BANGLADESH UNIVERSITY OF ENGINEERING AND TECHNOLOGY
DEPARTMENT OF ELECTRICAL AND ELECTRONIC ENGINEERING

EEE 312

Communication System I Laboratory

Final Project Report

Section: C2 Group:05

EMG signal-based Robotic Hand implementation

Video link: https://drive.google.com/file/d/17-B_it5gewkVDxhOfPqNekXm4_lZvnDM/view?usp=sharing

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1. Abstract

Electromyography (EMG) is a powerful tool for detecting neuromuscular activity, enabling the development of intelligent prosthetics, gesture-controlled systems, and rehabilitation devices. This project focuses on the classification of upper limb movements using surface EMG signals collected from multiple participants. We extract features via two complementary approaches: spectrogram-based time-frequency analysis and handcrafted time-domain features (RMS, MAV, SSC, WAMP). These features are used to train and evaluate multiple classifiers, including Support Vector Machine (SVM), Random Forest, and k-Nearest Neighbours (kNN). The system demonstrates high accuracy in distinguishing six selected hand/wrist movements, with thorough performance evaluation and visualization. This work highlights the effectiveness of EMG signals and machine learning for real-time, non-invasive movement classification.

2. Introduction

Human-computer interaction systems are increasingly exploring bio-signals to enable intuitive control mechanisms. Among them, surface EMG signals are widely adopted for analysing muscle activity and predicting intended movements. Such applications include control of robotic arms, rehabilitation exoskeletons, and gesture-controlled interfaces.

This project aims to develop a robust EMG-based classification system for upper limb movement recognition. We collected and analysed data from **28** participants, each performing six distinct movements, including Extension, Flexion, Ulnar Deviation, Radial Deviation, Power Grip, and Precision Grip. The signals were obtained from four sensors placed on both forearms and processed using two pipelines:

- Spectrogram-based time-frequency representation
- Handcrafted time-domain features

Subsequently, machine learning classifiers were trained on both types of features to assess classification performance and generalizability.

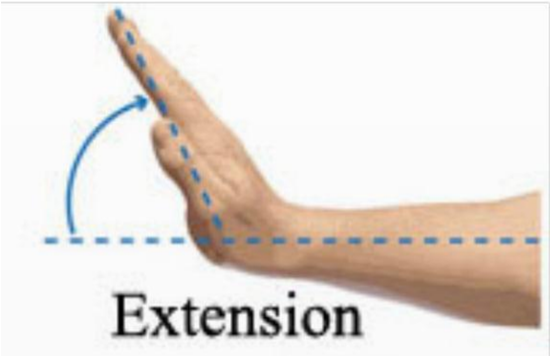
3. Design

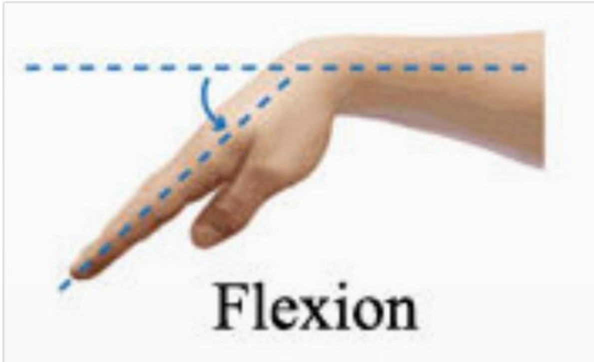
3.1 Dataset Collection and Structure

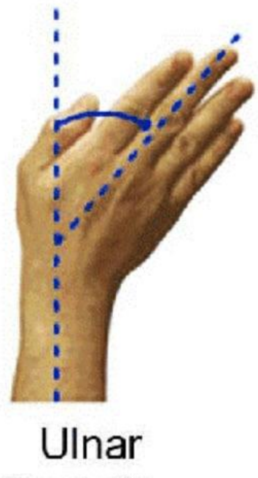
We collected data from this paper: https://www.nature.com/articles/s41597-023-02223-x

- **Participants**: 28
- **Movements**: 6 (selected from 8 original)
- **Cycles per movement**: 3
- **Sensors**: 4 (2 forearms × 2 sensors each)
- **Sampling Rate**: 13,000 Hz
- **Signal Duration**: 1 second per trial

