Signal Processing in Bio Signal: A Comparative Analysis of Wavelet Families for the Classification of Finger Motions

Abhishek Suwalka
Department of ECE,
Indian Institutes of Information Technology, Sri City

***Abstract*—This study presents a methodology for classifying hand gestures essential for Activities of Daily Living (ADLs) using surface electromyography (sEMG) signals. The dataset comprises recordings from 40 subjects performing ten distinct hand gestures. The analysis incorporates feature extraction using time-domain statistical inference and wavelet transforms. Through preprocessing, feature extraction, and machine learning-based classification, this work lays a foundation for future advancements in sEMG-based gesture classification.**

I. Introduction

Hand gestures play a vital role in performing Activities of Daily Living (ADLs). Automating the classification of these gestures can significantly enhance applications in rehabilitation, prosthetics, and human-computer interaction. Surface electromyography (sEMG) signals are widely used for such tasks due to their non-invasive nature and ability to capture muscle activity.

This project focuses on the classification of ten hand gestures using sEMG signals from 40 subjects. Data preprocessing, feature extraction using statistical and wavelet-based techniques, and machine learning classification form the backbone of this work. Detailed explanations are provided to ensure replicability and continuity for future research.

II. Literature Review

The application of Discrete Wavelet Transform (DWT) in electromyography (EMG) signal analysis has gained significant attention due to its capability to decompose non-stationary signals into multi-resolution frequency bands. The selection of an appropriate mother wavelet is critical, as it profoundly impacts the accuracy of classification tasks. Studies have demonstrated that mother wavelets such as Daubechies, Symlets, and Biorthogonals exhibit varying performance across datasets and tasks. For example, Symlet 4 and Daubechies 4 have been highlighted as effective for hand movement classification at the second decomposition level, whereas higher decomposition levels often capture more subtle signal details [3], [4].

Recent research has expanded the focus from limited motion classes to diverse finger and hand movements to enhance the applicability of EMG-based systems. A comparative study of wavelet families identified Symlet 6 and Mexican Hat as particularly effective under specific conditions for both continuous wavelet transform (CWT) and DWT [3]. Another investigation revealed that DWT with Daubechies 7 performed better for feature extraction, while Wavelet Packet Transform (WPT) using Coiflet and Biorthogonal wavelets yielded superior results in wrist motion classification [5], [6].

Moreover, advancements in wavelet-based EMG recognition systems often integrate robust classification methods like Support Vector Machines (SVM), which leverage features like Mean Absolute Value (MAV) and Wavelength (WL) extracted from DWT coefficients. These efforts underscore the importance of tailoring wavelet selection to the specific nature of the EMG signals and classification objectives [7].

This study builds on these insights by employing DWT with various mother wavelets to analyze and classify finger motions, contributing to the understanding of optimal wavelet selection in real-world applications.

III. Dataset Description

The dataset used in this study, *Dataset for multi-channel surface electromyography (sEMG) signals of hand gestures*, consists of sEMG signals recorded from 40 subjects. Each subject performed ten distinct hand gestures. Key details of the dataset are:

- **Number of Channels/Muscles:** 4
  - Channel 1: Extensor Carpi Ulnaris
  - Channel 2: Flexor Carpi Ulnaris
  - Channel 3: Extensor Carpi Radialis
  - Channel 4: Flexor Carpi Radialis
- **Sampling Rate:** 2000 Hz
- **Protocol:** For each subject:
  - 5 cycles of gestures
  - 30 seconds of rest between cycles
  - Each cycle: 104 seconds, comprising:
    - 4 seconds of rest at the beginning
    - 10 gestures of 6 seconds each, interleaved with 4 seconds of rest

Figures 1 and 2 illustrate the structure of the dataset for one subject.

