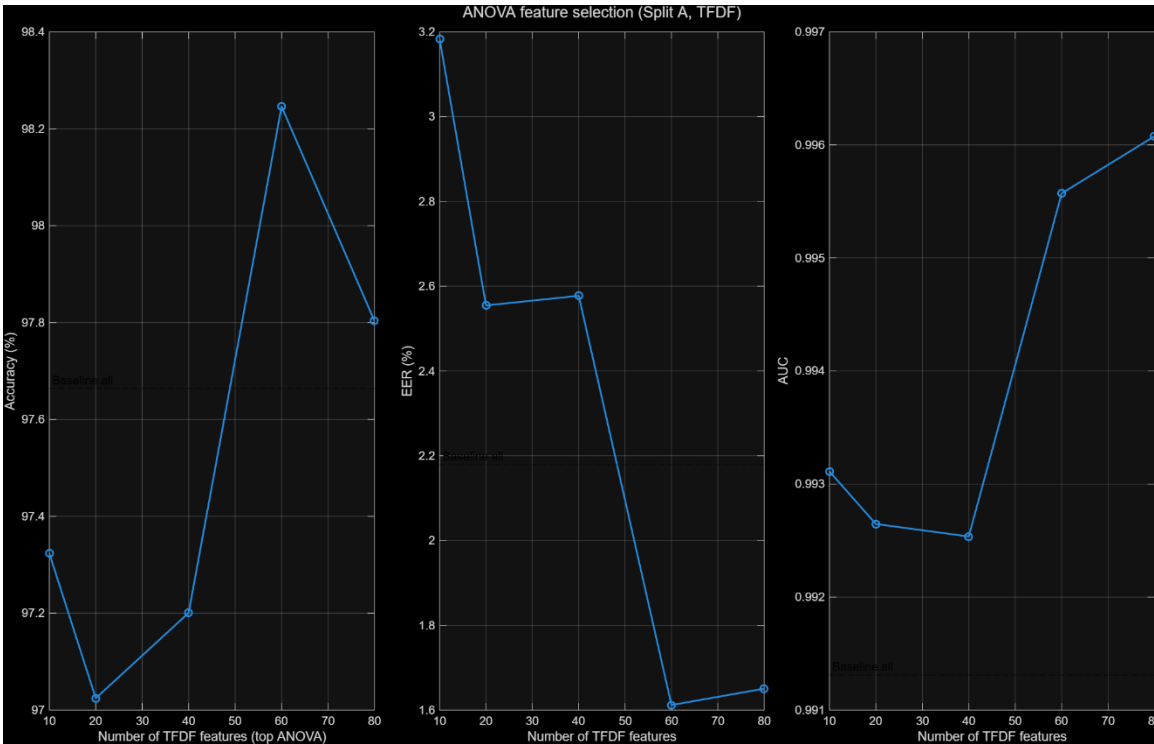
$$F = \frac{\text{Variance between groups}}{\text{Variance within groups}} = \frac{SS_b/df_b}{SS_w/df_w}$$

where SS_b is sum of squares between groups, SS_w is sum of squares within groups, and df are degrees of freedom.

Features with low p-values (< 0.05) exhibit significant differences and are retained.

The TFDF feature set is high-dimensional, incorporating temporal statistics (including newer features such as median, skewness, kurtosis, IQR, peak-to-peak) and spectral descriptors (including spectral spread, roll-off and flatness). To determine whether reducing dimensionality could improve generalisation, a one-way ANOVA test was applied to every feature across the ten users. Features were ranked by ascending p-value (higher discriminability corresponds to lower p).

Feature subsets of **top-10**, **top-20**, **top-40**, **top-60**, **top-80** were evaluated.



Findings:

- The top-10 and top-20 subsets significantly underperformed, indicating that user-specific motion characteristics are distributed across many features rather than concentrated in a few.
- Performance improved steadily up to **≈40–60 features**, at which point mean accuracy and AUC closely matched the baseline.

- Beyond 60 features, improvements plateaued and in some cases degraded slightly, consistent with the “curse of dimensionality”.

