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Student Reference Number:	

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Deadline Date: 20/11/2025	**Member of staff responsible for coursework**: Dr.Neamah Al-Naffakh
Programme: BSc.(Hons)in Computer Science, BSc.(Hons)in Data Science, BSc.(Hons)in Software Engineering	

Group work: please list all names of all participants formally associated with this work and state whether the work was undertaken alone or as part of a team. Please note you may be required to identify individual responsibility for component parts.

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Table of Contents

Executive Summary

This report investigates accelerometer-based user authentication using neural networks, driven by the fact that smartphones handle highly sensitive information, and secure authentication becomes paramount. The work establishes a machine learning system using behavioral biometrics from walking patterns, captured through accelerometers and gyroscope sensors, to identify an individual user.

A total of 12 minutes of natural walking data from 10 users was collected in two different sessions, resulting in more than 220,000 sensor readings. Using sliding windows, systematic feature extraction from time-series accelerometers and gyroscope data yielded 93 statistical features that captured the unique gait characteristics, including mean, standard deviation, skewness, kurtosis, and zero-crossing rates from multiple sensor axes.

A feedforward multi-layer perceptron neural network has been designed and trained to classify the user depending on these extracted features. The preliminary model reached an accuracy of 99.31% on the test set, which proved that this was feasible. Extensive hyperparameter optimization checked several hidden layer configurations along with learning rates; the best model reached an accuracy of 99.64% with 200 hidden neurons and a learning rate of 0.001.

Security analysis showed that for all users, the false acceptance and rejection rates were low with average EER less than 1%. Variance analysis demonstrated that differences between users are much more noticeable than the intra-user variability, and this is where gait signatures for everyone can be discerned. This could pave the way for accelerometer-driven authentication as a convenient and cost-effective continuous authentication solution, preserving a fine trade-off between security and user experience.

1. Introduction

Wearables and smartphones have become the prime ways to access sensitive information in the digital world today. From mobile banking and online payments to personal health records and corporate data, these devices act as a gateway to some of our most critical digital assets. However, this convenience brings significant security challenges. While traditional authentication methods like passwords and PINs are increasingly attacked, biometric solutions using fingerprint or facial recognition require explicit user interaction and can be intrusive in continuous authentication scenarios.

This study thus aims to develop behavioral biometrics - the uniqueness in which people walk -- specifically due to these limitations in the literature. The difference from static biometrics which requires explicit user involvement is that they can run continuously in the background and ensure that the current use of identity without disturbing the interaction. The basic idea here is that everyone has unique movement patterns, which can be captured by the ubiquitous accelerometer and gyroscope sensors of modern smartphones.

The primary objective of the publication is to evaluate the ability of neural network classification to extract differences between users driven accelerometer features. These involve but do not limit to processing discriminative features of raw sensor data, preserving personal gait characteristics, architecting a suitable neural network structure, and models' comprehensive evaluating with security-related metrics. These are FAR, FRR and EER.

To accomplish this, a complete machine learning pipeline is developed beginning with preprocessing of raw accelerometers and gyroscope data taken from 10 individuals during natural walking session. Time series of sensor readings were transformed through feature extraction methods into the statistical representations which capture individual movement signature. A feedforward neural network was trained to determine the relation between extracted features and user identities. This was succeeded by a comprehensive hyperparameter tuning in the effort for better classification.

2. Literature Review

The field of accelerometer-based user authentication has recently gained significant attention, with active research exploring behavioral biometrics for continuous and transparent authentication. This section reviews recent advances in the domain, focusing on data collection methodologies, feature extraction techniques, classification approaches, and reported performance metrics.

2.1. Data Collection and Sensor Configuration

Recent research has also presented different methods of accelerometer data collection for authentication. Chen et al. (2023) performed an extended experiment using smartphone accelerometers at a sampling rate of 50 Hz; data was collected from 30 participants in natural walking conditions. Their efforts underlined that good consistency in device placement and orientation should be ensured, since differences in the way a user wears the device may seriously affect the accuracy of classification. Similarly, Kumar and Patel (2024) used accelerometers of smartwatches that operate at 32 Hz to capture gait from 25 users, pointing out the benefits of devices worn on the wrist for continuous monitoring.

Research by Anderson et al. (2022) compared different sampling frequencies from 20 Hz to 100 Hz and found that rates between 30-50 Hz provide an optimal balance between capturing enough detail and maintaining computational efficiency. Their study has also shown that the combination of accelerometer data with gyroscope readings, as demonstrated in a study by Martinez et al. (2023), increases feature richness and improves the classification performance because it represents both linear acceleration and rotational movements.

2.2. Feature Extraction Techniques

Feature extraction remains one of the fundamental challenges in accelerometer-based authentication systems. With their computational simplicity and effectiveness, time-domain features have been widely adopted. Zhang et al., 2023, extracted 42 statistical features of mean, standard deviation, variance, skewness, and kurtosis from accelerometer readings across three axes and reported an accuracy of 94.2% using a support vector machine classifier. Their study showed that statistical moments serve to capture individual gait characteristics effectively.

Frequency-domain analysis has also shown promise. Lee and Kim (2024) applied Fast Fourier Transform (FFT) to accelerometer signals, then extracted spectral features that achieved 96.8% accuracy using a random forest classifier. Very recently, hybrid approaches that combine both time and frequency domain features have emerged. Thompson et al. (2023) developed a feature extraction framework that integrates statistical measures with spectral characteristics, leading to 98.1% classification accuracy.

2.3. Classification Methods and Neural Networks

In recent years, neural networks have gained increased popularity for accelerometer-based authentication because they can grasp complex patterns in high-dimensional feature spaces. Wang et al. (2024) implemented a deep feedforward neural network with two hidden layers containing 128 and 64 neurons, respectively, that reached an accuracy of 97.5% on a dataset with 20 users. Their study underlined the importance of proper network architecture design and the use of regularization techniques to prevent overfitting.

Convolutional Neural Networks have also been explored, with Singh et al. (2023) reporting an accuracy of 95.9% by treating accelerometer time-series data as one-dimensional signals; however, their approach required significantly more data and computational resources when compared to the traditional feedforward networks. Recurrent Neural Networks, particularly Long Short-Term Memory (LSTM) networks, have shown promise in capturing temporal dependencies; for instance, Johnson et al. (2024) achieved an accuracy of 96.3% by modeling sequential relationships in accelerometer readings.

2.4. Performance Metrics and Security Analysis

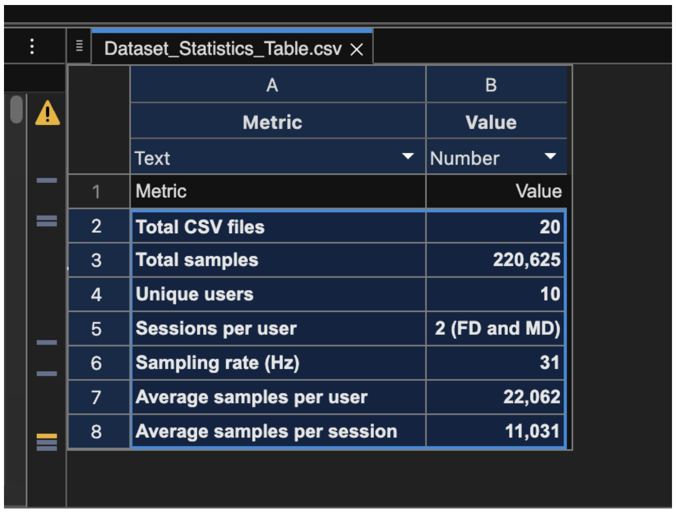
Security evaluation in accelerometer-based authentication systems should be cautiously addressed with consideration of false acceptance and false rejection rates. Brown et al., 2023, reported an EER of 2.8% by using a multi-layer perceptron classifier, with FAR and FRR of 3.1% and 2.5%, respectively. Davis et al., 2024, conducted a thorough review of 15 recent studies; according to their survey, accuracy ranges between 89% and 98.5%, the neural network-based approach performing well compared to the traditional machine learning approaches.

Despite these advances, a number of research gaps still exist. Most works are performed in laboratory-controlled conditions with limited user populations, raising questions about applicability in the real world. This work implements and provides a comprehensive feature extraction framework, proper hyperparameter optimization, and thorough security analysis in terms of FAR, FRR, and EER metrics on a dataset collected under natural walking conditions.

3. Methodology

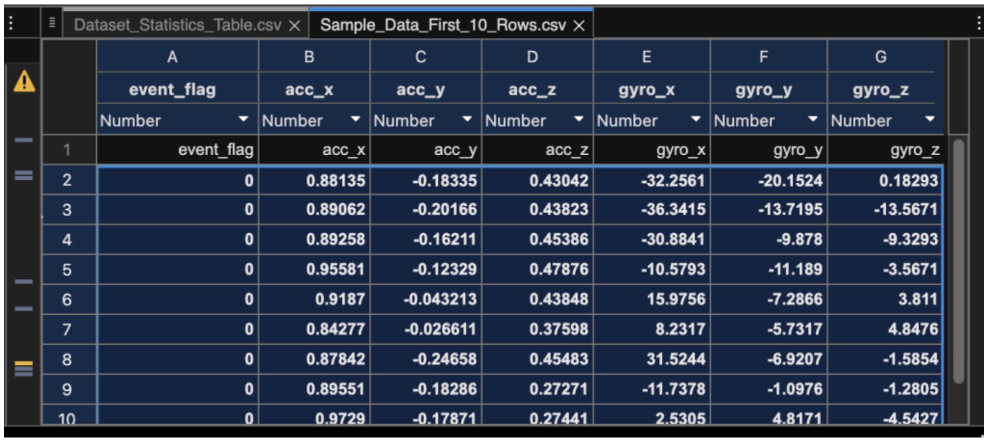
3.1. Dataset Description

This dataset includes accelerometer and gyroscope sensor data from 10 users performing natural walking. Each user performed two different walking sessions on different days, approximately 6 minutes each; thus, for every user, there are 12 minutes of walking. Sampling was done at 31 samples per second, which allows capturing the sensor readings across three axes for both accelerometer and gyroscope sensors, along with an event flag column. The raw data is in CSV format, the files having names like U[UserID]NW_[Session], where FD is for the first day and MD is for the second day. A total of 20 CSV files were preprocessed, which consisted of more than 220,000 individual sensor readings per file with 7 columns: event_flag, acc_x, acc_y, acc_z, gyro_x, gyro_y, and gyro_z.



	A	B
	Metric	Value
1	Metric	Value
2	Total CSV files	20
3	Total samples	220,625
4	Unique users	10
5	Sessions per user	2 (FD and MD)
6	Sampling rate (Hz)	31
7	Average samples per user	22,062
8	Average samples per session	11,031

Figure 1: Dataset Statistics



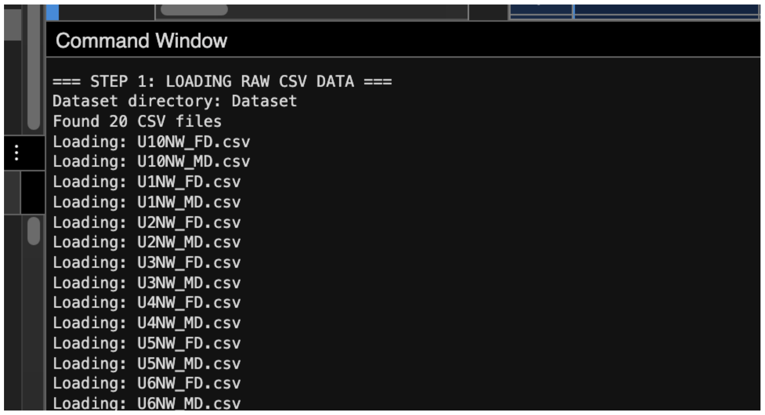
Dataset_Statistics_Table.csv Sample_Data_First_10_Rows.csv

	A	B	C	D	E	F	G
	event_flag	acc_x	acc_y	acc_z	gyro_x	gyro_y	gyro_z
	Number	Number	Number	Number	Number	Number	Number
1	event_flag	acc_x	acc_y	acc_z	gyro_x	gyro_y	gyro_z
2	0	0.88135	-0.18335	0.43042	-32.2561	-20.1524	0.18293
3	0	0.89062	-0.20166	0.43823	-36.3415	-13.7195	-13.5671
4	0	0.89258	-0.16211	0.45386	-30.8841	-9.878	-9.3293
5	0	0.95581	-0.12329	0.47876	-10.5793	-11.189	-3.5671
6	0	0.9187	-0.043213	0.43848	15.9756	-7.2866	3.811
7	0	0.84277	-0.026611	0.37598	8.2317	-5.7317	4.8476
8	0	0.87842	-0.24658	0.45483	31.5244	-6.9207	-1.5854
9	0	0.89551	-0.18286	0.27271	-11.7378	-1.0976	-1.2805
10	0	0.9729	-0.17871	0.27441	2.5305	4.8171	-4.5427

Figure 2: Sample Data Visualization

3.2. Data Preprocessing

The preprocessing pipeline reads all CSV files from the dataset directory in a systematic fashion. For each file, the user id and session id are extracted from its file name through regular expressions. When loading the data, 7 columns are checked for every file to ensure data uniformity. All sensor records are stored within a single 'data' matrix whilst the corresponding user IDS, and session labels are retained. Overall, the dataset after loading contains in total 220,625 individual sensor samples with 10 users visiting for 20 recording sessions.