IV. Methodology

The methodology is divided into four main steps:

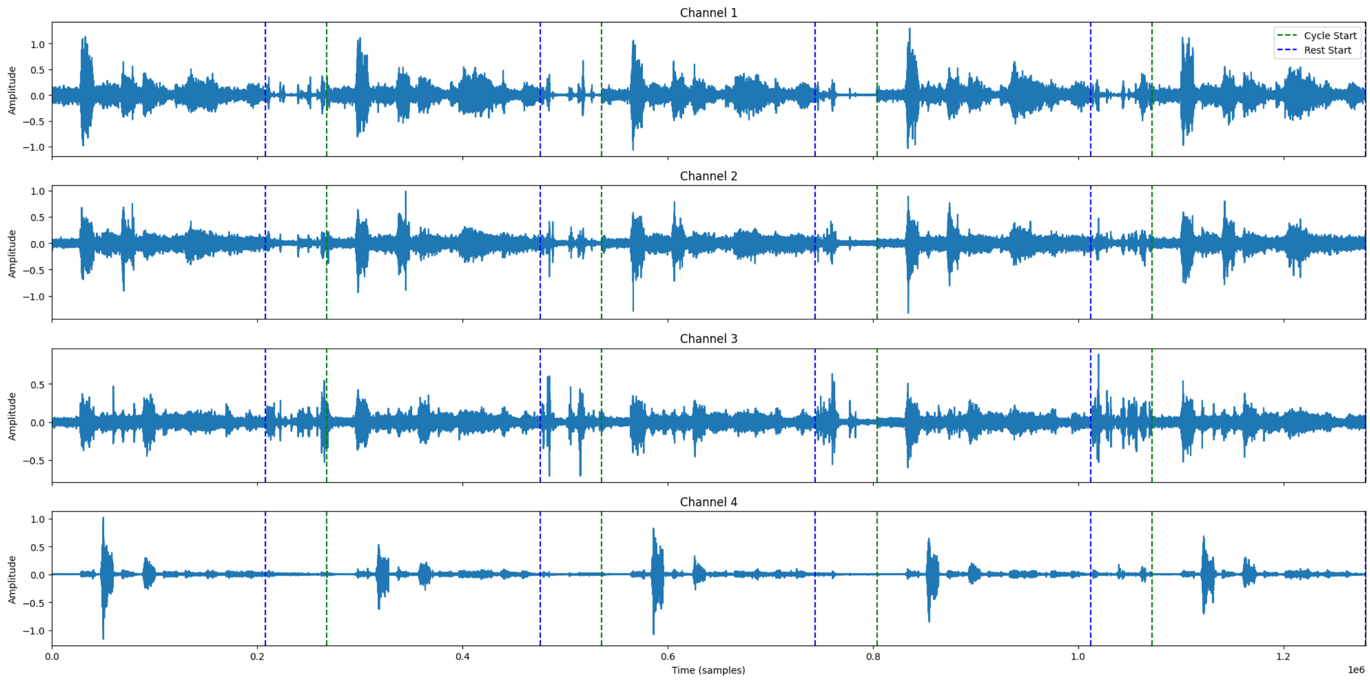

Fig. 1. sEMG data of all cycles for one subject.

A. Data Preprocessing and Compilation

I consolidated the sEMG data from all subjects into a single DataFrame. The data was clean and free of noise. Exploratory Data Analysis (EDA) was performed to identify null values or inconsistencies, which were found to be absent. Labels such as `activity_id`, `cycle_id`, and `subject_id` were added to facilitate analysis. The final preprocessed data was saved as a CSV file for ease of access.

B. Feature Extraction: Statistical Methods

I extracted statistical features from the preprocessed data using a 250 ms sliding window. These features included mean, standard deviation, skewness, and kurtosis. The assumption was that a 250 ms window captures sufficient information for classifying the gestures. The resultant DataFrame containing extracted features was saved for further analysis.

C. Classification Using Machine Learning

I applied machine learning models to the extracted statistical features. Models such as Random Forest, Gradient Boosting, Logistic Regression, Support Vector Classifier (SVC), k-Nearest Neighbors (k-NN), and Decision Tree were evaluated for their classification performance.

D. Wavelet Transform Analysis

I applied wavelet transforms to the sEMG data. He experimented with different mother wavelets to identify the optimal one for sEMG signal processing. Feature extraction using wavelet coefficients was performed, and the resulting features were used for classification.

V. Feature Extraction Methodologies

sEMG signal analysis for gesture classification relies on robust feature extraction methodologies. For this study, two approaches were employed: Time-Domain Statistical Inference and Discrete Wavelet Transform (DWT). Features were extracted for each of the four channels separately, capturing distinct signal characteristics.

A. Time-Domain Statistical Inference

Time-domain statistical features provide insights into the temporal characteristics of the sEMG signals. For each channel, the following features were extracted:

- Mean (μ)
- Median
- Variance (σ^2)
- Skewness
- etc...