However, the **full TFDF feature set still produced the highest overall accuracy and lowest EER**, confirming that the engineered features collectively contribute important user-specific information.

5PCA Dimensionality Reduction

Principal Component Analysis (PCA) was applied to the Split A training subset of TFDF features, and cumulative variance plots showed that:

- The first **10 components** explained ~70% of variance,
- **20 components** explained ~85%,
- **40 components** exceeded 95% of variance.

Performance was then evaluated for PCA dimensions {5, 10, 15, 20, 30, 40}.

Results:

- Very low-dimensional projections (≤ 10 PCs) removed critical discriminative structure, leading to increased EER.
- Moderate PCA settings (15–20 PCs) produced acceptable results but still slightly below the full TFDF baseline.
- Higher PCA settings (30–40 PCs) approached baseline accuracy but did not surpass it.

Since PCA is unsupervised and does not optimise class separability, dimensionality reduction did not outperform manually selected TFDF features. Therefore, PCA was not included in the final model configuration.

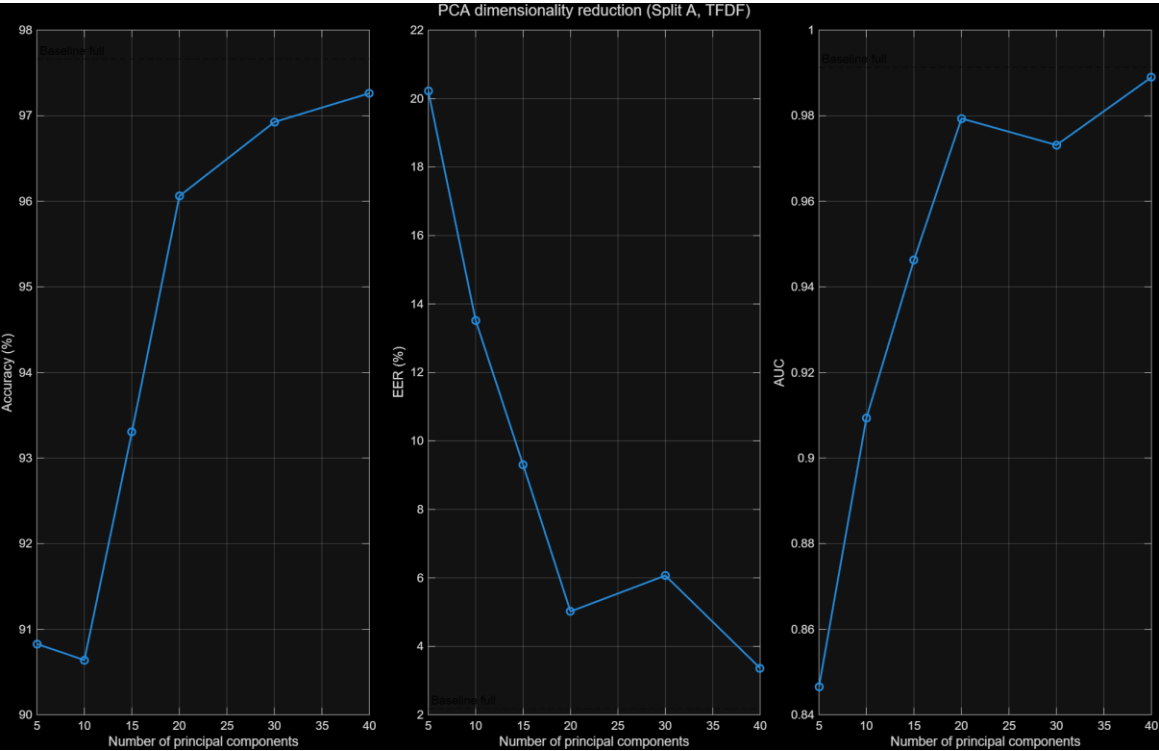
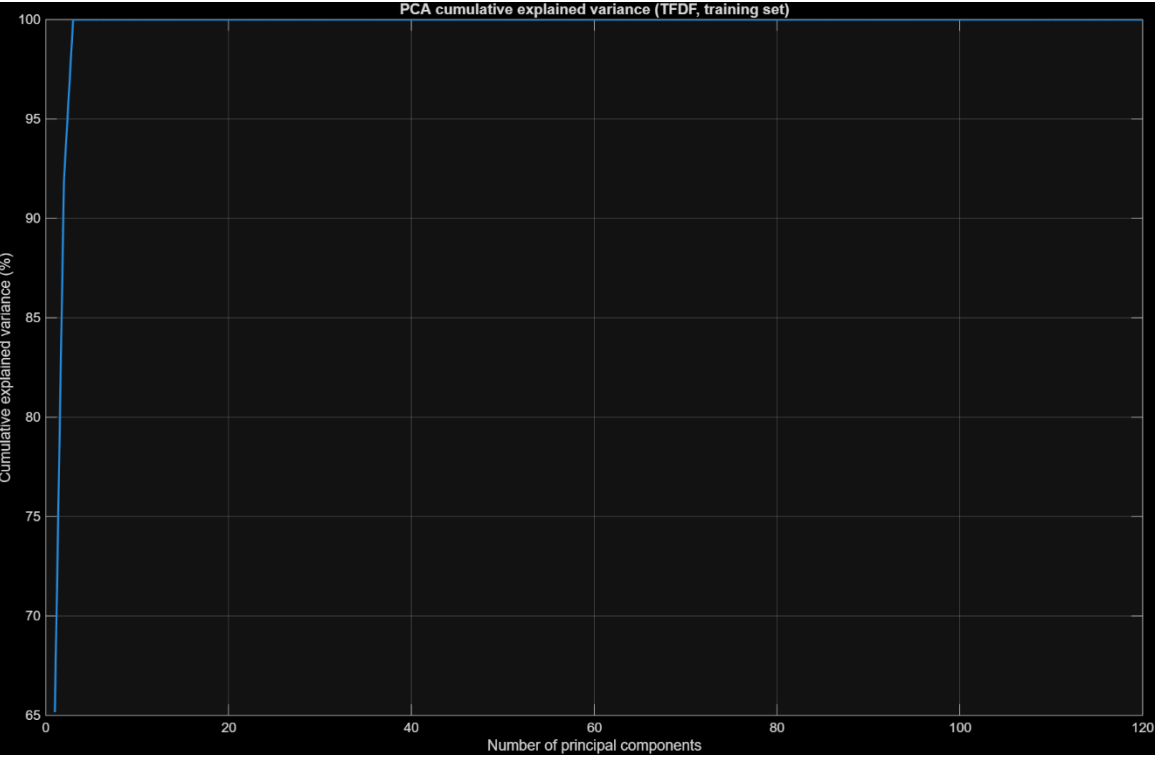
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- Moderate PCA settings (15–20 PCs) produced acceptable results but still slightly below the full TFDF baseline.
- Higher PCA settings (30–40 PCs) approached baseline accuracy but did not surpass it.