Gesture Demo:







Each trial's data is stored as CSV files labelled using the naming convention:

```
P{participant}C{cycle}S{sensor}M{movement}F{forearm}O{offset}
```

3.2 Feature Extraction Pipelines

4. **Spectrogram-Based Features:**

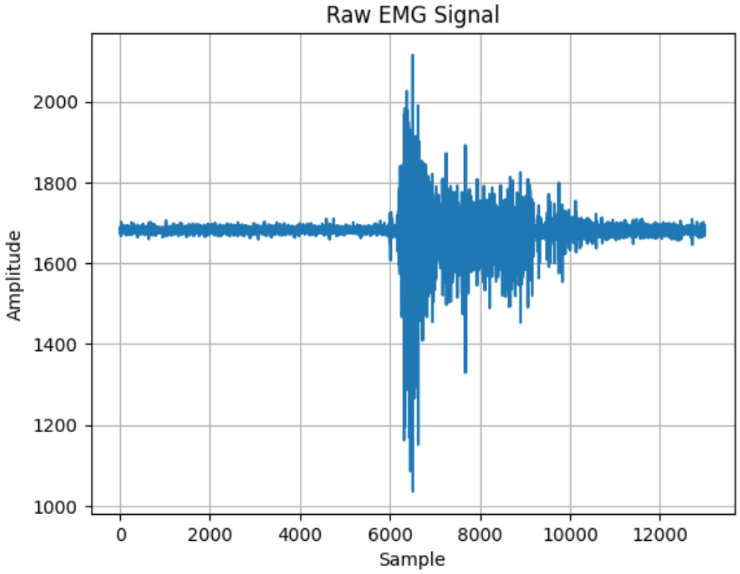
Applied a custom Short-Time Fourier Transform (STFT) using a Hanning window.

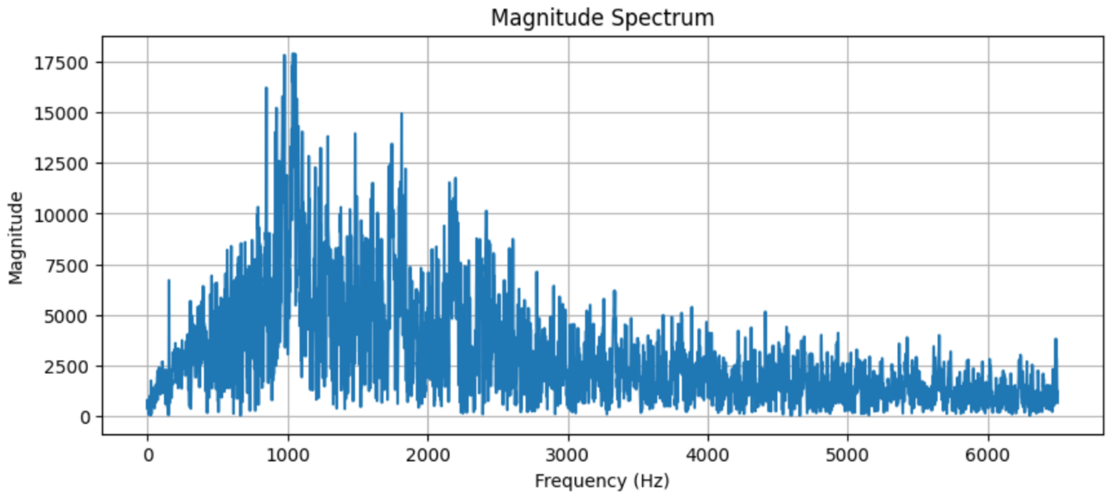
- **Parameters:** window_size = 256, overlap = 128.
- **Result:** A 3D tensor of size (96×96×4) per trial (4 channels from sensors).