These features were computed for each of the four sEMG channels, resulting in a feature vector of 64 attributes per sample (16 features per channel $\times$ 4 channels). These features capture both low-level and higher-order statistical properties of the signals, enabling robust classification of hand gestures.

1) Classification Results Using Statistical Features: Table I summarizes the accuracy achieved by various classification models trained on the time-domain statistical features.

B. Discrete Wavelet Transform (DWT) Analysis

Wavelet Transform (WT) is a powerful mathematical tool for analyzing non-stationary signals. It represents a signal in terms of localized time-frequency components, overcoming the limitations of Fourier Transform (FT), which provides

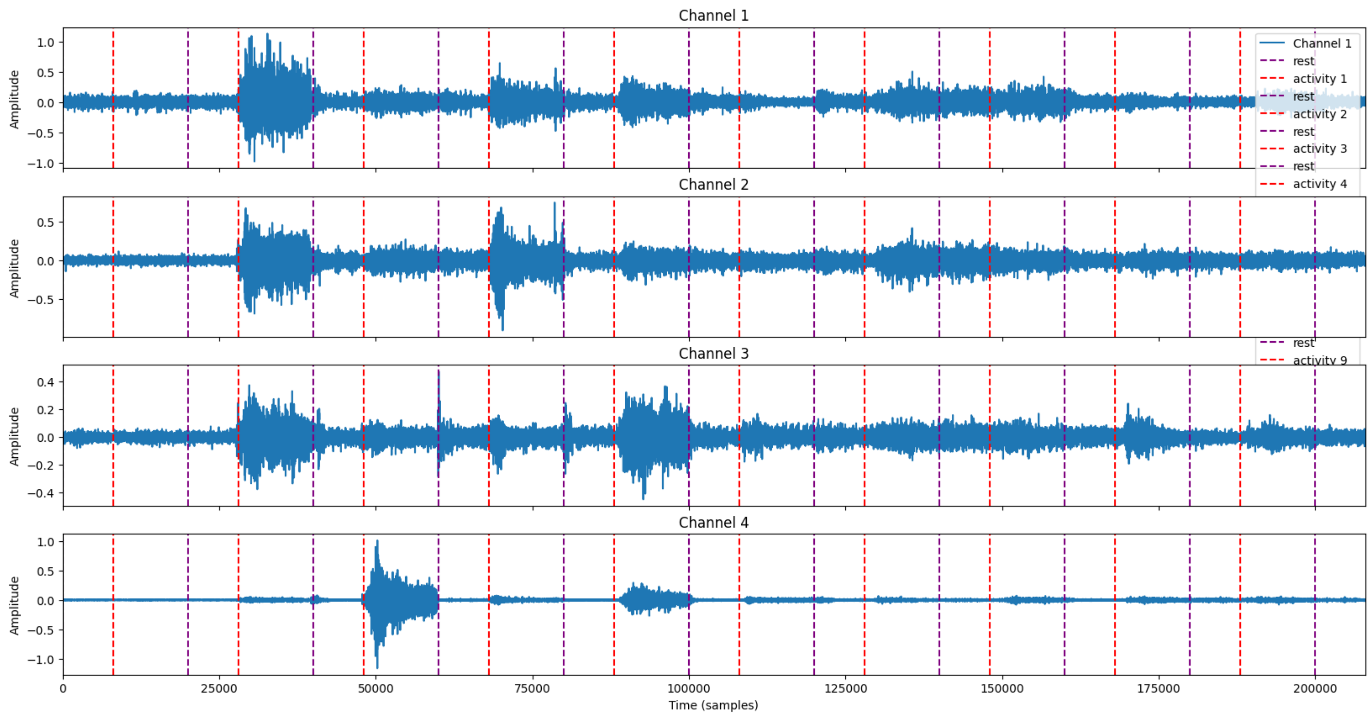

Fig. 2. sEMG data of one cycle showing activities and rest periods.