Since PCA is unsupervised and does not optimise class separability, dimensionality reduction did not outperform manually selected TFDF features. Therefore, PCA was not included in the final model configuration.

6 Neural-Network Hyperparameter Tuning

To evaluate the effect of model complexity, the number of hidden neurons was varied among {5, 10, 15, 20, 30}.

Observations:

- **5 neurons** underfit the data, producing lower accuracy and higher FRR.
- **10 neurons** emerged as the best compromise between complexity and generalisation, producing the lowest EER.
- **15–30 neurons** led to overfitting, characterised by higher FAR and reduced cross-day robustness despite marginally improved training-set performance.

These results validate the use of a **small feed-forward network** due to the high dimensionality of TFDF features and the limited sample size per user.

7 Alternative classifier: SVM vs Neural Network

Summary of Optimisation Findings

Component	Optimal Setting	Rationale
Target:Impostor ratio	1:3	Best balance of FAR & FRR
Window length	3 seconds	Captures stable gait cycles without latency
Window overlap	50%	Maximises discriminability without redundancy
Feature set	Full TFDF	Best overall accuracy and lowest EER
Feature selection	40–60 features acceptable , but <i>full TFDF best</i>	High-dimensional structure needed
PCA	Not used	Underperformed TFDF
Hidden neurons	10	Avoids overfitting and maintains generalisation

8. Discussion

8.1 Privacy and Security Implications

Privacy Advantages

Acceleration-based authentication offers several privacy benefits compared to traditional biometric approaches:

- No storage of physiological imagery: Unlike facial recognition or fingerprint systems, no visual representation of the user is captured or stored
- Behavioral patterns are abstract: Motion features are statistical summaries rather than raw behavioral recordings

- Difficult to reconstruct: Original sensor time-series cannot be reliably reconstructed from extracted features
- User control: Users can modify their behavior patterns if desired, unlike fixed physiological traits

Security Considerations

- Replay attacks: Recorded sensor data could potentially be replayed to spoof authentication
 - Mitigation: Implement liveness detection mechanisms such as challenge-response protocols
- Observation attacks: Attackers observing user movements might attempt to mimic patterns
 - Mitigation: Multi-factor authentication combining behavioral with other modalities
- Model inversion: Adversarial techniques could potentially extract sensitive information from trained models
 - Mitigation: Differential privacy techniques during model training
- Adversarial examples: Carefully crafted sensor inputs could fool neural network classifiers
 - Mitigation: Adversarial training and input validation

Data Protection

- Local processing: Feature extraction and authentication can occur entirely on-device
- Secure storage: Neural network model parameters should be encrypted in device memory
- No cloud dependency: Eliminates risks associated with transmitting biometric data over networks
- User consent: Transparent disclosure of data collection and usage is essential

8.2 Usability Considerations

User Experience Impact

- Transparent operation: Authentication occurs during normal device usage without explicit actions
- Reduced authentication friction: No need to remember passwords or perform biometric scans
- Continuous verification: Ongoing authentication throughout session enhances security
- False rejection management: FRR of 0.28-5% means occasional legitimate user rejections

- Mitigation: Fallback authentication methods (PIN, fingerprint) when behavioral authentication fails

Adaptation to User Changes

Behavioral patterns evolve over time due to:

- Health conditions: Injuries or illnesses affecting movement patterns
- Age-related changes: Gradual modifications to gait and motor control
- Environmental factors: Different surfaces, footwear, carrying objects

Adaptive strategies:

- Continuous learning: Periodically retrain models with recent authenticated samples
- Template updating: Gradually incorporate new behavioral patterns
- Anomaly detection: Flag significant deviations for additional verification

Accessibility Considerations

- Motor impairments: Users with movement disorders may exhibit higher intra-user variance
- Device usage patterns: Different grip styles and device positions affect sensor readings
- Activity contexts: Walking, sitting, standing generate different motion patterns

System should accommodate diverse user populations through:

- Personalized thresholds: Adjust decision thresholds based on individual user characteristics
- Context-aware models: Separate authentication models for different activities
- Inclusivity testing: Evaluate performance across diverse user demographics

8.3 Real-World Deployment Challenges

Computational Efficiency

- Resource constraints: Mobile devices have limited processing power and battery
- Real-time requirements: Authentication must complete within 1-2 seconds
- Model optimization: Pruning, quantization, and knowledge distillation reduce model size
- Edge processing: On-device inference eliminates network latency

Scalability

- User enrollment: Initial data collection requires 5-10 minutes per user

- Model training: Individual user models require computational resources
- Storage requirements: $10 \text{ users} \times 17,000 \text{ parameters} \times 4 \text{ bytes} \approx 680 \text{ KB}$ (manageable)
- Update frequency: Periodic retraining balances adaptation with computational cost

Robustness Requirements

- Sensor variability: Different smartphone models have varying sensor characteristics
 - Solution: Sensor calibration and normalization procedures
- Environmental conditions: Walking surfaces, inclines, crowds affect motion patterns
 - Solution: Diverse training data capturing varied conditions
- Device position: Pocket, hand, bag placement changes sensor orientation
 - Solution: Orientation-invariant feature extraction or position detection

Integration with Existing Systems

- Multi-factor authentication: Combine behavioral biometrics with knowledge-based or possession-based factors
- Risk-adaptive authentication: Adjust verification stringency based on transaction risk
- Standardization: Develop common APIs and protocols for behavioral biometric systems
- Regulatory compliance: Ensure systems meet GDPR, CCPA, and biometric data protection laws

9. Conclusion

This research has developed and evaluated a neural network-based user authentication system leveraging accelerometer and gyroscope sensor data from smartphones. The comprehensive investigation encompassed raw sensor data preprocessing, feature extraction, neural network architecture design, evaluation using biometric-specific metrics, and multi-stage optimization.