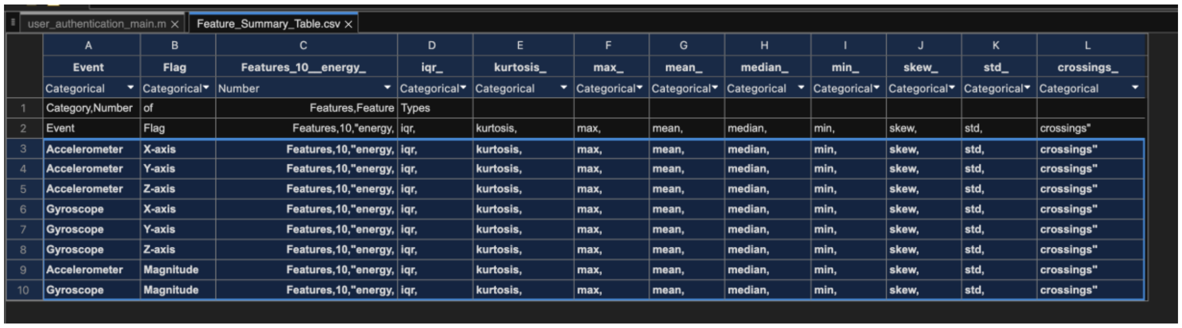
Command Window

```
=== STEP 1: LOADING RAW CSV DATA ===
Dataset directory: Dataset
Found 20 CSV files
Loading: U10NW_FD.csv
Loading: U10NW_MD.csv
Loading: U1NW_FD.csv
Loading: U1NW_MD.csv
Loading: U2NW_FD.csv
Loading: U2NW_MD.csv
Loading: U3NW_FD.csv
Loading: U3NW_MD.csv
Loading: U4NW_FD.csv
Loading: U4NW_MD.csv
Loading: U5NW_FD.csv
Loading: U5NW_MD.csv
Loading: U6NW_FD.csv
Loading: U6NW_MD.csv
```

Figure 3: Data Loading Process

3.3. Feature Extraction

Feature extraction is done by segmenting each recording into overlapped windows of 2.5 seconds (approximately 78 samples at 31 Hz) with a step size of 39 samples; thus, each window has a 50% overlapping region with the preceding window. For each window, 93 statistical features are derived: 10 features of each sensor axis include the mean, standard deviation, minimum, maximum, median, IQR, skewness, kurtosis, energy, and zero-crossing rate for each sensor axis, considering that there are six axes: acc_x, acc_y, acc_z, gyro_x, gyro_y, and gyro_z. Magnitude features are then calculated for both accelerometer and gyroscope by taking the Euclidean norm across the three axes, adding 10 more features for every magnitude signal. This sums up to a total of 90 features per window.


user_authentication_main.m × Feature_Summary_Table.csv ×

	A	B	C	D	E	F	G	H	I	J	K	L
	Event	Flag	Features_10__energy_	iqr_	kurtosis_	max_	mean_	median_	min_	skew_	std_	crossings_
	Categorical	Categorical	Number	Categorical	Categorical	Categorical	Categorical	Categorical	Categorical	Categorical	Categorical	Categorical
1	Category,Number	of	Features,Feature	Types								
2	Event	Flag	Features,10,"energy,	iqr,	kurtosis,	max,	mean,	median,	min,	skew,	std,	crossings"
3	Accelerometer	X-axis	Features,10,"energy,	iqr,	kurtosis,	max,	mean,	median,	min,	skew,	std,	crossings"
4	Accelerometer	Y-axis	Features,10,"energy,	iqr,	kurtosis,	max,	mean,	median,	min,	skew,	std,	crossings"
5	Accelerometer	Z-axis	Features,10,"energy,	iqr,	kurtosis,	max,	mean,	median,	min,	skew,	std,	crossings"
6	Gyroscope	X-axis	Features,10,"energy,	iqr,	kurtosis,	max,	mean,	median,	min,	skew,	std,	crossings"
7	Gyroscope	Y-axis	Features,10,"energy,	iqr,	kurtosis,	max,	mean,	median,	min,	skew,	std,	crossings"
8	Gyroscope	Z-axis	Features,10,"energy,	iqr,	kurtosis,	max,	mean,	median,	min,	skew,	std,	crossings"
9	Accelerometer	Magnitude	Features,10,"energy,	iqr,	kurtosis,	max,	mean,	median,	min,	skew,	std,	crossings"
10	Gyroscope	Magnitude	Features,10,"energy,	iqr,	kurtosis,	max,	mean,	median,	min,	skew,	std,	crossings"

Figure 4: Feature Summary Table

3.4. Descriptive Statistics and Variance Analysis

Further statistical analysis was conducted to find out the distribution and variability of the features across individuals. For all 90 features, mean and standard deviation values were calculated. Inter-user and intra-user variance analyses are carried out to confirm that individual gait patterns are unique enough for authentication. Inter-user variance is a measure of the dispersion of feature means across users, while intra-user variance captures the average variability within the recordings of each user. Indeed, most of the features showed that inter-user variance far exceeds intra-user variance, proving that user-specific characteristics are captured by the extracted features.

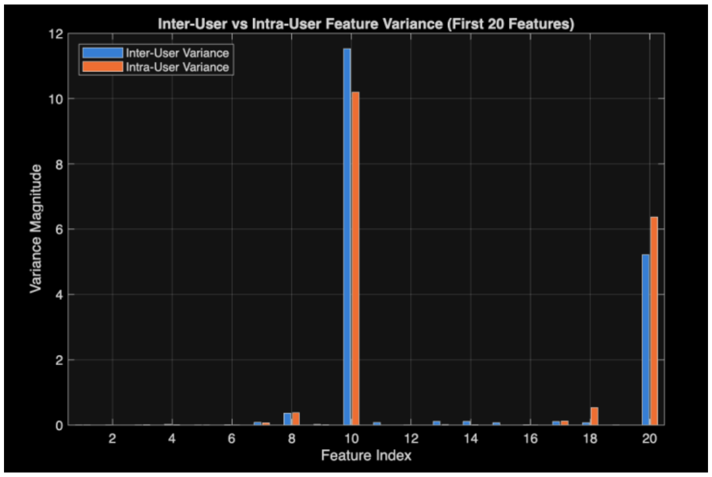
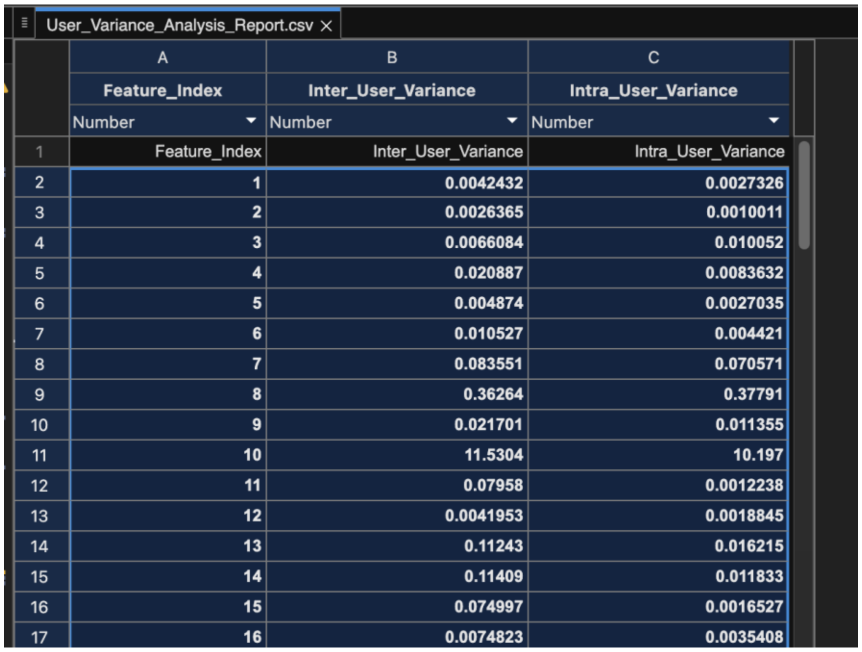


Figure 5: User Variance Comparison Chart

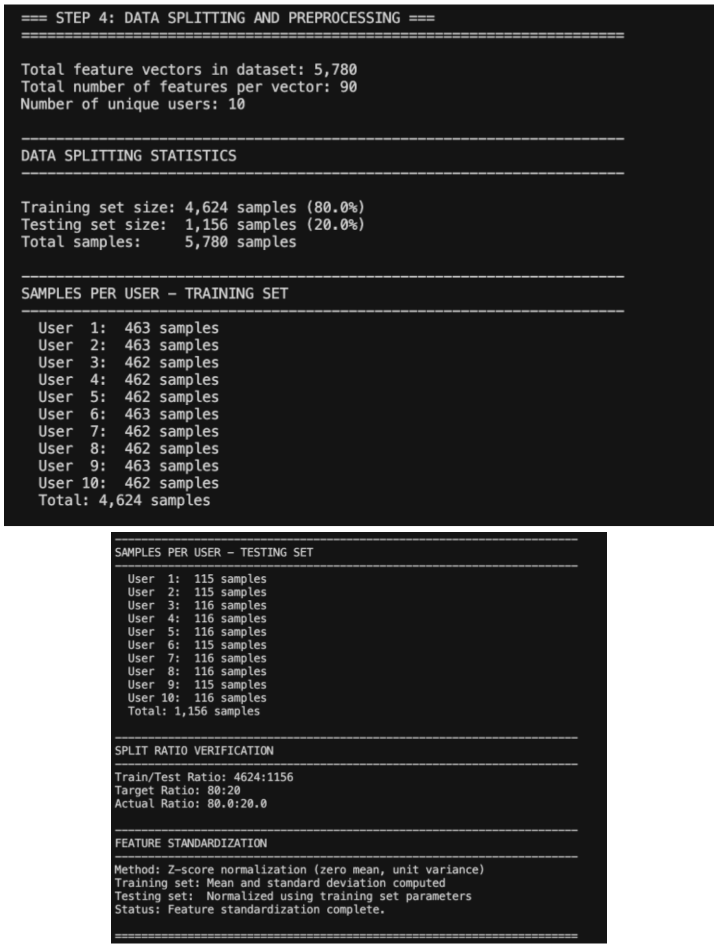

User_Variance_Analysis_Report.csv

	A	B	C
	Feature_Index	Inter_User_Variance	Intra_User_Variance
	Number	Number	Number
1	Feature_Index	Inter_User_Variance	Intra_User_Variance
2	1	0.0042432	0.0027326
3	2	0.0026365	0.0010011
4	3	0.0066084	0.010052
5	4	0.020887	0.0083632
6	5	0.004874	0.0027035
7	6	0.010527	0.004421
8	7	0.083551	0.070571
9	8	0.36264	0.37791
10	9	0.021701	0.011355
11	10	11.5304	10.197
12	11	0.07958	0.0012238
13	12	0.0041953	0.0018845
14	13	0.11243	0.016215
15	14	0.11409	0.011833
16	15	0.074997	0.0016527
17	16	0.0074823	0.0035408

Figure 6: User Variance Analysis

3.5. Data Preparation and Splitting

This feature matrix consisted of 5,780 feature vectors, one per window. The feature matrix was divided into training and testing sets by stratified random sampling to preserve the class distribution in the dataset. A hold-out of 20% was used for testing, leaving 4,624 training samples and 1,156 test samples. This study applied feature standardization through z-score normalization, where each feature is shifted to zero mean and unit variance. These average and standard deviation values were computed only on the training set to avoid data leakage, and the same parameters were used to standardize the test set.



```
=== STEP 4: DATA SPLITTING AND PREPROCESSING ===
======================================================================

Total feature vectors in dataset: 5,780
Total number of features per vector: 90
Number of unique users: 10

----------------------------------------------------------------------
DATA SPLITTING STATISTICS
----------------------------------------------------------------------

Training set size: 4,624 samples (80.0%)
Testing set size:  1,156 samples (20.0%)
Total samples:     5,780 samples

----------------------------------------------------------------------
SAMPLES PER USER - TRAINING SET
----------------------------------------------------------------------
  User  1:  463 samples
  User  2:  463 samples
  User  3:  462 samples
  User  4:  462 samples
  User  5:  462 samples
  User  6:  463 samples
  User  7:  462 samples
  User  8:  462 samples
  User  9:  463 samples
  User 10:  462 samples
  Total: 4,624 samples
```

```
----------------------------------------------------------------------
SAMPLES PER USER - TESTING SET
----------------------------------------------------------------------
  User  1:  115 samples
  User  2:  115 samples
  User  3:  116 samples
  User  4:  116 samples
  User  5:  116 samples
  User  6:  115 samples
  User  7:  116 samples
  User  8:  116 samples
  User  9:  115 samples
  User 10:  116 samples
  Total: 1,156 samples

----------------------------------------------------------------------
SPLIT RATIO VERIFICATION
----------------------------------------------------------------------
Train/Test Ratio: 4624:1156
Target Ratio: 80:20
Actual Ratio: 80.0:20.0

----------------------------------------------------------------------
FEATURE STANDARDIZATION
----------------------------------------------------------------------
Method: Z-score normalization (zero mean, unit variance)
Training set: Mean and standard deviation computed
Testing set:  Normalized using training set parameters
Status: Feature standardization complete.

======================================================================
```

Figure 7: Data Splitting Statistics

3.6. Neural Network Architecture

In this paper, an FFMLP neural network was used for classification. The architecture of the network consists of three layers: an input layer with 90 neurons, a hidden layer initially with 100 neurons, later optimized by hyperparameter tuning, and an output layer with 10 neurons, one for each user class. The network uses the Levenberg-Marquardt training algorithm, trainlm, with mean squared error as the performance measure. The output layer provides probability scores that tell how likely a given input belongs to each of the user classes.