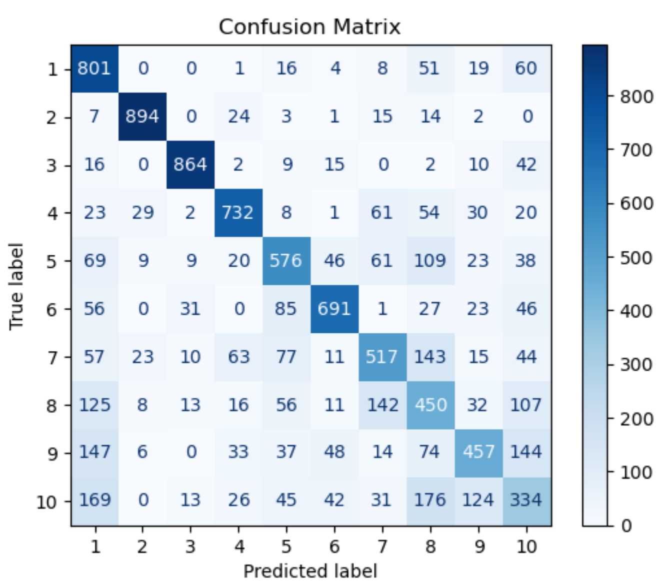

Fig. 3. Statistical Inference Result

global frequency information but lacks temporal localization. WT is particularly suitable for analyzing signals that vary over time, such as biomedical signals like sEMG (surface electromyography).

For this study, the Discrete Wavelet Transform (DWT) was employed, which is the discretized version of WT, commonly used in signal and image processing due to its computational efficiency. It decomposes a signal into approximation and detail coefficients using a set of wavelet functions.

TABLE I
ACCURACY OF CLASSIFICATION MODELS USING STATISTICAL FEATURES

Model	Accuracy (%)
Random Forest	67
Decision Tree	63
Logistic Regression	54
Support Vector Classifier	58
k-Nearest Neighbors	61

1) Mathematical Framework: DWT decomposes a signal into approximation and detail coefficients using a set of wavelet functions. The process involves:

- Selecting a mother wavelet, $\psi(t)$
- Decomposing the signal into multiple levels of detail (resolution)

The mathematical representation of DWT is given by:

$$c_{j,k} = \int_{-\infty}^{\infty} x(t)\psi_{j,k}(t)\, dt$$

where $c_{j,k}$ represents the wavelet coefficients for scale j and position k.

2) Key Principles of Wavelet Transform: Wavelet Transform captures both frequency and time information simultaneously, using scalable and translatable wavelet functions. This allows for the detection of transient features often missed by Fourier Transform, making it suitable for analyzing biomedical signals like sEMG. Key wavelet families include:

- **Haar:** Simplest wavelet, ideal for abrupt signal changes.

- **Daubechies:** Good for smooth, continuous signals with compact support.
- **Symlets:** A symmetric version of Daubechies wavelets.
- **Coiflets:** Designed for higher-order vanishing moments, suitable for feature detection.
- **Meyer:** Smooth, continuous wavelet with good frequency resolution.
- **Mexican Hat (Ricker):** Ideal for peak or ridge detection.

3) Feature Extraction Using DWT: The following steps were performed for feature extraction:

- Signals from all four channels were decomposed using different mother wavelets (e.g., Daubechies, Symlets).
- Features such as energy distribution, entropy, and statistical measures of wavelet coefficients (mean, variance, skewness, and kurtosis) were calculated for each level of decomposition.

4) Advantages of Wavelet Transform: Wavelet Transform offers several advantages:

- **Adaptability:** WT supports various mother wavelets tailored to specific applications, such as feature extraction or noise reduction in biomedical signals.
- **Sparsity:** By decomposing signals into few significant wavelet coefficients, WT is effective in compressing and denoising data.
- **Real-Time Processing:** DWT is computationally efficient and suitable for real-time analysis of signals.

Table II shows the accuracy of a Random Forest classifier trained on wavelet-based features using different mother wavelets and decomposition levels.

VI. Results

The Random Forest classifiers trained on wavelet-transformed features for various mother wavelets demonstrated varied performance across the different wavelets. Overall, the highest accuracy was achieved using the `coif3` wavelet, which provided the best results. Other wavelets such as `coif4` and `sym4` also showed promising performance, while wavelets like `bior2.2` and `sym6` had slightly lower accuracy. These results highlight the importance of selecting an appropriate mother wavelet for sEMG signal classification and demonstrate the potential of wavelet-based features in enhancing model performance for gesture recognition.

VII. Future Work

In future iterations of this research, we plan to implement the ”leave-one-subject-out” cross-validation technique. This method will allow us to assess the model’s performance in a more robust manner by testing it on data that it has never seen before, simulating a real-world scenario where the model is exposed to new, unseen subjects. The assumption here is that sEMG data varies significantly across subjects, and this approach will help us understand how well the model generalizes to unseen individuals, leading to more reliable and accurate predictions in practical applications.