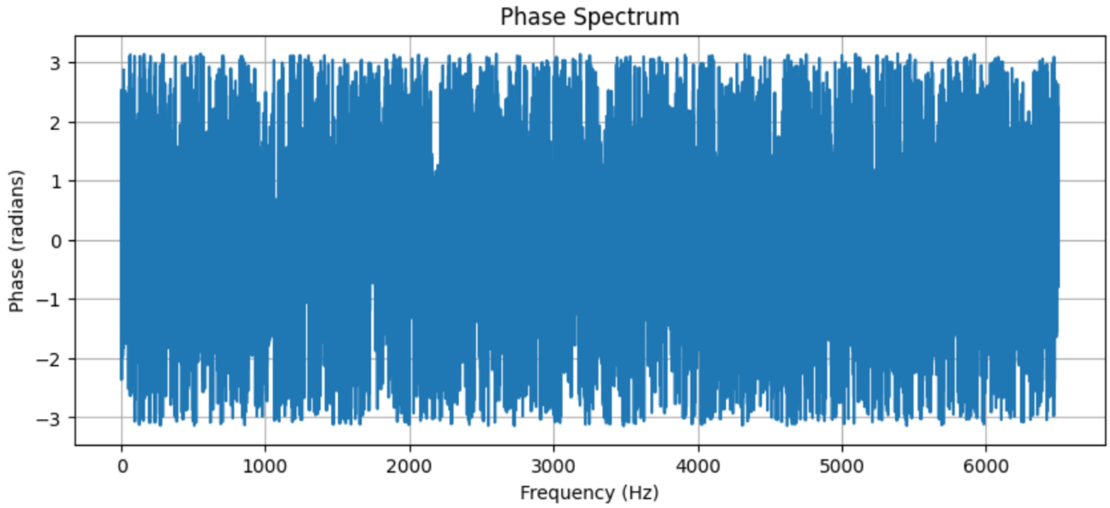
Log-transformed (`log1p`) for better contrast.

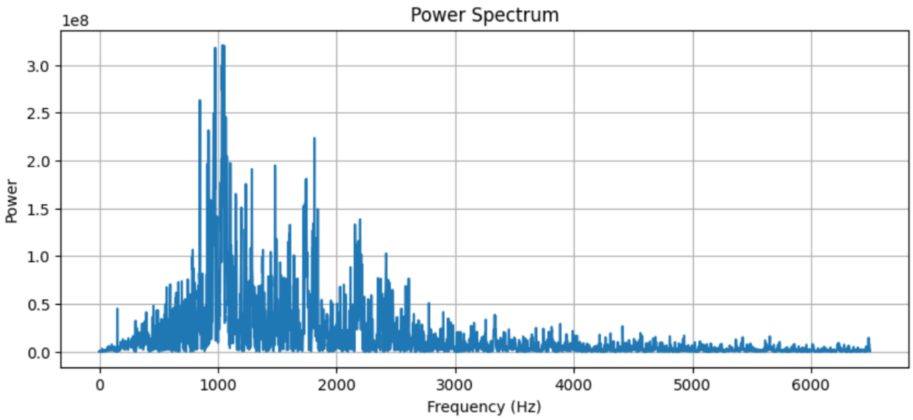
STFT Algorithm

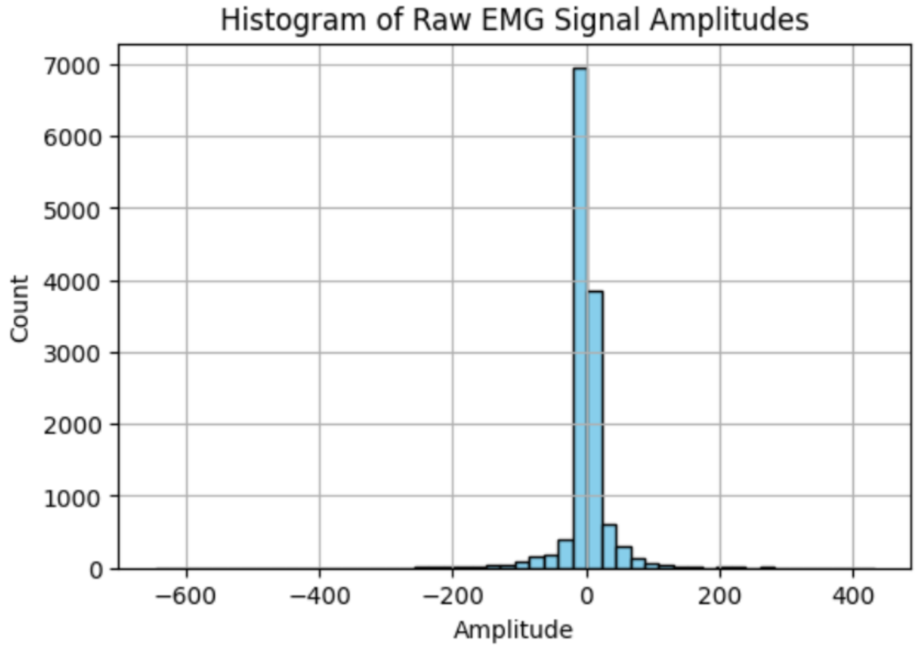
Output Signal:

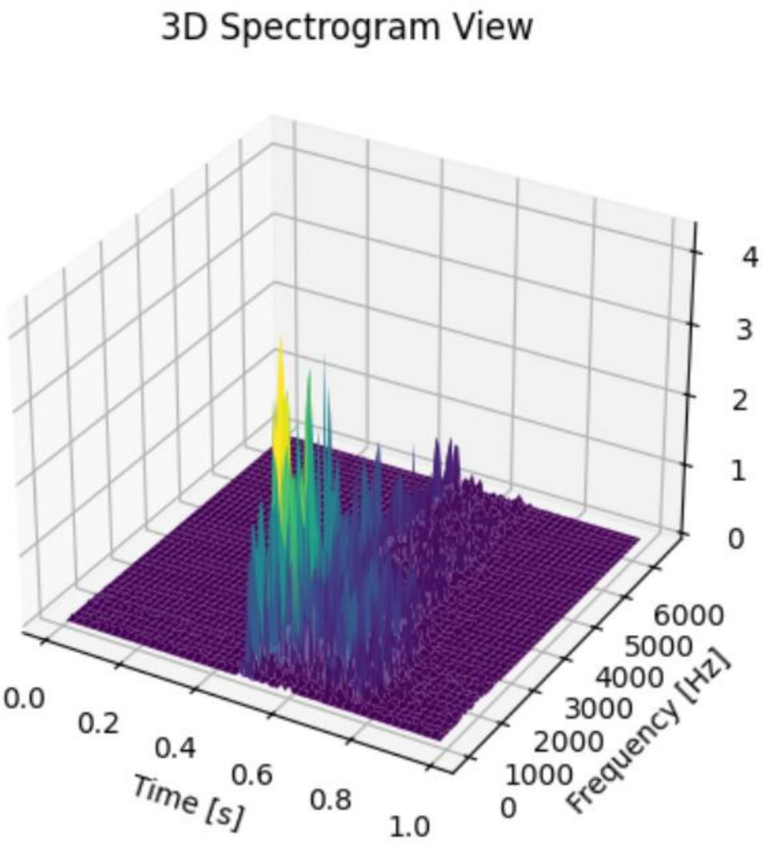


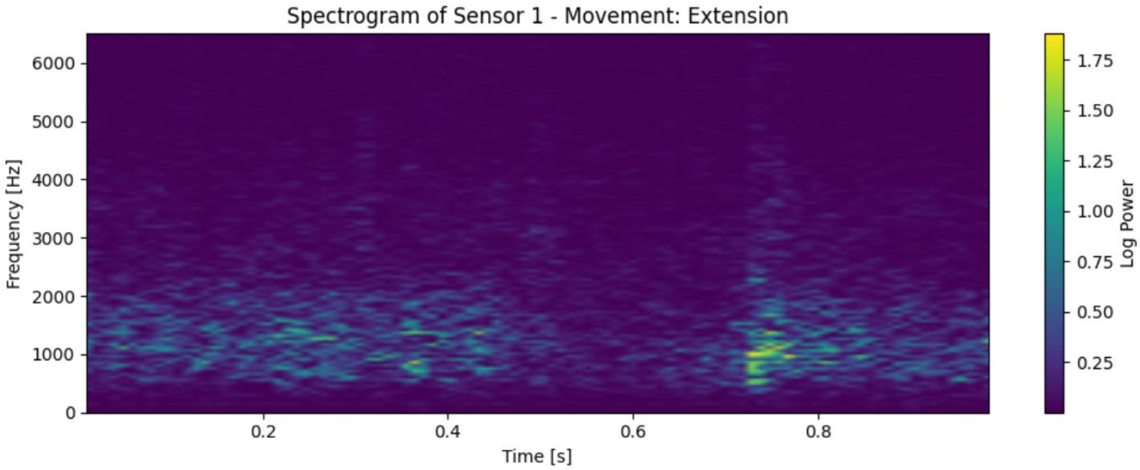

Magnitude Spectrum
Magnitude
17500
15000
12500
10000
7500
5000
2500
0
0
1000
2000
3000
4000
5000
6000
Frequency (Hz)