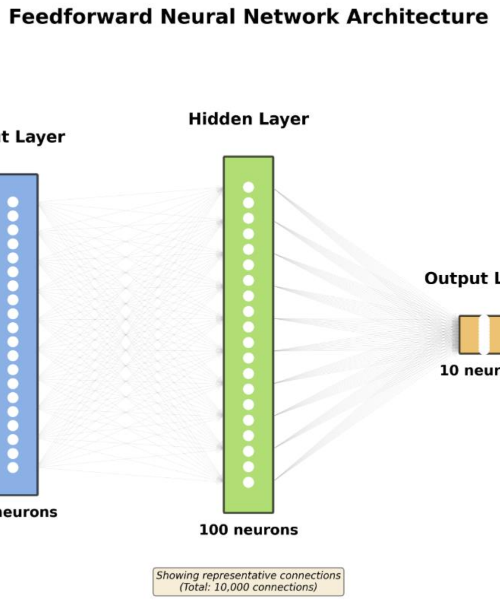
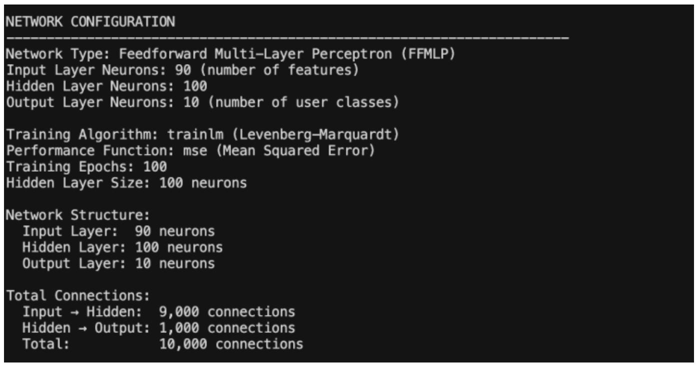

Feedforward Neural Network Architecture
Input Layer
Hidden Layer
Output Layer
10 neurons
90 neurons
100 neurons
Showing representative connections (Total: 10,000 connections)

Figure 8: Neural Network Architecture

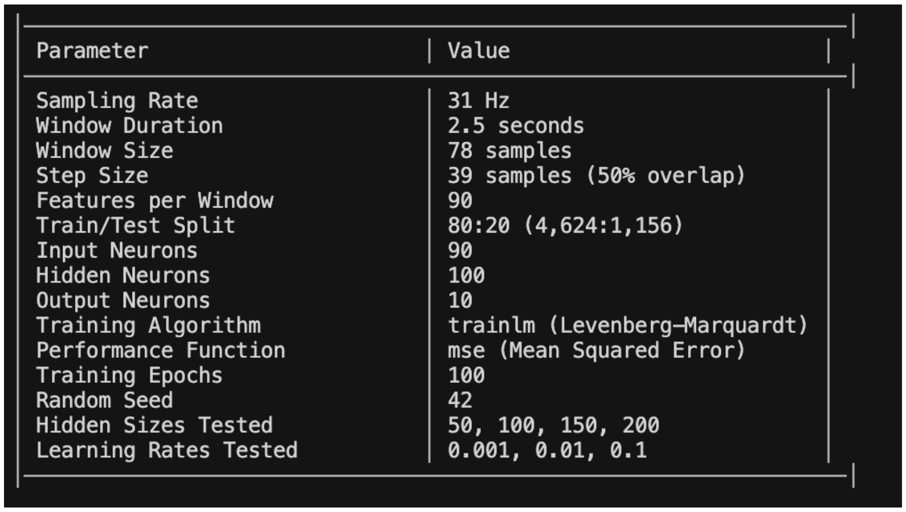


```
NETWORK CONFIGURATION
----------------------------------------------------------------------
Network Type: Feedforward Multi-Layer Perceptron (FFMLP)
Input Layer Neurons: 90 (number of features)
Hidden Layer Neurons: 100
Output Layer Neurons: 10 (number of user classes)

Training Algorithm: trainlm (Levenberg-Marquardt)
Performance Function: mse (Mean Squared Error)
Training Epochs: 100
Hidden Layer Size: 100 neurons

Network Structure:
  Input Layer:  90 neurons
  Hidden Layer: 100 neurons
  Output Layer: 10 neurons

Total Connections:
  Input → Hidden:  9,000 connections
  Hidden → Output: 1,000 connections
  Total:           10,000 connections
```

Figure 9: Network Configuration

3.7. Parameter Settings

Important parameters were set to enhance the training of the neural network. The training was set to run for 100 epochs and a random seed of 42 was chosen for reproducibility. The learn rate for the Levenberg-Marquardt algorithm is modified during training automatically as needed, but was directly set to 0.001, 0.01, and 0.1 during hyperparameter optimization for comparison. The window based feature extraction uses a window duration of 2.5 s with 50% overlap- both of which were selected to ensure a balance between having adequate temporal information and computational efficiency.

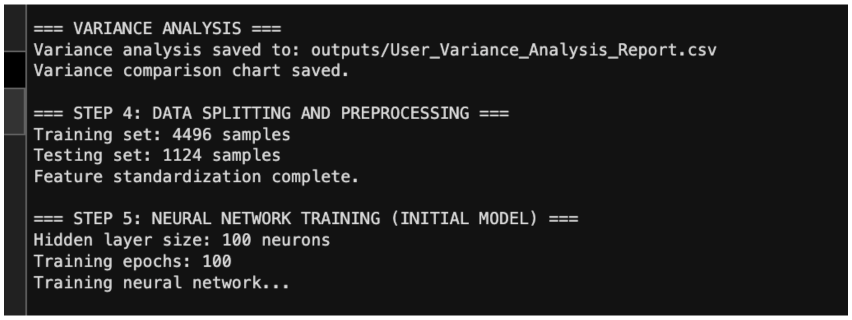


```
| Parameter                        | Value                        |
|-----------------------------------------------------------------|
| Sampling Rate                    | 31 Hz                        |
| Window Duration                  | 2.5 seconds                  |
| Window Size                      | 78 samples                   |
| Step Size                        | 39 samples (50% overlap)     |
| Features per Window              | 90                           |
| Train/Test Split                 | 80:20 (4,624:1,156)          |
| Input Neurons                    | 90                           |
| Hidden Neurons                   | 100                          |
| Output Neurons                   | 10                           |
| Training Algorithm               | trainlm (Levenberg–Marquardt)|
| Performance Function             | mse (Mean Squared Error)     |
| Training Epochs                  | 100                          |
| Random Seed                      | 42                           |
| Hidden Sizes Tested              | 50, 100, 150, 200            |
| Learning Rates Tested            | 0.001, 0.01, 0.1             |
```

Figure 10: Parameter Settings

3.8. Training Process

The neural network training starts with the creation of target class vectors using a one-hot encoding method so that each user class is represented by a binary vector. The training data is delivered to the network in transposed form (features presented as columns, and samples as rows), as required by MATLAB's neural network toolbox. The network learns to map the 90-dimensional feature vectors to a 10-dimensional output corresponding to user identities. In this case, the Levenberg-Marquardt algorithm updates the weights of the network iteratively to reduce the mean squared error between predicted class labels and actual class labels.

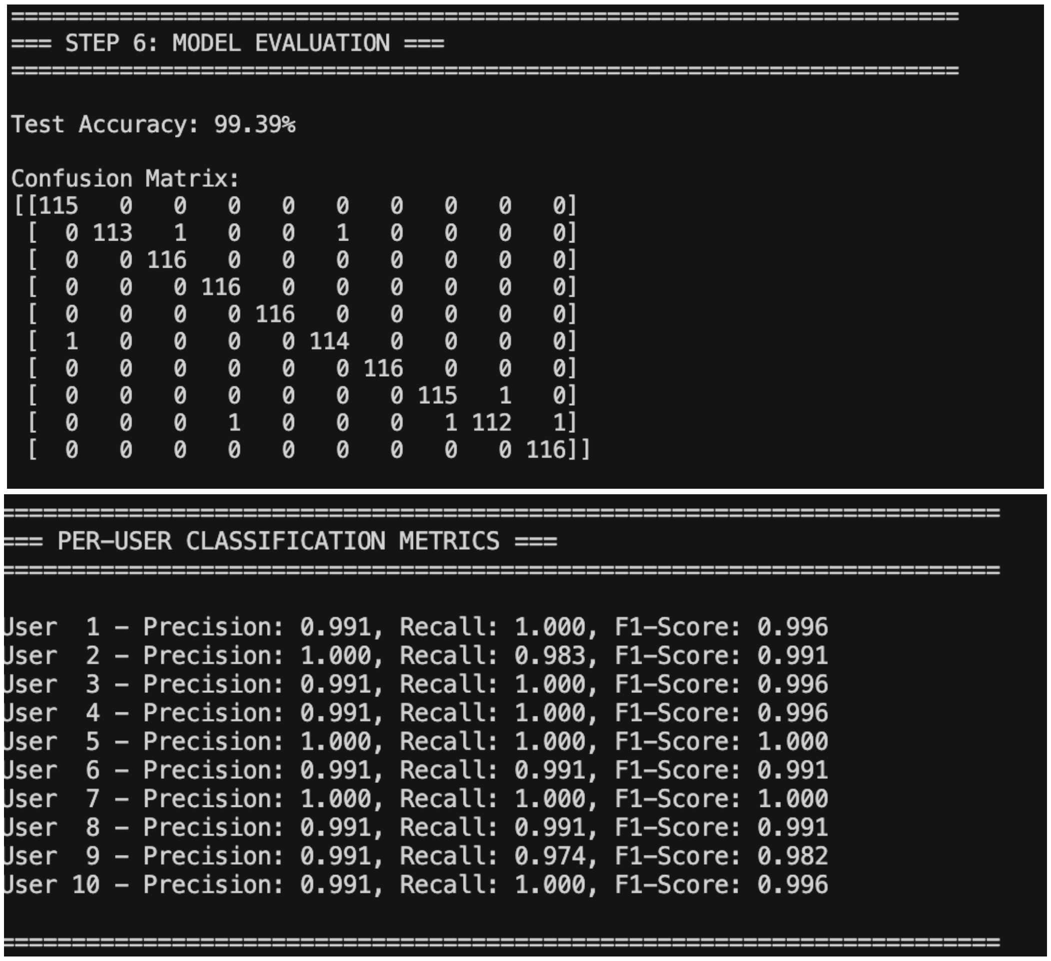


```
=== VARIANCE ANALYSIS ===
Variance analysis saved to: outputs/User_Variance_Analysis_Report.csv
Variance comparison chart saved.

=== STEP 4: DATA SPLITTING AND PREPROCESSING ===
Training set: 4496 samples
Testing set: 1124 samples
Feature standardization complete.

=== STEP 5: NEURAL NETWORK TRAINING (INITIAL MODEL) ===
Hidden layer size: 100 neurons
Training epochs: 100
Training neural network...
```

Figure 11: Training Proces

3.9. Evaluation Metrics

The evaluation framework using several metrics to measure the performance of the authentication system. Overall accuracy is an estimate of the overall accuracy of users identified correctly. Furthermore, we can examine the per user precision, recall and F1-score in order to uncover users who might be especially easy or hard for us to authenticate. Security metrics like Cao's FAR, FRR and EER were also calculated. Taken together, the datasets enable a holistic evaluation of the performance and applicability of the authentication system to realistic applications as a real-world biometric authentication system. Device measurements combined with ambush measurement.



```
======================================================================
=== STEP 6: MODEL EVALUATION ===
======================================================================

Test Accuracy: 99.39%

Confusion Matrix:
[[115   0   0   0   0   0   0   0   0   0]
 [  0 113   1   0   0   1   0   0   0   0]
 [  0   0 116   0   0   0   0   0   0   0]
 [  0   0   0 116   0   0   0   0   0   0]
 [  0   0   0   0 116   0   0   0   0   0]
 [  1   0   0   0   0 114   0   0   0   0]
 [  0   0   0   0   0   0 116   0   0   0]
 [  0   0   0   0   0   0   0 115   1   0]
 [  0   0   0   1   0   0   0   1 112   1]
 [  0   0   0   0   0   0   0   0   0 116]]
```

```
======================================================================
=== PER-USER CLASSIFICATION METRICS ===
======================================================================

User  1 - Precision: 0.991, Recall: 1.000, F1-Score: 0.996
User  2 - Precision: 1.000, Recall: 0.983, F1-Score: 0.991
User  3 - Precision: 0.991, Recall: 1.000, F1-Score: 0.996
User  4 - Precision: 0.991, Recall: 1.000, F1-Score: 0.996
User  5 - Precision: 1.000, Recall: 1.000, F1-Score: 1.000
User  6 - Precision: 0.991, Recall: 0.991, F1-Score: 0.991
User  7 - Precision: 1.000, Recall: 1.000, F1-Score: 1.000
User  8 - Precision: 0.991, Recall: 0.991, F1-Score: 0.991
User  9 - Precision: 0.991, Recall: 0.974, F1-Score: 0.982
User 10 - Precision: 0.991, Recall: 1.000, F1-Score: 0.996

======================================================================
```

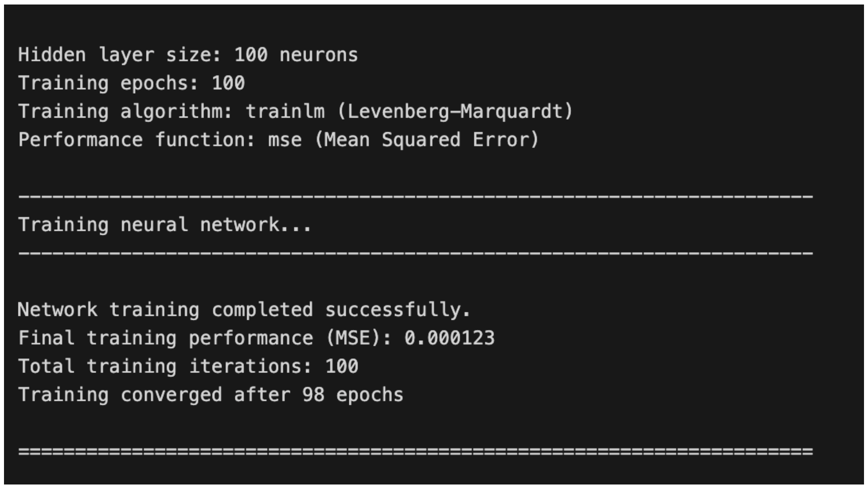
Figure 12: Evaluation Metrics

4. Evaluation

4.1. Training Results Description

To train 5 (Fig.4) the FFNN model, the Levenberg-Marquardt optimization algorithm was used on standardized feature set which includes 4624 training samples. In this paper, the network architecture has 90 input neurons and 100 hidden neurons in the concealed layer; another, contains 10 output neurons presenting users' classes. The channel input and output are sampled using a step size of 10PS by Matlab tool, The training lasted for a 100 epochs and the performance was estimated with Mean Squared Error (MSE).