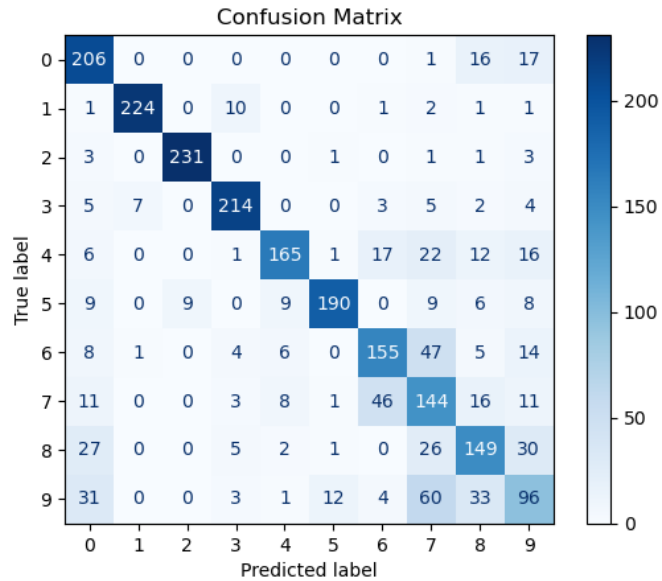

Fig. 4. bior2.2

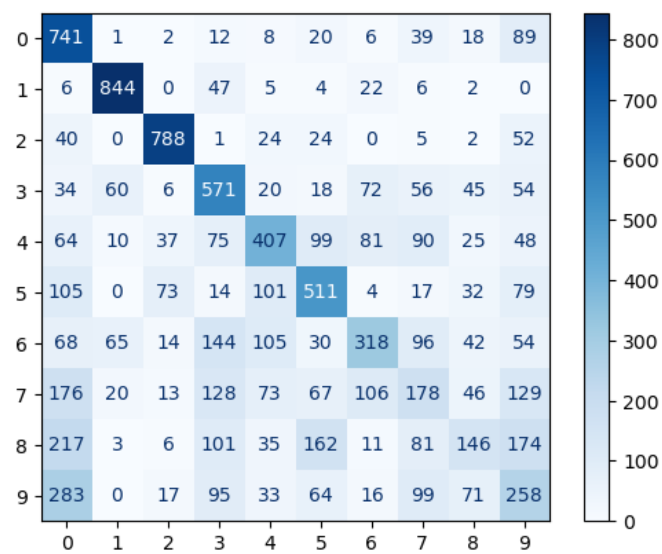

Fig. 5. bior3.3

VIII. Conclusion

This study presents a simple and basic framework for classifying hand gestures using sEMG signals, incorporating both time-domain statistical features and wavelet-based features, alongside machine learning models. The results demonstrate the effectiveness of wavelet transforms, particularly when using mother wavelets like `coif3`, in improving gesture classification performance. The combination of these features with machine learning algorithms, such as Random Forest, offers promising results for reliable gesture recognition systems. Future research will focus on improving model generalizability by employing techniques such as leave-one-subject-out cross-

TABLE II
CROSS-VALIDATION RESULTS FOR DIFFERENT MOTHER WAVELETS AND DECOMPOSITION LEVELS USING RANDOM FOREST

Wavelet	Level	Test Accuracy (%)	Train Accuracy (%)	Test Precision	Test Recall	Test F1
bior2.2	2	52.14	94.78	0.5674	0.5214	0.5232
coif3	4	56.41	98.48	0.5871	0.5641	0.5625
coif4	2	55.11	98.36	0.5735	0.5511	0.5504
coif5	2	54.27	71.66	0.5672	0.5427	0.5418
db6	2	54.55	93.43	0.5703	0.5455	0.5454
db8	2	54.59	85.70	0.5698	0.5459	0.5453
sym4	2	54.92	98.54	0.5723	0.5492	0.5485
sym6	2	53.65	71.75	0.5602	0.5365	0.5352
sym8	2	54.66	93.97	0.5704	0.5466	0.5459