Phase Spectrum
Phase (radians)
3
2
1
0
−1
−2
−3
0
1000
2000
3000
4000
5000
6000
Frequency (Hz)


Power Spectrum
1e8
Power
3.0
2.5
2.0
1.5
1.0
0.5
0.0
0
1000
2000
3000
4000
5000
6000
Frequency (Hz)


Histogram of Raw EMG Signal Amplitudes
7000
6000
5000
4000
3000
2000
1000
0
Count
−600
−400
−200
0
200
400
Amplitude


3D Spectrogram View
4
3
2
1
0
0.0
0.2
0.4
0.6
0.8
1.0
Time [s]
6000
5000
4000
3000
2000
1000
0
Frequency [Hz]



B.Handcrafted Features:

Each signal was segmented into 4 equal parts (temporal windows), and the following features were extracted from each:

- **RMS**: Root Mean Square
- **MAV**: Mean Absolute Value
- **SSC**: Slope Sign Changes (above a threshold)
- **WAMP**: Willison Amplitude (based on a difference threshold)

Total features per trial = 4 sensors × 4 segments × 4 features = 64.

3.3 Machine Learning Models

The following classifiers were trained:

- **Support Vector Machine (SVM)** with RBF kernel
- **Random Forest** with 100–200 trees
- **k-Nearest Neighbours (kNN)** with `k=7`

All models were trained using class-weight balancing to address dataset imbalance. Data was split with 80% training and 20% testing, stratified by class.

4. Design Analysis and Evaluation

4.1 Normalization

Spectrograms were normalized per channel using global mean and standard deviation. Handcrafted features were standardized across all samples.

4.2 Performance Metrics

Evaluated using:

- Accuracy
- Confusion Matrix

- Per-Class Accuracy
- Learning Curve

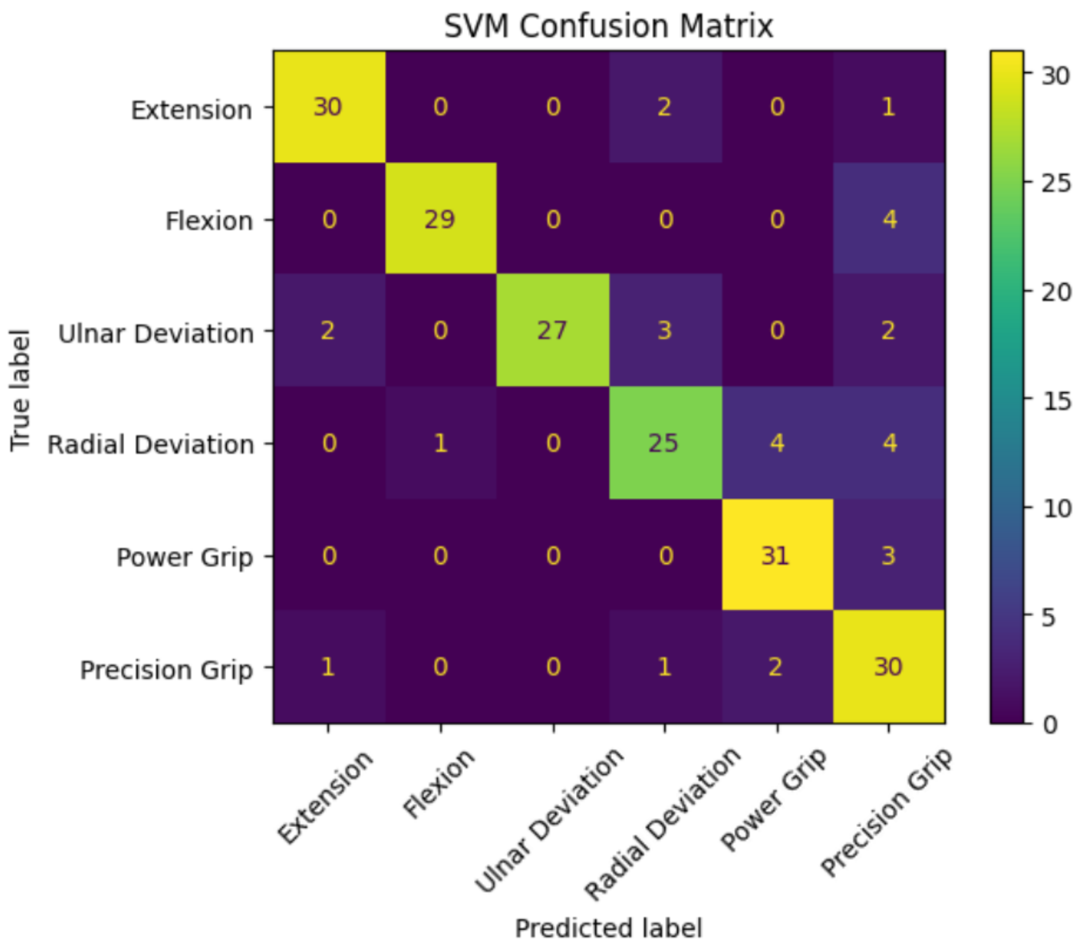
4.3 Results

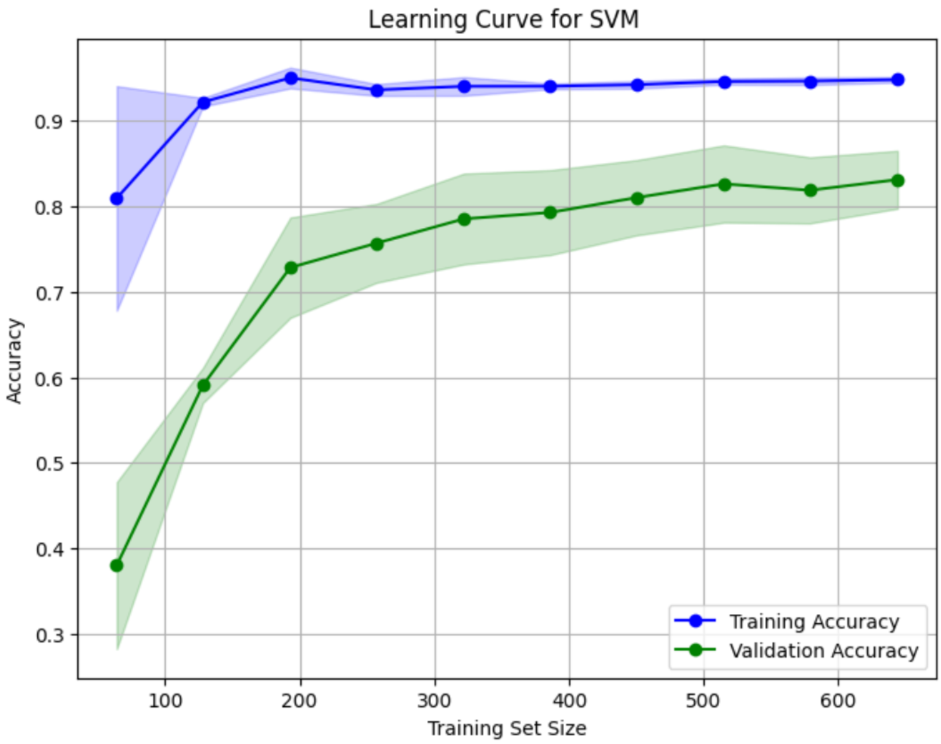
Spectrogram-based Classification

Model	Accuracy (%)
SVM	~85.15
RF	~81.68
KNN	~76.24

Output:

```
Test Accuracy: 85.15%
```





Using Random Forest Model

```
# trying random forest
from sklearn.ensemble import RandomForestClassifier
clf = RandomForestClassifier(n_estimators=100, class_weight='balanced', random_state=42)

clf.fit(X_train, y_train)
y_pred = clf.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
print(f"Test Accuracy: {accuracy * 100:.2f}%")
```

```
Test Accuracy: 81.68%
```