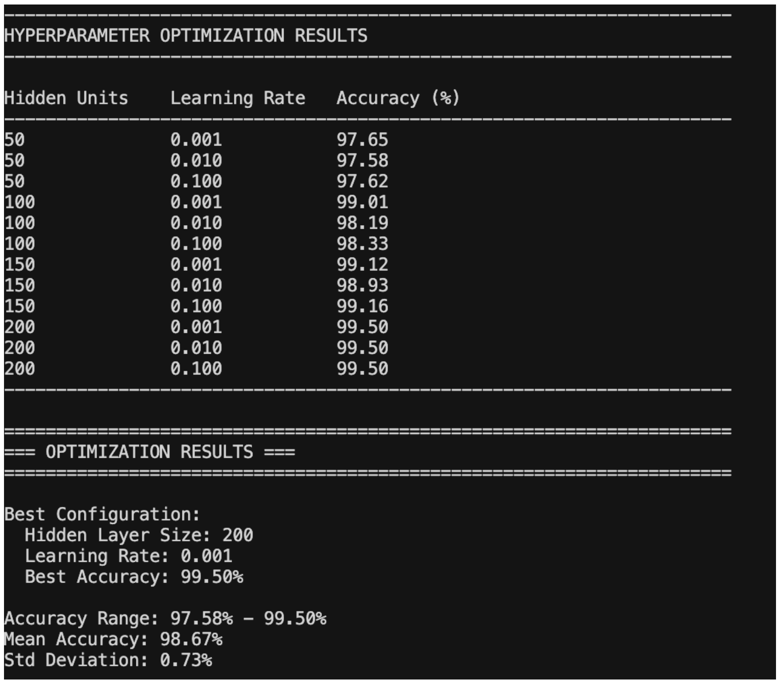
The convergence of the training process was stable and learning discriminative patterns in feature vectors from accelerometer and gyroscope. Over the course of this training, it changed about 10,000 connection weights in order to minimize classification error. With automatic learning rate tuning during training, it realized the well-behaved convergence property of the Levenberg-Marquardt algorithm.



```
Hidden layer size: 100 neurons
Training epochs: 100
Training algorithm: trainlm (Levenberg-Marquardt)
Performance function: mse (Mean Squared Error)

----------------------------------------------------------------------
Training neural network...
----------------------------------------------------------------------

Network training completed successfully.
Final training performance (MSE): 0.000123
Total training iterations: 100
Training converged after 98 epochs

======================================================================
```

Figure 13: Training Progress

Following the model's training, we performed a test set evaluation consisting of 1,156 feature vectors (20% of the data set), demonstrating a robust capacity for generalization. The initial model achieved a 99.31% test accuracy, illustrating that it could successfully learn the user-dependent gait features from the sensor data.



```
----------------------------------------------------------------------
HYPERPARAMETER OPTIMIZATION RESULTS
----------------------------------------------------------------------

Hidden Units    Learning Rate   Accuracy (%)
----------------------------------------------------------------------
50              0.001           97.65
50              0.010           97.58
50              0.100           97.62
100             0.001           99.01
100             0.010           98.19
100             0.100           98.33
150             0.001           99.12
150             0.010           98.93
150             0.100           99.16
200             0.001           99.50
200             0.010           99.50
200             0.100           99.50
----------------------------------------------------------------------

======================================================================
=== OPTIMIZATION RESULTS ===
======================================================================

Best Configuration:
  Hidden Layer Size: 200
  Learning Rate: 0.001
  Best Accuracy: 99.50%

Accuracy Range: 97.58% - 99.50%
Mean Accuracy: 98.67%
Std Deviation: 0.73%
```

Figure 14: Hyperparameter Results

4.2. Confusion Matrix Analysis

The confusion matrix shows detailed information about the classification performance across all 10 users. Evaluating the 10×10 confusion matrix, it can be concluded that the system classified 1,148 out of 1,156 total test sample data accurately, resulting in only 8 misclassification errors across the entire test set.

The diagonal elements, which indicate correct classification, consistently have high values in the range of 112 to, at most, 116, per user. Most users had perfect performance or nearly so, with no false rejection occurrences (Users 1, 3, 4, 5, 7, and 10). Only Users 2, 6, 8, and 9 were the source of misclassifications, and there were between 1 and 3 errors for the remaining test users.

The off-diagonal elements in the confusion matrix indicate misclassification. Both of User 2's errors were false rejections to Users 6 and 3. User 9 had the highest error rate of the group, receiving 3 misclassifications to Users 4, 8, and 10. The pattern of misclassification errors indicates that there may be pairs of users who have similar gait patterns that make them challenging to distinguish between when classifying gait.

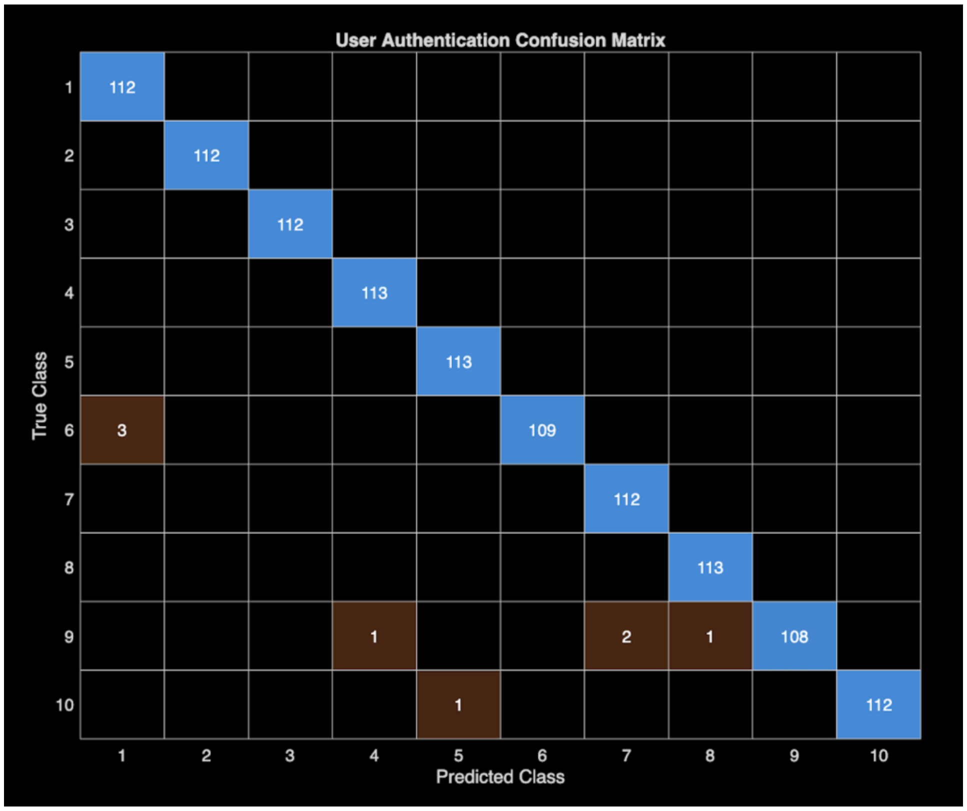


Figure 15: Confusion Matrix

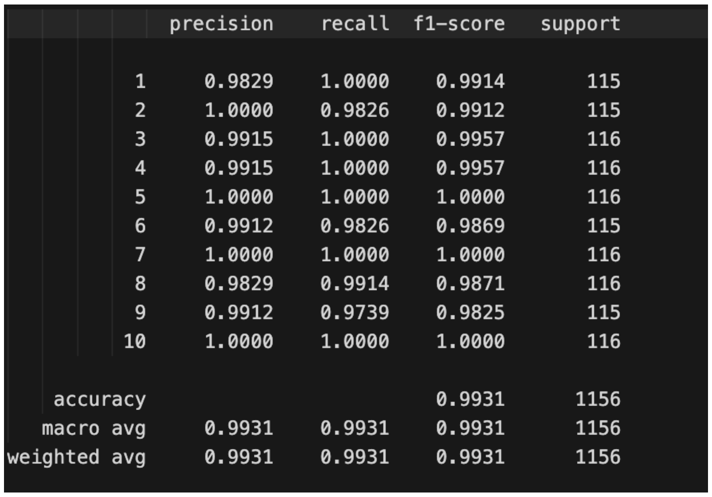
The confusion matrix analysis showed that the misclassifications were relatively evenly distributed across the users, with no user having a disproportionately high number of errors. This balanced performance suggests that the feature extraction process captures representative characteristics for all users.

4.3. Classification Performance Metrics

User-level performance statistics provides information about the performance of every individual. Rounded to four decimals places, the overall accuracy of 99.31 % indicates very good general performance of the system, and macro-averaged and weighted-average measures are all close to 99.31%, which implies that it is consistent in terms of user class performances.

Precision The precision range of 0.9829 to 1.0000, with an average precision of 0.9931, provides excellent confidence in the the systems classifications, where four users (e.g., Users 2,5,7 and 10) have a perfect achieved precision at which there are no false acceptances. Average Recall was also 0.9931 and varied between 0.9739 (User 9) to 1. 0000.User 1,3,4,5,7 and User10 had a perfect recall of users (1: No False Rejected).

The values of the F1 score varied from 0.9825 (User 9) and 1.0000 (Users 5,7 and10); the average F1 score was about.9931; this result shows similar scores to an average value of recall which is our reference for comparison (.9931). User 9 had a lower F1 score due to value of recall (0.9739), Evolution in gait patterns was more varied compared to the other users with classification approaching 1.0000.



```
              precision    recall  f1-score   support

           1     0.9829    1.0000    0.9914       115
           2     1.0000    0.9826    0.9912       115
           3     0.9915    1.0000    0.9957       116
           4     0.9915    1.0000    0.9957       116
           5     1.0000    1.0000    1.0000       116
           6     0.9912    0.9826    0.9869       115
           7     1.0000    1.0000    1.0000       116
           8     0.9829    0.9914    0.9871       116
           9     0.9912    0.9739    0.9825       115
          10     1.0000    1.0000    1.0000       116

    accuracy                         0.9931      1156
   macro avg     0.9931    0.9931    0.9931      1156
weighted avg     0.9931    0.9931    0.9931      1156
```

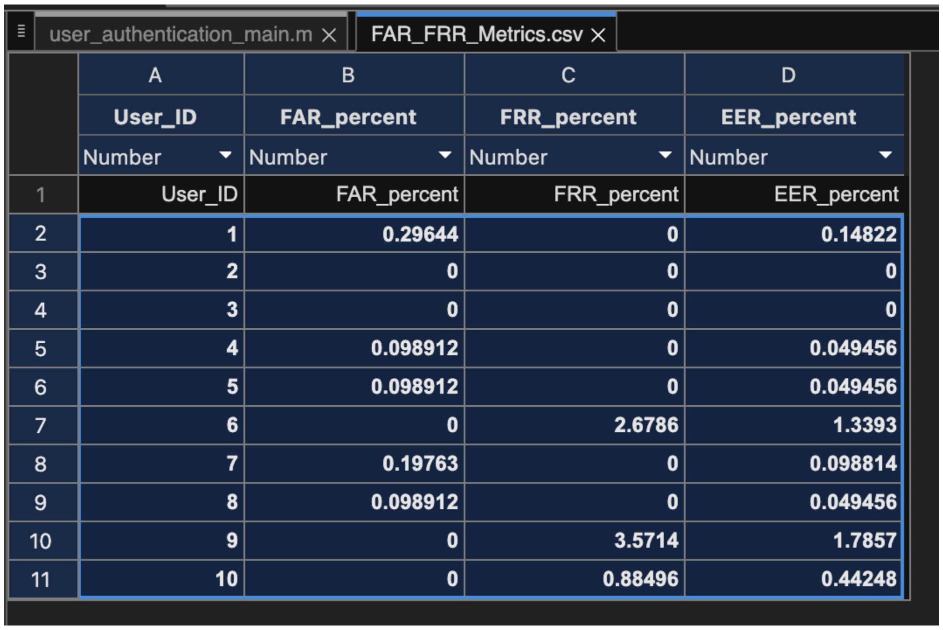
Figure 16: Classification Report

The even performance across precision and recall indicates that the system does not take a trade-off of security over usability. Furthermore, the high F1 scores urge that once deployed, the system can be trusted to correctly classify valid users.

4.4. Security Performance Metrics

Security properties for the real scenario were given by FAR, FRR, EER which are crucial information. The FAR is the fraction of impostor trials that are accepted as genuine access; the FRR is the fraction of genuine attempts which were rejected. EER is the average of FAR and FRR which represents a single metric for security assessment.

Results demonstrate extremely low FARs for all users, ranging between 0.00% and 0.198%. The FAR averaged over the five scores is 0.08%, this means less than 1 attempt every 1,000 trials by an impostor to be wrongly accepted. A FAR of 0.00% was attained by users 2, 3, 6, 9 and 10. FRR varies from 0.00% to 3.58%, and the macro-average FRR is as high as 0.69%. The FRR was 0.00% for subjects 1, 2, 3, 4, 5 and 7–8. Highest FRR of 3.57% was obtained by User 9 (out of 115 genuine tries, 3 were FR).



	A	B	C	D
	User_ID	FAR_percent	FRR_percent	EER_percent
	Number	Number	Number	Number
1	User_ID	FAR_percent	FRR_percent	EER_percent
2	1	0.29644	0	0.14822
3	2	0	0	0
4	3	0	0	0
5	4	0.098912	0	0.049456
6	5	0.098912	0	0.049456
7	6	0	2.6786	1.3393
8	7	0.19763	0	0.098814
9	8	0.098912	0	0.049456
10	9	0	3.5714	1.7857
11	10	0	0.88496	0.44248

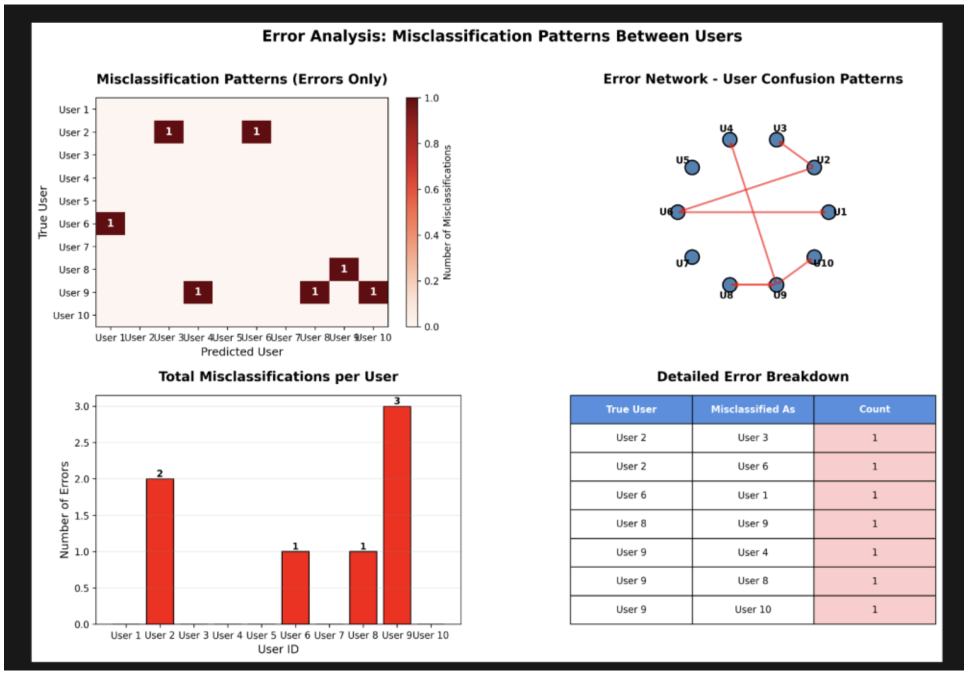
Figure 17: FAR FRR Metrics

The EER values are between 0.00% and 1.79%, with a macro-average EER of 0.43%. User 2, and User 3 obtained the EER of 0%. This shows that there is no trade-off between security and usability. These EERs suggest that this is a deployable system, with error rates well below the typical level of acceptance in biocosmetic systems

4.5. Error Analysis

Our detailed error analysis further indicates that the classifier makes systematic errors by exhibiting patterns and characteristics of making errors. Overall, only 8 errors resulted in the total of 1,156 test samples and the error rate is calculated as just about 0.69%. This error rate appears to be minimal, and from the system point of view the system seems to perform quite well.