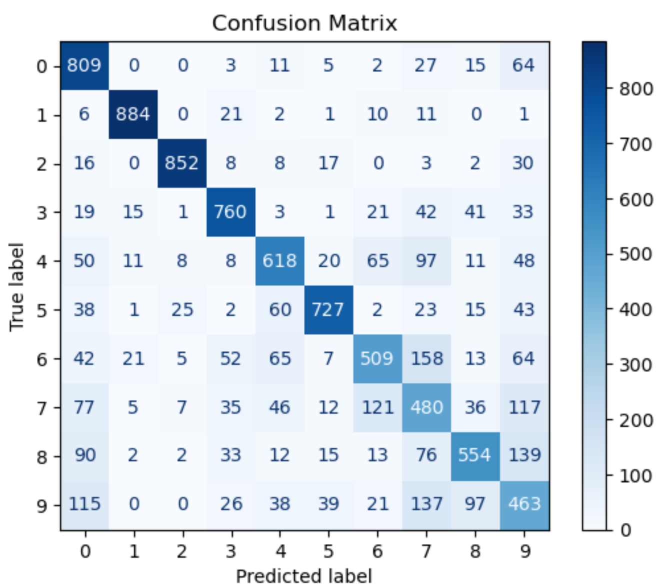

Fig. 6. coif3

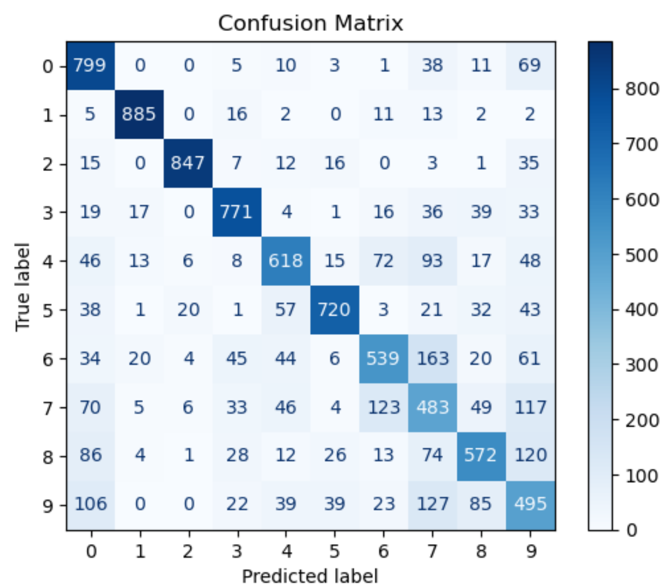

Fig. 7. coif4

validation, which will provide deeper insights into how well the model generalizes to unseen subjects and enhance the robustness of the classification system.

ACKNOWLEDGMENT

We acknowledge the contributions of both team members.

We also wish to express our gratitude to Dr. Lokendra Chouhan for offering valuable guidance throughout the project.

We also wish to express our gratitude to Dr. Anish Chand Turlapaty for providing computational resources throughout the project.

Additionally, we acknowledge the work by Mehmet Akif Ozdemir, Deniz Hande Kisa, Onan Guren, and Aydin Akan for their contribution to the dataset titled ”Dataset for multi-channel surface electromyography (sEMG) signals of hand gestures.”

REFERENCES

[1] M. A. Ozdemir, D. H. Kisa, O. G. Aydin, and A. Akan, ”Dataset for multi-channel surface electromyography (sEMG) signals of hand gestures,” Data Article, 2024.

[2] N. K. Karnam, A. C. Turlapaty, S. R. Dubey, and B. Gokaraju, ”EMAHA-DB1: A New Upper Limb sEMG Dataset for Classification of Activities of Daily Living,” *IEEE Transactions on Instrumentation and Measurement*, vol. 72, 2023.

[3] J. Too, A. R. Abdullah, N. M. Saad, N. M. Ali, and H. Musa, ”A Detail Study of Wavelet Families for EMG Pattern Recognition,” *International Journal of Electrical and Computer Engineering*, vol. 8, no. 6, pp. 4221–4229, Dec. 2018.

[4] F. A. Omari, J. Hui, C. Mei, and G. Liu, ”Pattern Recognition of Eight Hand Motions Using Feature Extraction of Forearm EMG Signal,” *Proceedings of the National Academy of Sciences, India Section A: Physical Sciences*, vol. 84, no. 3, pp. 473–480, Sep. 2014.