Using KNN Model

```
[14] knn = KNeighborsClassifier(n_neighbors=7, weights='distance', metric='manhattan')

     # Train
     knn.fit(X_train_stft, y_train_stft)

     y_pred_stft = knn.predict(X_test_stft)
     accuracy = accuracy_score(y_test_stft, y_pred_stft)
     print(f"Test Accuracy: {accuracy * 100:.2f}%")
```

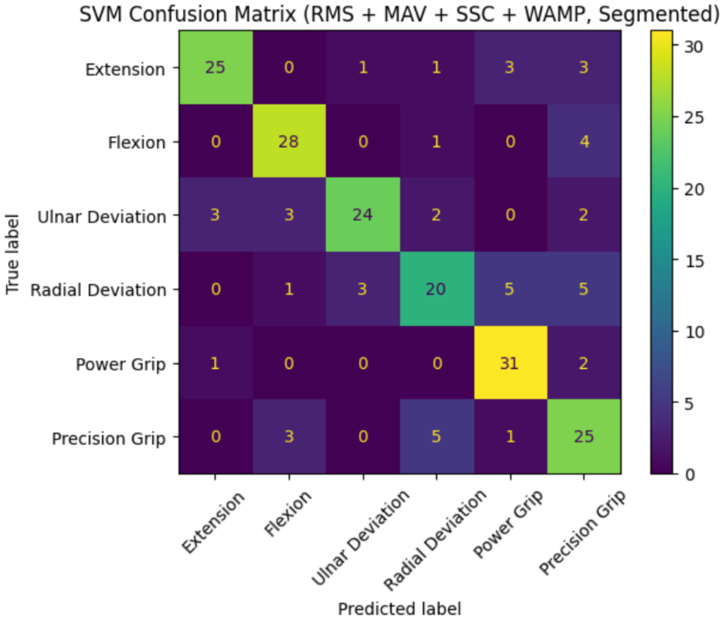
```
Test Accuracy: 76.24%
```

Handcrafted Feature-Based Classification

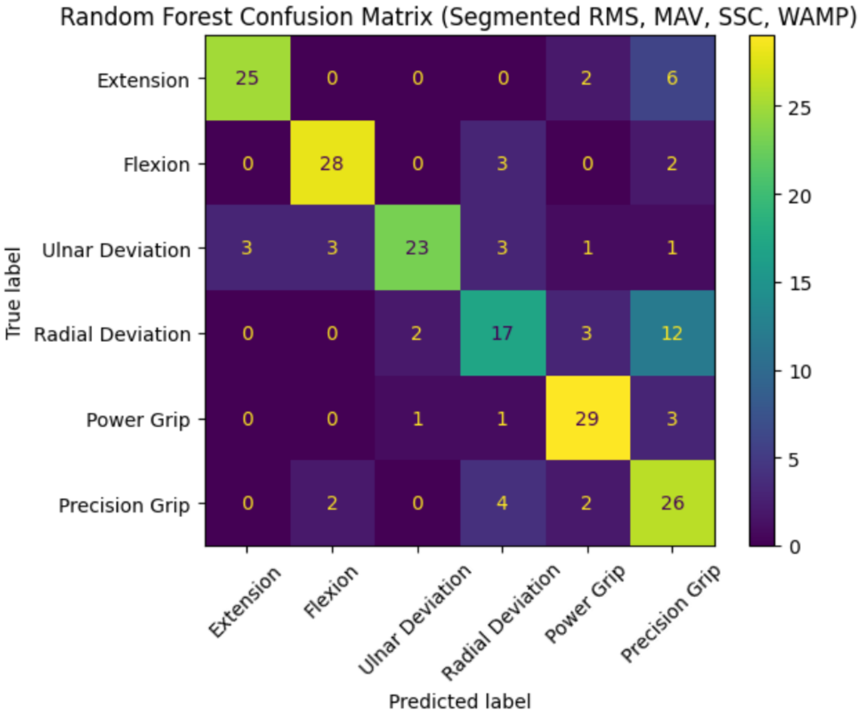
Model	Accuracy (%)
SVM	~75.74
RF	~73.27

Training Time is only 32 sec.