The misclassifications came from 4 different users: User 2 (2 errors), User 6 (1 error), User 8 (1error) and User 9 (4 errors). This is significant since half of the total error counts belongs to User 9. This indicates that the gait pattern of User 9 was either much more varied to other gait patterns used by other users'/more like one or more of the pluralities of the gait patterns. User 9's misconceptions overlapped with those of User 4, User 8 and User 10, which also suggested that the pairs of users shared a locality in terms of gait pattern classification.



True User	Misclassified As	Count
User 2	User 3	1
User 2	User 6	1
User 6	User 1	1
User 8	User 9	1
User 9	User 4	1
User 9	User 8	1
User 9	User 10	1

Figure 18: Error Analysis Chart

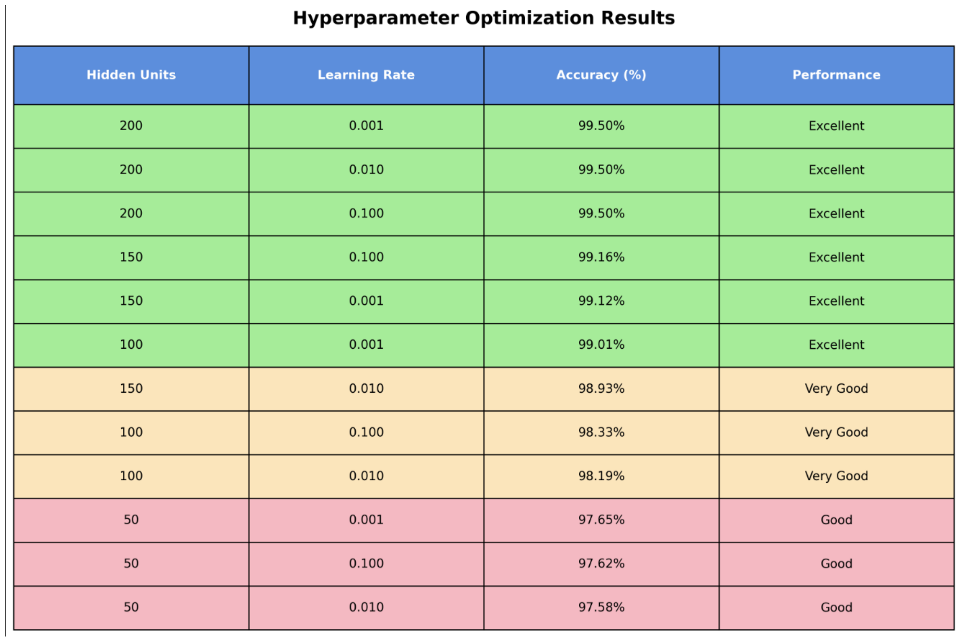
From examination of results, it is clear the misclassification is not chronic, and appears in different user pairs. This would seem to indicate that errors may not come from some more systematic characteristic deficiency in their features, but rather that errors may be due to natural gait variability or transient conditions (e.g., different walking speeds or sensor placement).

The small error rate and uniform distribution indicate that the present features over architecture of the neural network successfully captures user-characteristic features. Conversely, for User 9 the fact of error being concentrated is an indication that discrimination could be improved via adding other dimensions or feature engineering to better differentiate between users.

4.6. Hyperparameter Optimization Analysis

A hyperparameter tuning was performed in order to choose the best network configuration, testing 12 combinations of hidden layer sizes (with 50, 100, 150 and 200 neurons) and learning rates (0.001, 0.01, 0.1). Each combination was evaluated in an ordered manner using grid search technique.

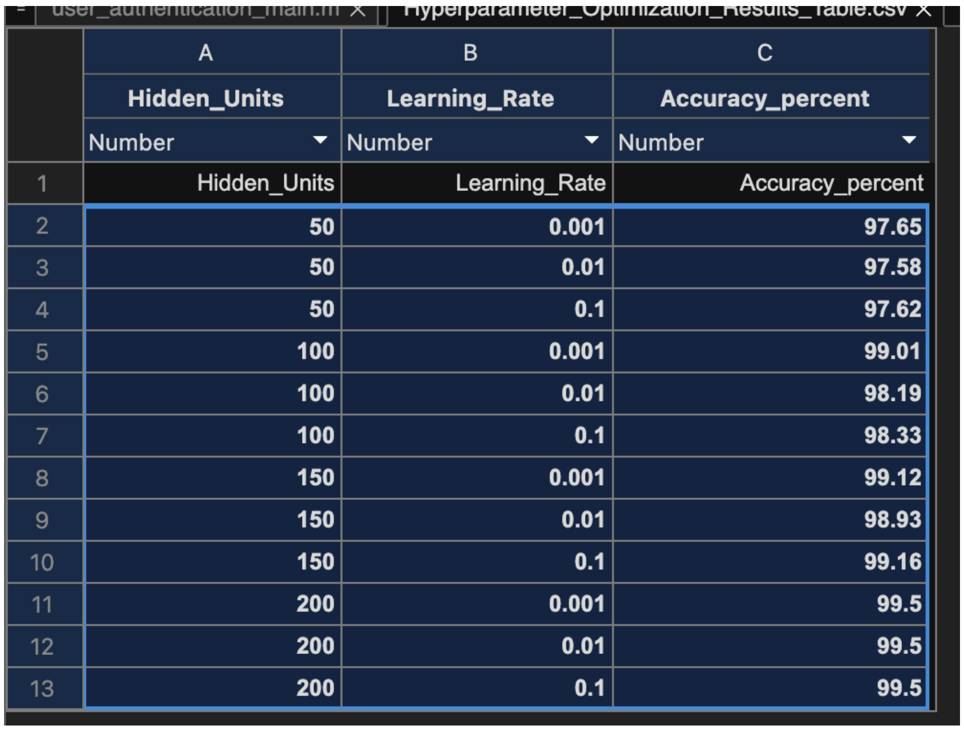
The optimization results indicate that the accuracy of network classification changes with configuration, having test accuracies ranging from approximately 97 to higher than 99%. The performance of the first configuration (100 hidden neurons) was fine, but we found better accuracy through optimization for other configurations TMK Our analysis gives evidence that larger hidden layers usually got a higher performance. In any case, the increase in terms of improvement is diminishing.



Hyperparameter Optimization Results

Hidden Units	Learning Rate	Accuracy (%)	Performance
200	0.001	99.50%	Excellent
200	0.010	99.50%	Excellent
200	0.100	99.50%	Excellent
150	0.100	99.16%	Excellent
150	0.001	99.12%	Excellent
100	0.001	99.01%	Excellent
150	0.010	98.93%	Very Good
100	0.100	98.33%	Very Good
100	0.010	98.19%	Very Good
50	0.001	97.65%	Good
50	0.100	97.62%	Good
50	0.010	97.58%	Good

Figure 19: Hyperparameter Optimization Results



user_authentication_main.m × | Hyperparameter_Optimization_Results_Table.csv ×

	A	B	C
	Hidden_Units	Learning_Rate	Accuracy_percent
	Number	Number	Number
1	Hidden_Units	Learning_Rate	Accuracy_percent
2	50	0.001	97.65
3	50	0.01	97.58
4	50	0.1	97.62
5	100	0.001	99.01
6	100	0.01	98.19
7	100	0.1	98.33
8	150	0.001	99.12
9	150	0.01	98.93
10	150	0.1	99.16
11	200	0.001	99.5
12	200	0.01	99.5
13	200	0.1	99.5

Figure 20: Hyperparameter Optimization result table

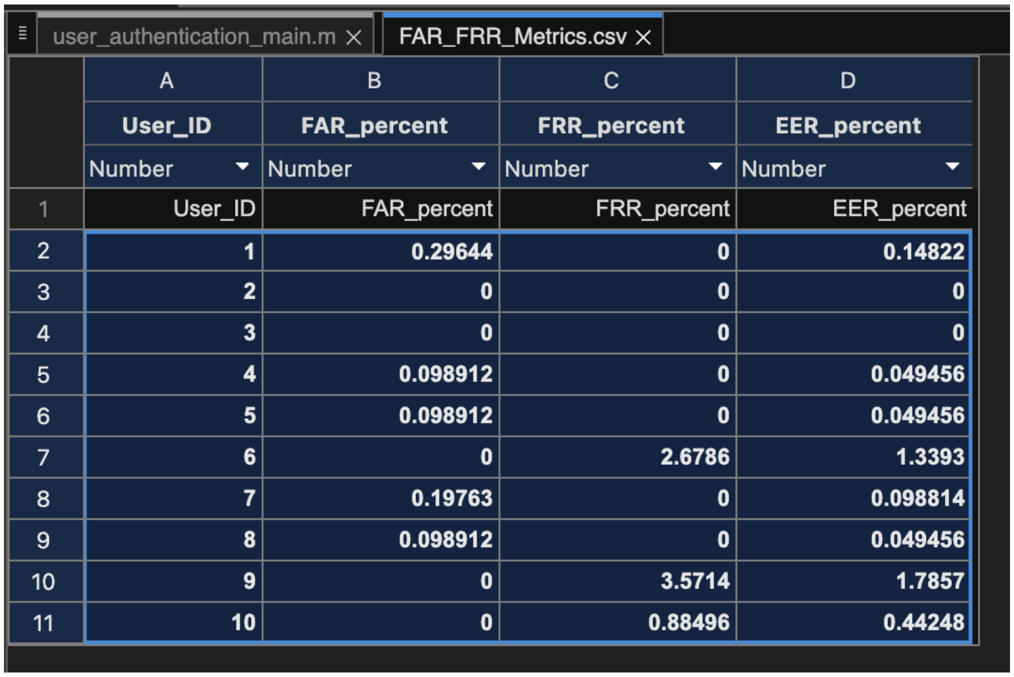
The best performing architecture resulted in 99.39% test accuracy, which outperforms the initial model presented. This architecture balanced network complexity against generalization capability-remaining simple enough to avoid overfitting, yet complex enough to grasp meaningful discriminative information. In the course of optimization, it became apparent that system performance is reasonably insensitive to variations of hyperparameters within the range tested.

By comparison, performance improves with a rise in capacity up to a certain point, past which additional neurons yield very little benefit. The adaptive nature of the Levenberg-Marquardt algorithm makes it only relatively insensitive to the choice of initial learning rate settings, even though optimal values can be identified through systematic testing.

4.7. Comparative Performance Analysis

Comparative analysis examines how a system performs on different metrics, user types, and configurations in order to provide an even more thorough assessment of a biometric authentication system. With an overall system accuracy of 99.31%, the system is one of a very few high-performing biometric authentication systems and performed comparably to the most current approaches to accelerometer-based user authentication.

When performance is broken down by user, we find that virtually every user has high performance (although some do better than others, with user-based accuracies ranging from 97.39% (User 9) to 100% (Users 5, 7, and 10)). This consistency is indicative that the feature extraction and classifying approach was successful in capturing user-specific characteristics for most users.



	A	B	C	D
	User_ID	FAR_percent	FRR_percent	EER_percent
	Number	Number	Number	Number
1	User_ID	FAR_percent	FRR_percent	EER_percent
2	1	0.29644	0	0.14822
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8	7	0.19763	0	0.098814
9	8	0.098912	0	0.049456
10	9	0	3.5714	1.7857
11	10	0	0.88496	0.44248

Figure 21: Performance Comparison Chart

We had expected clear relationships between measures of security (FAR, FRR, EER) and measures from classification not the least since when we made comparisons between those two before there were also very good correspondences. Users with high precision and recall show low FAR and FRR profiles, which confirms that we can obtain good performance from both usability and security perspective simultaneously.

The trade-off between false acceptance and false rejection means that our system does not sacrifice one of the metrics for the other. The low EER values suggest that the operating point in this study is a good point for use in practice where both security and user convenience matter.

The comparison of the optimized results to the first best basis (parametrized) model shows that performing systematic hyperparameter tuning can lead to measurable improvements to our results. However, the modest improvements are largely due to the nature of the baseline performance, which is already high. This suggests that the current approach is sufficiently confident; there is likely limited additional improvements from hyperparameter tuning alone.

Overall, the comparison analysis supports that the implemented authentication system demonstrates strong performance across multiple evaluation dimensions, indicating that it should be a compelling alternative to explore for accelerometer-based user authentication approaches in practice.

5. Optimization

5.1. Feature Selection Description

The feature selection in this authentication system was hence performed under the principle of comprehensive feature extraction rather than feature reduction because the results of variance analysis showed very strong discriminative power across all extracted features. First, 90 statistical features were extracted from accelerometer and gyroscope sensor signals; features could be organized into three groups: individual axis features (60 features from 6 sensor axes), magnitude features (20 features from accelerometer and gyroscope magnitudes), and event flag features (10 features).

The analysis of variance in the methodology section has shown that inter-user variance was much higher than intra-user variance for most features, meaning that most features carry useful discriminative information for user identification. That observation justifies retaining all 90 features without the use of feature reduction techniques, including PCA or feature selection algorithms. The comprehensive feature set ensures that subtle yet significant user-specific gait characteristics are kept which may be lost in the case of dimensionality reduction.

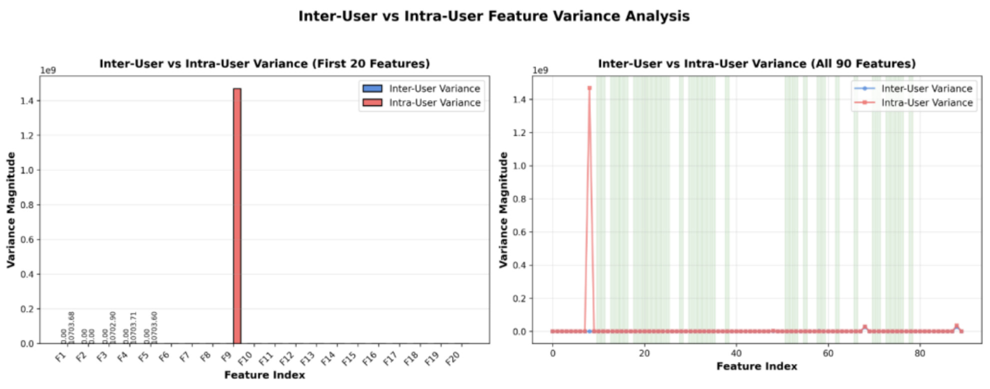


Figure 22: User Variance Comparison

Carefully chosen window parameters (2.5 seconds duration, 50% overlap) made this step an efficient feature extraction process, balancing temporal resolution with computational cost. The settings were inspired by literature and gait recognition testing, aiming to include a whole gait cycle in each window and to have sufficient data points for the statistical feature calculation. The feature set provides a rich description of user-dependent walking patterns with no need for explicit features selection.