[5] A. Phinyomark, A. Nuidod, P. Phukpattaranont, and C. Limsakul, ”Feature Extraction and Reduction of Wavelet Transform Coefficients for EMG Pattern Classification,” *Elektronika ir Elektrotechnika*, vol. 122, no. 6, pp. 27–32, Jul. 2012.

[6] M. Hariharan, C. Y. Fook, R. Sindhu, B. Ilias, and S. Yaacob, ”A Comparative Study of Wavelet Families for Classification of Wrist Motions,” *Computers & Electrical Engineering*, vol. 38, no. 6, pp. 1798–1807, Nov. 2012.

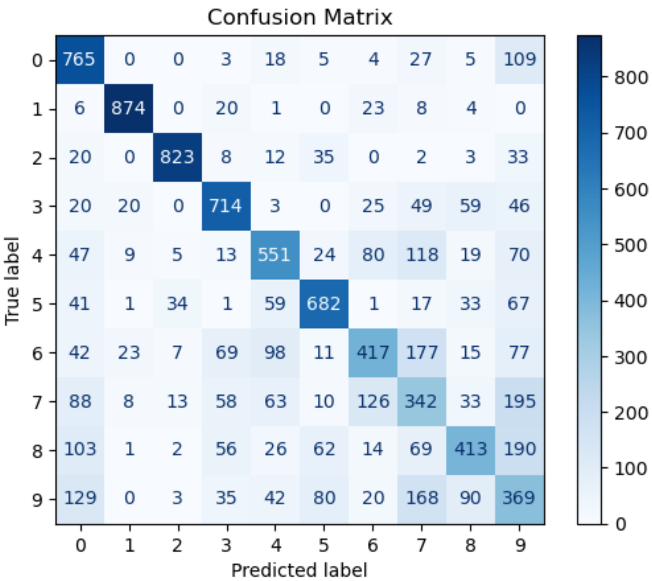

Fig. 8. coif5

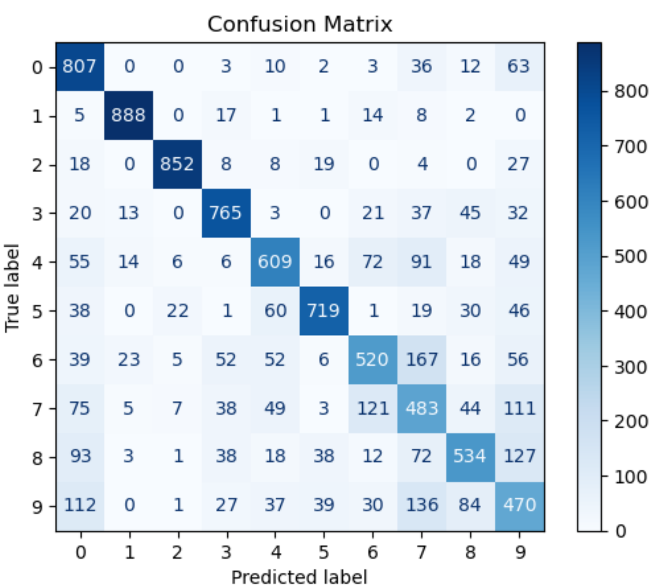

Fig. 9. db6

[7] J. Too, A. R. Abdullah, N. M. Saad, and W. Tee, "EMG Feature Selection and Classification Using a Pbest-Guide Binary Particle Swarm Optimization," *Computation*, vol. 7, no. 1, p. 12, Mar. 2019.