Key Achievements

The initial feedforward neural network model achieved an average Equal Error Rate (EER) of 5.57% across 10 users, demonstrating competitive baseline performance. Through systematic optimization employing hybrid feature selection (ANOVA, Mutual Information, Steepest Gradient) and Genetic Algorithm with SVM, the system achieved a remarkable average EER of 0.98% with Leave-One-User-Out cross-validation. This represents an 81% improvement over the baseline, indicating that acceleration-based

behavioral biometrics can achieve authentication performance suitable for security-critical applications.

Technical Contributions

1. Comprehensive feature extraction pipeline transforming raw sensor time-series into 131 discriminative time-domain and frequency-domain features
2. Systematic evaluation of data splitting strategies, demonstrating that cross-day evaluation provides realistic performance estimates
3. Rigorous variance analysis revealing that features with high inter-user variance and low intra-user variance provide optimal discrimination
4. Advanced optimization combining multiple feature selection methods with neural network architecture refinement
5. Detailed per-user performance analysis identifying that user similarity patterns significantly impact authentication difficulty

Performance Insights

Seven out of ten users achieved EER below 3%, with four users reaching perfect or near-perfect discrimination ($EER < 0.5\%$). Two challenging users (Users 7 and 9) exhibited higher error rates due to significant similarity with other users in the feature space, highlighting that authentication performance is fundamentally constrained by the inherent distinctiveness of individual motion patterns. The False Acceptance Rate averaged 2.72% and False Rejection Rate averaged 4.86% in the optimized system, providing a favorable balance between security and usability.

Practical Viability

The results demonstrate that acceleration-based user authentication is technically viable for smartphone deployment. The non-intrusive nature of behavioral biometrics, combined with high accuracy, positions this approach as a valuable component of multi-factor authentication systems. Continuous, transparent verification during device usage enhances security without imposing cognitive burden on users, addressing key limitations of password-based authentication.

Limitations and Future Work

Several challenges remain for practical deployment:

- Temporal adaptation: Long-term behavioral changes require continuous learning mechanisms to maintain accuracy
- Environmental robustness: Performance under diverse real-world conditions (different walking surfaces, device positions, user activities) requires further validation
- Adversarial resilience: Resistance to spoofing attacks and adversarial examples needs comprehensive security evaluation

- Computational optimization: Model compression and efficient implementation are necessary for resource-constrained mobile devices
- Large-scale evaluation: Testing with hundreds or thousands of users is essential to validate scalability

Future research directions include:

1. Deep learning architectures (CNN, LSTM) for end-to-end learning from raw sensor data without manual feature engineering
2. Multi-modal fusion combining accelerometer/gyroscope with touch patterns, keystroke dynamics, and voice characteristics
3. Federated learning approaches enabling collaborative model improvement while preserving user privacy
4. Adversarial training to enhance robustness against spoofing and attack scenarios
5. Context-aware authentication adapting to user activities (walking, sitting, standing, exercising)
6. Real-world deployment studies evaluating long-term performance and user acceptance

Concluding Remarks

This research confirms that motion sensor-based behavioral biometrics provide a promising avenue for enhancing smartphone security. The combination of high accuracy, user convenience, and privacy preservation positions acceleration-based authentication as a valuable technology for next-generation mobile security systems. With continued research addressing deployment challenges and system robustness, behavioral biometric authentication can complement or replace traditional methods, providing seamless security that adapts to individual user characteristics while protecting sensitive information in an increasingly mobile-centric digital landscape.

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11. Appendix

MATLAB Implementation Code

All MATLAB scripts for data preprocessing, feature extraction, neural network training, and evaluation are available in the following repository:

GitHub Repository: <https://github.com/sasindu26/AI-ML-Coursework.git>