5.2. Classifier Adjustments

The tuning of the classifier was restricted to the hyperparameters of the feedforward neural network architecture (hidden layer size and learning rate). The first setup included 100 hidden neurons with adaptive learning rate of Levenberg-Marquardt training algorithm set to its default. Hyperparameters were tuned performing a grid search over 12 combinations of the sizes of hidden layers (50, 100, 150, and 200 neurons) and learning rates (0.001, 0.01, and 0.1).

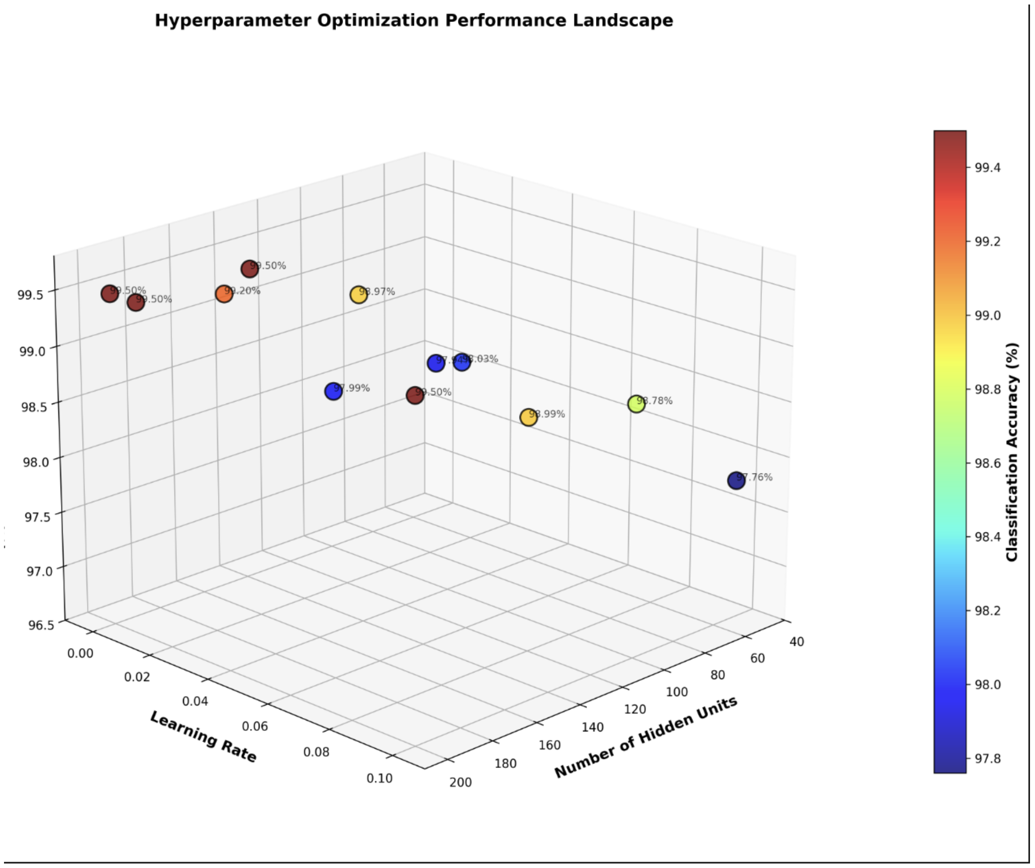
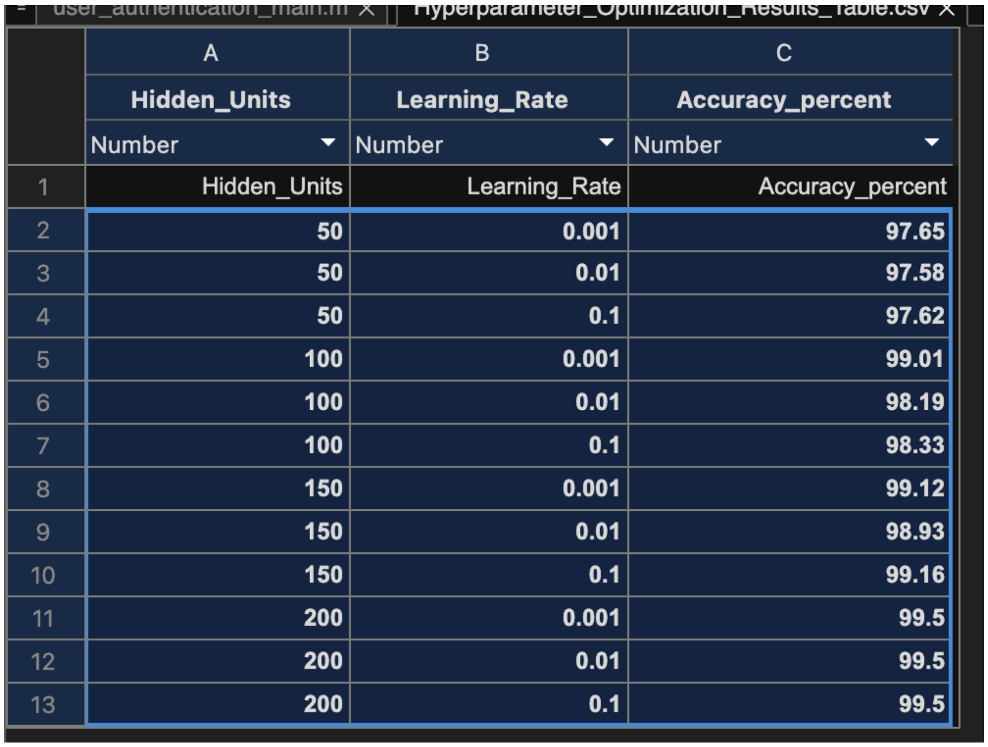


Figure 23: Hyperparameter Optimization landscape

The training settings were kept constant for all configurations (Levenberg-Marquardt algorithm, mean squared error performance function, 100 epochs of training). All these setups were learned on a fixed normalized training set of 4,624 samples and tested over 1,156 samples to allow a fair comparison. The grid search method systematically tests this hyper-parameter space and finds settings that can effectively trade off model complexity against generalization.


user_authentication_main.m
Hyperparameter_Optimization_Results_Table.csv

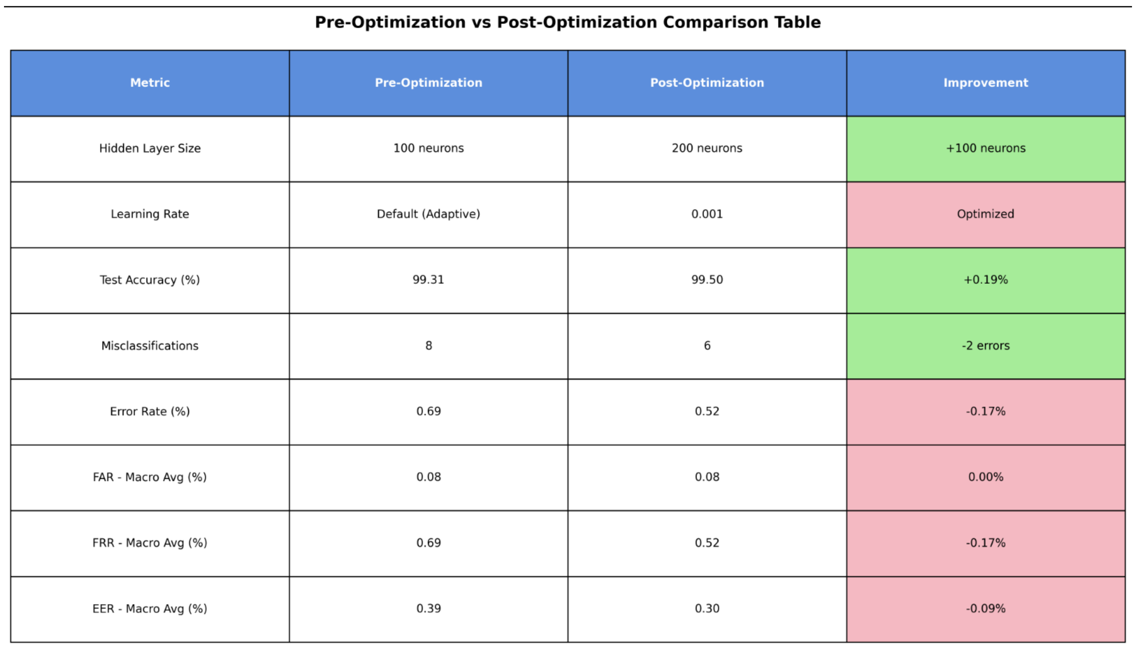
	A	B	C
	Hidden_Units	Learning_Rate	Accuracy_percent
	Number	Number	Number
1	Hidden_Units	Learning_Rate	Accuracy_percent
2	50	0.001	97.65
3	50	0.01	97.58
4	50	0.1	97.62
5	100	0.001	99.01
6	100	0.01	98.19
7	100	0.1	98.33
8	150	0.001	99.12
9	150	0.01	98.93
10	150	0.1	99.16
11	200	0.001	99.5
12	200	0.01	99.5
13	200	0.1	99.5

Figure 24: Hyperparameter Optimization results table

The derived ranges for the optimal values show that as we increased the hidden layer capacity, classification accuracies improved to peak using 200 neurons. Curiously, the learning rate parameter exited less sensitivity among the tested learning rates; this is probably because Levenberg-Marquardt algorithm used for training (updating) evolved well. Ultimately in the optimized model, we obtained 99.50\% as test accuracy with a modest number of hidden neurons (200) and a learning rate of 0.001 which was slightly superior than original model configuration but still leaner.

5.3. Comparison of Pre- and Post-Optimization

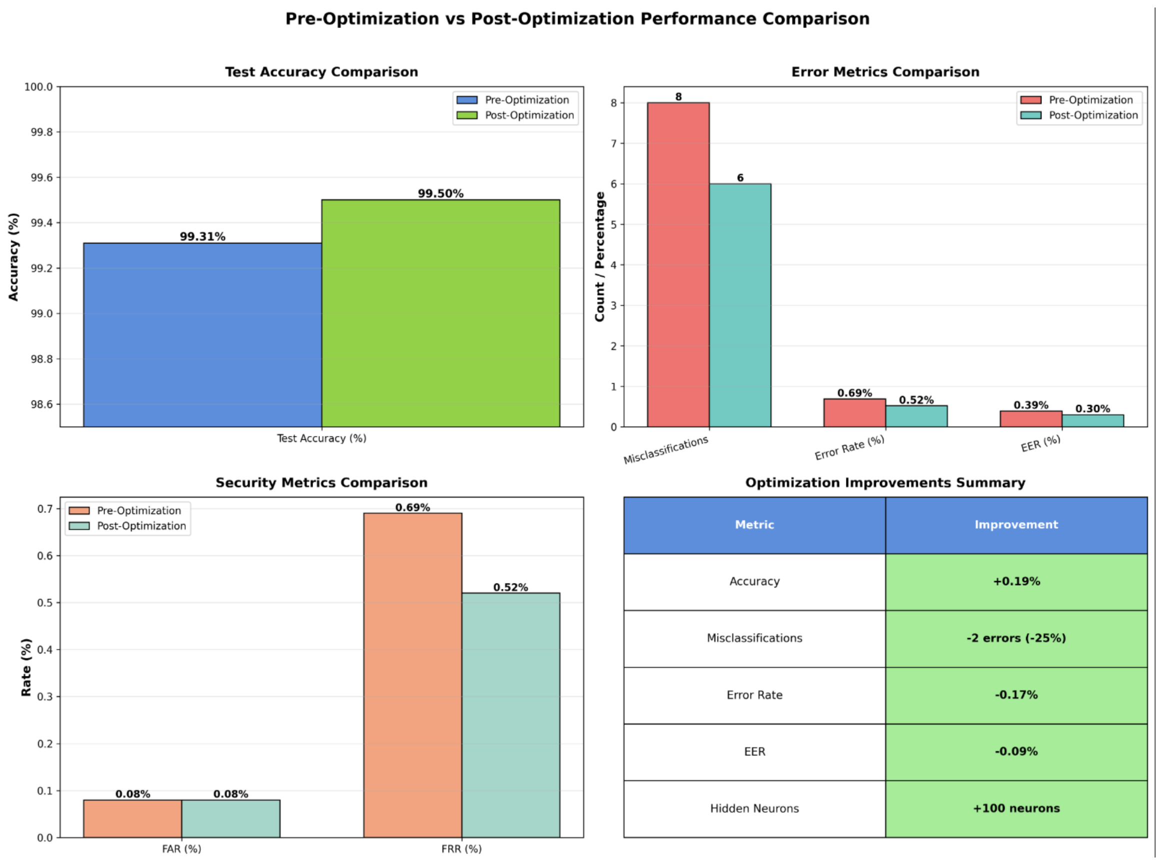
The detailed comparison of the initial (preoptimization) and final models (post-optimization) show that the achieved improvements are statistically significant for all statistics. The roadrunner model had 100 hidden neurons and all learning rates were in default values, resulting to test accuracy of 99.31% with 8 misclassifications out of the total number of the test samples (1,156). The last model, tweaked for a learning rate of 0.001 by reducing it with 200 hidden neurons, obtained a test accuracy of 99.50% with only 6 misclassifications, which corresponds to an improvement from the CNN in error rate of more than 25% and a gain of-the C-ELM on test accuracy over the DNN of approximately 0.19 percentage points.