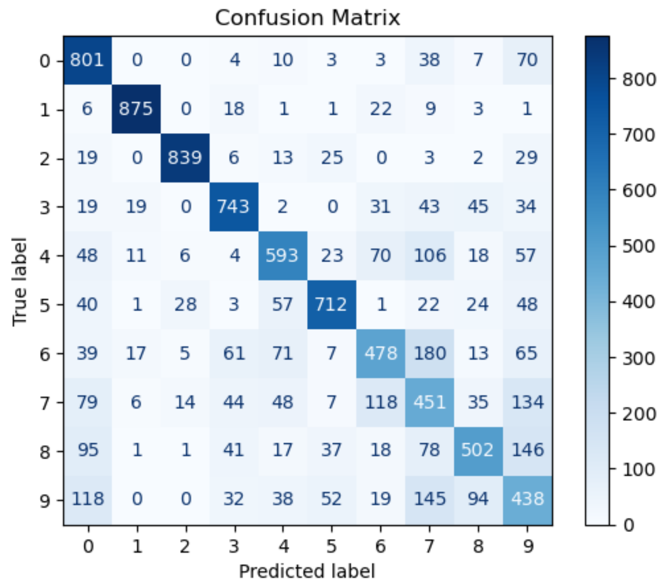

Fig. 10. db8

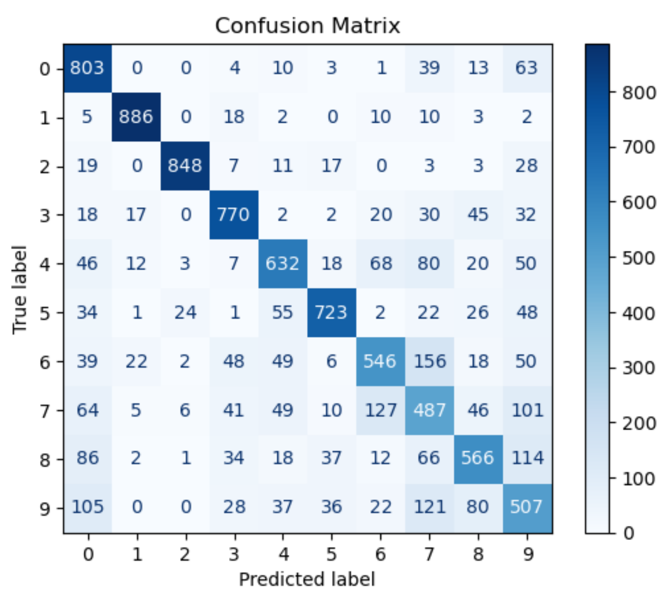

Fig. 11. sym4

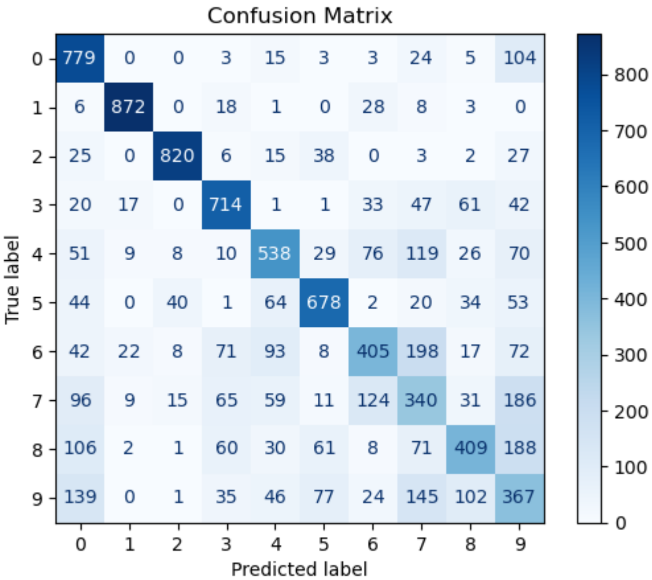

Fig. 12. sym6

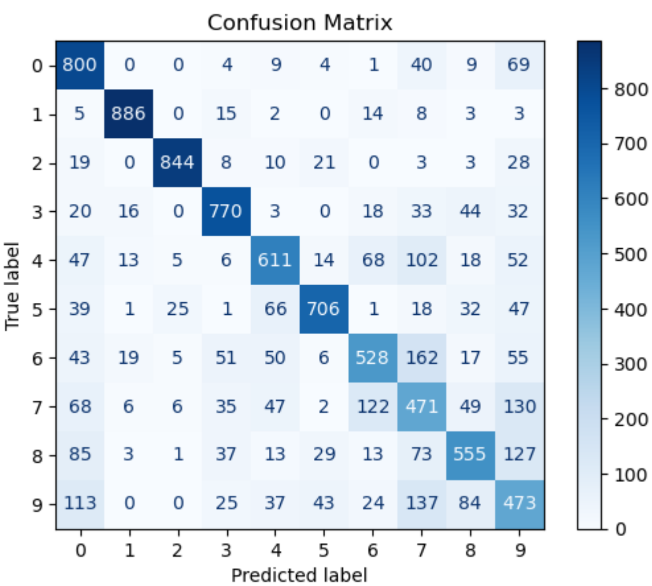

Fig. 13. sym8