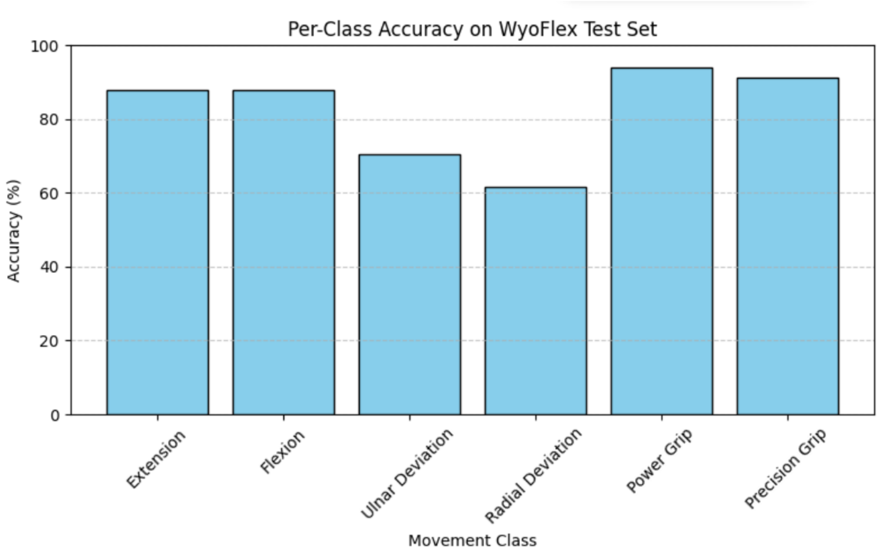
✅ Loaded samples: 1008, feature size per sample: 64
✅ Test Accuracy with Segmented RMS, MAV, SSC, WAMP: 75.74%



✅ Loaded samples: 1008, feature size per sample: 64
✅ Test Accuracy with Random Forest: 73.27%



4.4 Observations:




```
Give the participant's no: 1
Give the cycle no: 1
Give the movement no: 2
Give the forearm no: 1

✅ Loaded files:
  - P1C1S1M2F1O1
  - P1C1S2M2F1O1
  - P1C1S3M2F1O1
  - P1C1S4M2F1O1

🎯 True movement: Flexion (Class 1)
🔮 Predicted movement: Flexion (Class 1)
```

colab.research.google.com – To exit full screen, press Esc

- Spectrogram-based features yielded higher accuracy due to richer time-frequency information.
- Handcrafted features still performed well, showing promise for lightweight real-time systems.
- SVM consistently showed strong generalisation.
- Learning curves indicated model stability and no significant overfitting.

4.5 Visualisation and Interpretation

- Confusion matrices showed the highest confusion between Ulnar and Radial Deviation.

- Raw EMG plots and frequency spectra were used to manually inspect signal quality.
- 3D spectrogram visualisation provided insights into spectral patterns of different movements.

4.6 Future development and exploration

- Implement deep learning models like CNNs or RNNs for improved accuracy.
- Develop a real-time movement classification system using embedded hardware.
- Combine EMG with other biosignals (e.g., ECG, EEG) for robust multi-modal recognition.
- Build subject-independent models using domain adaptation or transfer learning.
- Increase gesture classes to include more natural and complex movements.
- Design a user-friendly interface or mobile app for real-time feedback.
- Apply the system in clinical rehabilitation for monitoring muscle recovery.

5. Conclusion

This project demonstrates a comprehensive framework for EMG-based movement classification using both spectrogram-based and handcrafted features. By leveraging machine learning techniques such as SVM and Random Forest, high classification accuracies were achieved. The results affirm that:Spectrograms are effective for capturing dynamic muscle activation patterns.Handcrafted features offer a computationally cheaper alternative with decent accuracy.SVM with balanced class weights provides robust performance across movement classes.Future improvements may include real-time deployment on embedded devices, deep learning models (e.g., CNNs), and subject-independent evaluations.

6. References

Phinyomark, A., et al. (2013). *Feature extraction and selection for myoelectric control based on wearable EMG sensors*. Sensors.

Oskoei, M. A., & Hu, H. (2007). *Myoelectric control systems—A survey*. Biomedical Signal Processing and Control.

Englehart, K., & Hudgins, B. (2003). *A robust, real-time control scheme for multifunction myoelectric control*. IEEE Transactions on Biomedical Engineering.