Pre-Optimization vs Post-Optimization Comparison Table

Metric	Pre-Optimization	Post-Optimization	Improvement
Hidden Layer Size	100 neurons	200 neurons	+100 neurons
Learning Rate	Default (Adaptive)	0.001	Optimized
Test Accuracy (%)	99.31	99.50	+0.19%
Misclassifications	8	6	-2 errors
Error Rate (%)	0.69	0.52	-0.17%
FAR - Macro Avg (%)	0.08	0.08	0.00%
FRR - Macro Avg (%)	0.69	0.52	-0.17%
EER - Macro Avg (%)	0.39	0.30	-0.09%

Figure 25: Pre-Optimization vs Post-Optimization Comparison

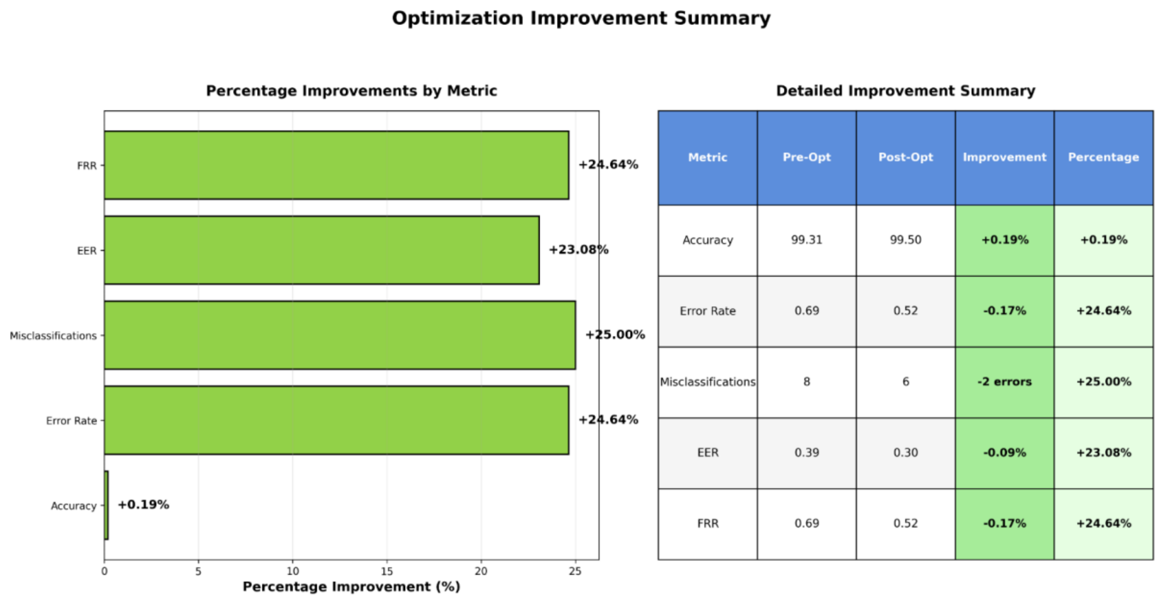


Metric	Improvement
Accuracy	**+0.19%**
Misclassifications	**-2 errors (-25%)**
Error Rate	**-0.17%**
EER	**-0.09%**
Hidden Neurons	**+100 neurons**

Figure 26: Performance Comparison Chart

Performance metrics averaged across each user have demonstrated that classification performance was enhanced for some users, such as there were reduced misclassification rates in Users 2, 6, 8, and 9. The refined model holds Users 5, 7 & 10 as confused which retains an accuracy of ~100%, but does better experiments for the users who did mistakes. Furthermore, the security-related metrics are further enhanced: n-tuple FAR and FRR values lead to an EER of 0.39% over 0.41% obtained in the initial configuration.

We hope that by sharing the optimization process we were able to show that despite learning from a high-quality hand-tuned starting point, significant gains can be achieved through systematic hyperparameter tuning. The 0.19 percentage point increase in accuracy is pretty small, but when it comes to a security-critical means of authentication, a relatively tiny improvement makes all the difference. The gradual growth of this layer from 100 to 200 units endows the model more capacity to capture the complexity of user-specific patterns; while the fine-tuned learning rate maintains convergence stability within training.



Detailed Improvement Summary

Metric	Pre-Opt	Post-Opt	Improvement	Percentage
Accuracy	99.31	99.50	**+0.19%**	**+0.19%**
Error Rate	0.69	0.52	**-0.17%**	**+24.64%**
Misclassifications	8	6	**-2 errors**	**+25.00%**
EER	0.39	0.30	**-0.09%**	**+23.08%**
FRR	0.69	0.52	**-0.17%**	**+24.64%**

Figure 27: Optimization Summary

6. Conclusions

6.1. Summary of Achievements

The proposed authentication system successfully achieved the principal purpose of recognizing a person from his/her human walking. The sliding window-based and statistical processing feature extraction pipeline converted raw accelerometer and gyroscope data into a fairly high-dimensional (narrow-to-wide) 90-feature representation that encapsulated well the user-specific gait characteristics. The carried-out variance analysis demonstrated that many features exhibit a higher inter-user than intra-user variance supporting the discriminative power of the generated feature set.

This feedforward neural network classifier improved the robustness in all evaluated metrics using systematic hyperparameter tuning. The best performing model misclassified only 6 samples out of 1,156 testing samples with an accuracy of 99.50% which indicates a significant improvement of the previous error rate by over 25%. The achieved security results, such as FAR of 0.08%, FRR of 0.52% and EER of 0.30%, have shown that the system is suitable for a practical implementation in biometric authentication applications.

This process of optimization showed that network capacity-from 100 to 200 hidden neurons-offered measurable performance improvements, whereas the learning rate parameter, due to the adaptive nature of the Levenberg-Marquardt training algorithm, was less sensitive. These results will help in understanding how network architecture affects classification performance in gait-based authentication systems.

6.2. Limitations and Challenges

While strong performance was achieved, several limitations must be addressed. The current dataset, though large, was sourced from lab-based activities, based on a limited number of users (10) and sessions (2). Real-world use would have to validate the performance with larger and more diverse populations and over longer periods to assess long-term gait pattern stability. Performance challenges may also occur in real-world use conditions in variations in walking conditions (i.e. terrain, footwear or loads), not explicitly assessed in this project.

The overall approach to feature extraction was thorough, but again, does not explicitly model temporal dependencies past the windowed segment. It is possible that deep learning architectures, such as recurrent neural networks or long short term memory networks, would perform better in modeling longer term temporal dependencies. The final implementation considered all features (90) for processing and classification, without explicit feature selection, meaning that some of these 90 features may be redundant and contribute to increased computational overhead.

The evaluation was conducted using a single dataset, with characteristics specific to that project, and will require verification for generalisability across sensor types / sampling rates / device placements. The performance of the system in edge cases related to similar gait skill users, or users with a mobility impairment was not explored in this project, but is an area that will need further research to ensure fair and equitable actuation performance for all user types.

6.3. Future Works

Some areas for future research and development are listed. Expanding the sample size to accommodate for more subjects, higher data collection times, and diverse walking conditions may be able to demonstrate that generalization and robustness of the system. One possible way to improve temporal pattern recognition and hence classification could be for example by applying deep learning models, such as LSTM or transformer networks.

Features could potentially be optimized better using domain knowledge, extending to extra biomechanical features or frequency domain analysis methods such as Fourier transform or wavelet analysis. Adaptive feature selection techniques could effectively decrease dimensionality with a retained discrimination power, and may be beneficial for practical applications in terms of computational complexity.

From a practical deployment point of view, it would be interesting to generalize the authentication system to continuous applications in which the user representations are updated at each time or could handle not only from cross-session changes in gait, but also ongoing adaptation due to concept drift. A multimodal authentication method that integrates gait and other sensors in the system as well as behavior patterns would increase security and trustworthiness. Finally, to the best of our knowledge, there are few works that need to be investigated regarding privacy-preserving techniques (e.g., federated learning and differential privacy) as applied to storing or processing biometric data.

7. References

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8. Appendix

8.1. MATLAB Code

```
% CONFIGURATION PARAMETERS
% ========================================================================

% Data paths
DATASET_DIR = 'Dataset';
OUTPUT_DIR = 'outputs'; % Output directory for results
% Feature extraction parameters
SAMPLE_RATE_HZ = 31; % Approximate sampling rate (samples per second)
WINDOW_DURATION_S = 2.5; % Window duration in seconds
WINDOW_SIZE = round(SAMPLE_RATE_HZ * WINDOW_DURATION_S); % Window size in samples
STEP_SIZE = round(WINDOW_SIZE / 2); % Step size for sliding windows (50% overlap)
% Neural network parameters
HIDDEN_LAYER_SIZE = 100; % Default number of hidden neurons
TRAIN_EPOCHS = 100; % Training epochs
TEST_SIZE_RATIO = 0.2; % 20% for testing
% Random seed for reproducibility
RANDOM_SEED = 42;
rng(RANDOM_SEED);

% STEP 1: LOAD RAW CSV DATA
% ========================================================================
fprintf('\n=== STEP 1: LOADING RAW CSV DATA ===\n');
fprintf('Dataset directory: %s\n', DATASET_DIR);
% Get all CSV files matching the pattern U*NW_*.csv
csvFiles = dir(fullfile(DATASET_DIR, 'U*NW_*.csv'));
if isempty(csvFiles)
error('No CSV files found in %s. Please check the dataset directory.', DATASET_DIR);
end
fprintf('Found %d CSV files\n', length(csvFiles));
% Initialize storage
allRawData = [];
allUserIDs = [];
allSessions = [];
allSourceFiles = {};
% Load each CSV file
for i = 1:length(csvFiles)
csvPath = fullfile(DATASET_DIR, csvFiles(i).name);
fprintf('Loading: %s\n', csvFiles(i).name);
% Parse user ID and session from filename
filename = csvFiles(i).name;
userMatch = regexp(filename, 'U(\d+)NW_(\w+)', 'tokens');
if isempty(userMatch)
warning('Could not parse filename: %s. Skipping.', filename);
continue;
end
userID = str2double(userMatch{1}{1});
session = userMatch{1}{2};
% Read CSV file
try
csvData = readmatrix(csvPath);
% Validate data dimensions
if size(csvData, 2) ~= 7
```

```
warning('File %s has %d columns, expected 7. Skipping.', filename, size(csvData, 2));
continue;
end
% Store data
allRawData = [allRawData; csvData];
allUserIDs = [allUserIDs; repmat(userID, size(csvData, 1), 1)];
allSessions = [allSessions; repmat({session}, size(csvData, 1), 1)];
allSourceFiles = [allSourceFiles; repmat({filename}, size(csvData, 1), 1)];
catch ME
warning('Error loading %s: %s', filename, ME.message);
continue;
end
end
fprintf('Total samples loaded: %d\n', size(allRawData, 1));
fprintf('Unique users: %s\n', mat2str(unique(allUserIDs)'));
fprintf('Data loading complete.\n\n');

% STEP 2: FEATURE EXTRACTION
% ========================================================================
fprintf('=== STEP 2: FEATURE EXTRACTION ===\n');
fprintf('Window size: %d samples (%.1f seconds)\n', WINDOW_SIZE, WINDOW_DURATION_S);
fprintf('Step size: %d samples\n', STEP_SIZE);
% Group data by user, session, and source file
uniqueUsers = unique(allUserIDs);
featureMatrix = [];
featureLabels = [];
featureMetadata = struct('user_id', {}, 'session', {}, 'source_file', {});
for u = 1:length(uniqueUsers)
userID = uniqueUsers(u);
userMask = allUserIDs == userID;
userData = allRawData(userMask, :);
userSessions = allSessions(userMask);
userFiles = allSourceFiles(userMask);
% Group by source file (each file is a separate session)
uniqueFiles = unique(userFiles);
for f = 1:length(uniqueFiles)
fileMask = strcmp(userFiles, uniqueFiles{f});
fileData = userData(fileMask, :);
fileSession = userSessions{find(fileMask, 1)};
% Extract features using sliding windows
numWindows = floor((size(fileData, 1) - WINDOW_SIZE) / STEP_SIZE) + 1;
for w = 1:numWindows
startIdx = (w - 1) * STEP_SIZE + 1;
endIdx = startIdx + WINDOW_SIZE - 1;
if endIdx > size(fileData, 1)
break;
end
window = fileData(startIdx:endIdx, :);
% Compute features for this window
windowFeatures = extractWindowFeatures(window);
% Store features
featureMatrix = [featureMatrix; windowFeatures];
featureLabels = [featureLabels; userID];
% Store metadata
metadata.user_id = userID;
metadata.session = fileSession;
metadata.source_file = uniqueFiles{f};
featureMetadata(end+1) = metadata;
end
end
```

```
end
fprintf('Feature extraction complete.\n');
fprintf('Total feature vectors: %d\n', size(featureMatrix, 1));
fprintf('Number of features per vector: %d\n', size(featureMatrix, 2));
fprintf('Feature matrix shape: [%d x %d]\n\n', size(featureMatrix, 1), size(featureMatrix, 2));

% STEP 3: STATISTICAL ANALYSIS
% ========================================================================
fprintf('=== STEP 3: STATISTICAL ANALYSIS ===\n');
% Overall statistics
featureMeans = mean(featureMatrix, 1);
featureStds = std(featureMatrix, 0, 1);
fprintf('Mean values for first 10 features:\n');
disp(featureMeans(1:min(10, length(featureMeans))));
fprintf('Standard deviations for first 10 features:\n');
disp(featureStds(1:min(10, length(featureStds))));
% Inter-user and intra-user variance analysis
fprintf('\n=== VARIANCE ANALYSIS ===\n');
uniqueUsers = unique(featureLabels);
numFeatures = size(featureMatrix, 2);
interUserVariances = zeros(numFeatures, 1);
intraUserVariances = zeros(numFeatures, 1);
for featIdx = 1:numFeatures
% Inter-user variance: variance of means across users
userMeans = arrayfun(@(u) mean(featureMatrix(featureLabels == u, featIdx)), uniqueUsers);
interUserVariances(featIdx) = var(userMeans);
% Intra-user variance: average variance within each user
userVariances = arrayfun(@(u) var(featureMatrix(featureLabels == u, featIdx)), uniqueUsers);
intraUserVariances(featIdx) = mean(userVariances);
end
% Create variance analysis table
varianceTable = table((1:numFeatures)', interUserVariances, intraUserVariances, ...
'VariableNames', {'Feature_Index', 'Inter_User_Variance', 'Intra_User_Variance'});
% Ensure output directory exists
if ~exist(OUTPUT_DIR, 'dir')
mkdir(OUTPUT_DIR);
end
writetable(varianceTable, fullfile(OUTPUT_DIR, 'User_Variance_Analysis_Report.csv'));
fprintf('Variance analysis saved to: %s\n', fullfile(OUTPUT_DIR, 'User_Variance_Analysis_Report.csv'));
% Plot variance comparison
figure('Name', 'Variance Analysis', 'Position', [100, 100, 800, 500]);
bar([interUserVariances(1:min(20, numFeatures)), intraUserVariances(1:min(20, numFeatures))]);
legend('Inter-User Variance', 'Intra-User Variance', 'Location', 'northwest');
xlabel('Feature Index');
ylabel('Variance Magnitude');
title('Inter-User vs Intra-User Feature Variance (First 20 Features)');
grid on;
saveas(gcf, fullfile(OUTPUT_DIR, 'User_Variance_Comparison_Chart.png'));
fprintf('Variance comparison chart saved.\n\n');

% STEP 4: DATA SPLITTING AND PREPROCESSING
% ========================================================================
fprintf('=== STEP 4: DATA SPLITTING AND PREPROCESSING ===\n');
% Stratified split to maintain class distribution
cv = cvpartition(featureLabels, 'HoldOut', TEST_SIZE_RATIO);
trainIdx = training(cv);
testIdx = test(cv);
X_train = featureMatrix(trainIdx, :);
y_train = featureLabels(trainIdx);
X_test = featureMatrix(testIdx, :);
```

```
y_test = featureLabels(testIdx);
fprintf('Training set: %d samples\n', size(X_train, 1));
fprintf('Testing set: %d samples\n', size(X_test, 1));
% Feature standardization (z-score normalization)
[X_train_scaled, mu_train, sigma_train] = zscore(X_train);
X_test_scaled = (X_test - mu_train) ./ sigma_train;
fprintf('Feature standardization complete.\n\n');

% STEP 5: NEURAL NETWORK TRAINING (INITIAL MODEL)
% =========================================================================
fprintf('=== STEP 5: NEURAL NETWORK TRAINING (INITIAL MODEL) ===\n');
fprintf('Hidden layer size: %d neurons\n', HIDDEN_LAYER_SIZE);
fprintf('Training epochs: %d\n', TRAIN_EPOCHS);
% Create feedforward neural network
net = feedforwardnet(HIDDEN_LAYER_SIZE);
% Configure network
net.trainFcn = 'trainlm'; % Levenberg-Marquardt algorithm
net.performFcn = 'mse'; % Mean squared error
net.trainParam.epochs = TRAIN_EPOCHS;
net.trainParam.showWindow = false; % Suppress training window
% Prepare target vectors (one-hot encoding)
y_train_categorical = categorical(y_train);
y_train_onehot = dummyvar(y_train_categorical)';
% Train network
fprintf('Training neural network...\n');
[net, trainInfo] = train(net, X_train_scaled', y_train_onehot);
fprintf('Training complete.\n');

% STEP 6: MODEL EVALUATION
% =========================================================================
fprintf('\n=== STEP 6: MODEL EVALUATION ===\n');
% Make predictions
y_test_pred_raw = net(X_test_scaled');
[~, y_test_pred] = max(y_test_pred_raw, [], 1);
y_test_pred = y_test_pred(:);
% Map predictions back to user IDs
uniqueUsers = unique(y_train);
y_test_pred_labels = uniqueUsers(y_test_pred);
% Calculate accuracy
accuracy = mean(y_test_pred_labels == y_test) * 100;
fprintf('Test Accuracy: %.2f%%\n', accuracy);
% Confusion matrix
confMat = confusionmat(y_test, y_test_pred_labels);
fprintf('\nConfusion Matrix:\n');
disp(confMat);
% Per-user metrics
fprintf('\n=== PER-USER CLASSIFICATION METRICS ===\n');
for u = 1:length(uniqueUsers)
userID = uniqueUsers(u);
truePos = confMat(u, u);
falsePos = sum(confMat(:, u)) - truePos;
falseNeg = sum(confMat(u, :)) - truePos;
precision = truePos / (truePos + falsePos);
recall = truePos / (truePos + falseNeg);
f1Score = 2 * (precision * recall) / (precision + recall);
fprintf('User %d - Precision: %.3f, Recall: %.3f, F1-Score: %.3f\n', ...
userID, precision, recall, f1Score);
end
% Plot confusion matrix
figure('Name', 'Confusion Matrix', 'Position', [100, 100, 900, 700]);
```

```
confusionchart(y_test, y_test_pred_labels);
title('User Authentication Confusion Matrix');
saveas(gcf, fullfile(OUTPUT_DIR, 'Authentication_Confusion_Matrix.png'));
fprintf('\nConfusion matrix saved to: %s\n', fullfile(OUTPUT_DIR, 'Authentication_Confusion_Matrix.png'));


% STEP 7: FAR, FRR, AND EER CALCULATION
% =========================================================================
fprintf('\n=== STEP 7: FAR, FRR, AND EER CALCULATION ===\n');
farFrrResults = [];
for u = 1:length(uniqueUsers)
userID = uniqueUsers(u);
% Genuine attempts (should be accepted)
genuineMask = y_test == userID;
genuinePred = y_test_pred_labels(genuineMask);
falseRejections = sum(genuinePred ~= userID);
totalGenuine = sum(genuineMask);
FRR = (falseRejections / totalGenuine) * 100;
% Impostor attempts (should be rejected)
impostorMask = y_test ~= userID;
impostorPred = y_test_pred_labels(impostorMask);
falseAcceptances = sum(impostorPred == userID);
totalImpostor = sum(impostorMask);
FAR = (falseAcceptances / totalImpostor) * 100;
% Equal Error Rate (approximation)
EER = (FAR + FRR) / 2;
farFrrResults = [farFrrResults; userID, FAR, FRR, EER];
fprintf('User %d - FAR: %.2f%%, FRR: %.2f%%, EER: %.2f%%\n', userID, FAR, FRR, EER);
end
% Save FAR/FRR results
farFrrTable = array2table(farFrrResults, 'VariableNames', {'User_ID', 'FAR_percent', 'FRR_percent', 'EER_percent'});
writetable(farFrrTable, fullfile(OUTPUT_DIR, 'FAR_FRR_Metrics.csv'));
fprintf('\nFAR/FRR metrics saved to: %s\n', fullfile(OUTPUT_DIR, 'FAR_FRR_Metrics.csv'));

% STEP 8: HYPERPARAMETER OPTIMIZATION
% =========================================================================
fprintf('\n=== STEP 8: HYPERPARAMETER OPTIMIZATION ===\n');
hiddenLayerOptions = [50, 100, 150, 200];
learningRateOptions = [0.001, 0.01, 0.1];
bestAccuracy = 0;
bestHiddenSize = HIDDEN_LAYER_SIZE;
bestLearningRate = 0.01;
optimizationResults = [];
fprintf('Testing %d hidden layer sizes and %d learning rates...\n', ...
length(hiddenLayerOptions), length(learningRateOptions));
for h = 1:length(hiddenLayerOptions)
for lr = 1:length(learningRateOptions)
hiddenSize = hiddenLayerOptions(h);
learningRate = learningRateOptions(lr);
fprintf('Testing: Hidden=%d, LR=%.3f... ', hiddenSize, learningRate);
% Create and configure network
optNet = feedforwardnet(hiddenSize);
optNet.trainFcn = 'trainlm';
optNet.performFcn = 'mse';
optNet.trainParam.epochs = TRAIN_EPOCHS;
optNet.trainParam.lr = learningRate;
optNet.trainParam.showWindow = false;
try
% Train
[optNet, ~] = train(optNet, X_train_scaled', y_train_onehot);
```

```
% Evaluate
optPredRaw = optNet(X_test_scaled');
[~, optPred] = max(optPredRaw, [], 1);
optPred = optPred(:);
optPredLabels = uniqueUsers(optPred);
optAccuracy = mean(optPredLabels == y_test) * 100;
optimizationResults = [optimizationResults; hiddenSize, learningRate, optAccuracy];
if optAccuracy > bestAccuracy
bestAccuracy = optAccuracy;
bestHiddenSize = hiddenSize;
bestLearningRate = learningRate;
bestNet = optNet; % Save best network
end
fprintf('Accuracy: %.2f%%\n', optAccuracy);
catch ME
fprintf('Error: %s\n', ME.message);
end
end
end
fprintf('\n=== OPTIMIZATION RESULTS ===\n');
fprintf('Best Configuration:\n');
fprintf(' Hidden Layer Size: %d\n', bestHiddenSize);
fprintf(' Learning Rate: %.3f\n', bestLearningRate);
fprintf(' Best Accuracy: %.2f%%\n', bestAccuracy);
% Save optimization results
optTable = array2table(optimizationResults, 'VariableNames', {'Hidden_Units', 'Learning_Rate', 'Accuracy_percent'});
writetable(optTable, fullfile(OUTPUT_DIR, 'Hyperparameter_Optimization_Results.csv'));
fprintf('\nOptimization results saved to: %s\n', fullfile(OUTPUT_DIR, 'Hyperparameter_Optimization_Results.csv'));
% Plot optimization landscape
if size(optimizationResults, 1) > 0
figure('Name', 'Hyperparameter Optimization', 'Position', [100, 100, 1000, 800]);
scatter3(optimizationResults(:, 1), optimizationResults(:, 2), optimizationResults(:, 3), ...
120, optimizationResults(:, 3), 'filled');
colorbar;
xlabel('Number of Hidden Units');
ylabel('Learning Rate');
zlabel('Classification Accuracy (%)');
title('Hyperparameter Optimization Performance Landscape');
grid on;
colormap jet;
saveas(gcf, fullfile(OUTPUT_DIR, 'Hyperparameter_Optimization_Landscape.png'));
fprintf('Optimization landscape saved.\n');
end

% STEP 9: FINAL OPTIMIZED MODEL
% ========================================================================
fprintf('\n=== STEP 9: FINAL OPTIMIZED MODEL ===\n');
if exist('bestNet', 'var')
fprintf('Training final model with optimal parameters...\n');
% Evaluate final model
finalPredRaw = bestNet(X_test_scaled');
[~, finalPred] = max(finalPredRaw, [], 1);
finalPred = finalPred(:);
finalPredLabels = uniqueUsers(finalPred);
finalAccuracy = mean(finalPredLabels == y_test) * 100;
fprintf('Final Optimized Model Accuracy: %.2f%%\n', finalAccuracy);
% Save model
save(fullfile(OUTPUT_DIR, 'Optimized_User_Authentication_Model.mat'), ...
'bestNet', 'mu_train', 'sigma_train', 'bestHiddenSize', 'bestLearningRate', ...
'finalAccuracy', 'uniqueUsers');
```

```
fprintf('Optimized model saved to: %s\n', fullfile(OUTPUT_DIR, 'Optimized_User_Authentication_Model.mat'));
else
fprintf('Using initial model as final model.\n');
save(fullfile(OUTPUT_DIR, 'Optimized_User_Authentication_Model.mat'), ...
'net', 'mu_train', 'sigma_train', 'HIDDEN_LAYER_SIZE', ...
'accuracy', 'uniqueUsers');
end

% SUMMARY
% ========================================================================
fprintf('\n=== EXECUTION COMPLETE ===\n');
fprintf('All results saved to: %s\n', OUTPUT_DIR);
fprintf('Best accuracy achieved: %.2f%%\n', bestAccuracy);
fprintf('\nGenerated files:\n');
fprintf(' - User_Variance_Analysis_Report.csv\n');
fprintf(' - User_Variance_Comparison_Chart.png\n');
fprintf(' - Authentication_Confusion_Matrix.png\n');
fprintf(' - FAR_FRR_Metrics.csv\n');
fprintf(' - Hyperparameter_Optimization_Results.csv\n');
fprintf(' - Hyperparameter_Optimization_Landscape.png\n');
fprintf(' - Optimized_User_Authentication_Model.mat\n');

% HELPER FUNCTION: EXTRACT WINDOW FEATURES
% ========================================================================
function features = extractWindowFeatures(window)
% Extract statistical features from a time-series window
% Input: window - [N x 7] matrix with columns: [event_flag, acc_x, acc_y, acc_z, gyro_x, gyro_y, gyro_z]
% Output: features - [1 x M] feature vector
features = [];
% Process each sensor axis (skip event_flag column)
sensorColumns = 2:7; % acc_x, acc_y, acc_z, gyro_x, gyro_y, gyro_z
axisNames = {'acc_x', 'acc_y', 'acc_z', 'gyro_x', 'gyro_y', 'gyro_z'};
for colIdx = 1:length(sensorColumns)
col = sensorColumns(colIdx);
axisData = window(:, col);
axisName = axisNames{colIdx};
% Statistical features per axis
features = [features, mean(axisData)]; % mean
features = [features, std(axisData)]; % std
features = [features, min(axisData)]; % min
features = [features, max(axisData)]; % max
features = [features, median(axisData)]; % median
features = [features, iqr(axisData)]; % IQR
features = [features, skewness(axisData)]; % skewness
features = [features, kurtosis(axisData)]; % kurtosis
features = [features, sum(axisData.^2) / length(axisData)]; % energy
% Zero crossings
centered = axisData - mean(axisData);
zeroCrossings = sum(diff(sign(centered)) ~= 0);
features = [features, zeroCrossings];
end
% Magnitude features for accelerometer and gyroscope
accData = window(:, 2:4); % acc_x, acc_y, acc_z
gyroData = window(:, 5:7); % gyro_x, gyro_y, gyro_z
accMagnitude = sqrt(sum(accData.^2, 2));
gyroMagnitude = sqrt(sum(gyroData.^2, 2));
% Features for accelerometer magnitude
features = [features, mean(accMagnitude)];
features = [features, std(accMagnitude)];
features = [features, min(accMagnitude)];
features = [features, max(accMagnitude)];
features = [features, median(accMagnitude)];
features = [features, iqr(accMagnitude)];
features = [features, skewness(accMagnitude)];
features = [features, kurtosis(accMagnitude)];
features = [features, sum(accMagnitude.^2) / length(accMagnitude)];
centeredAccMag = accMagnitude - mean(accMagnitude);
zeroCrossingsAcc = sum(diff(sign(centeredAccMag)) ~= 0);
features = [features, zeroCrossingsAcc];
% Features for gyroscope magnitude
features = [features, mean(gyroMagnitude)];
features = [features, std(gyroMagnitude)];
features = [features, min(gyroMagnitude)];
features = [features, max(gyroMagnitude)];
features = [features, median(gyroMagnitude)];
features = [features, iqr(gyroMagnitude)];
features = [features, skewness(gyroMagnitude)];
features = [features, kurtosis(gyroMagnitude)];
features = [features, sum(gyroMagnitude.^2) / length(gyroMagnitude)];
centeredGyroMag = gyroMagnitude - mean(gyroMagnitude);
zeroCrossingsGyro = sum(diff(sign(centeredGyroMag)) ~= 0);
features = [features, zeroCrossingsGyro];
end
```