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Original Research Article

Automated EMG Signal Classification at the Epoch Level Using Wavelet Scattering Features and KNN

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Abstract:
Accurate and efficient classification of electromyography (EMG) signals is essential for objective assessment of neuromuscular disorders. In this study, an automated EMG classification framework was developed at the epoch level by combining wavelet scattering–based feature extraction with a K-Nearest Neighbor (KNN) classifier. EMG recordings from amyotrophic lateral sclerosis (ALS), myopathy, and healthy control subjects were processed through a MATLAB-based pipeline. The raw signals were resampled to 23,437 Hz, baseline-corrected, and band-pass filtered between 20 and 2,500 Hz to eliminate motion and power-line artifacts. Each recording was divided into one-second epochs, and the Wavelet Scattering Transform (WST) was applied to extract robust, noise-insensitive time–frequency features. The resulting feature matrices were normalized and classified using multiple supervised algorithms within MATLAB's Classification Learner, including KNN and neural network models. Among the evaluated classifiers, the Fine KNN achieved the best overall performance, reaching a validation accuracy of 93.36% and a test accuracy of 95.98% while maintaining low computational cost. Neural network models achieved comparable accuracy but required substantially higher training time. The findings demonstrate that WST-based feature extraction combined with KNN classification provides a reliable, efficient, and reproducible approach for EMG signal analysis at the epoch level. This work underscores the potential of wavelet scattering as a compact and robust feature representation technique for biomedical signal processing applications.
Keywords: Biosignal Analysis, EMG, WST, Signal Processing, Classification

Introduction

Electromyography (EMG) is a fundamental technique in biomedical engineering for assessing the health of muscles and their associated motor neurons. By recording the electrical activity produced by skeletal muscles, EMG provides a direct window into the physiological state of neuromuscular systems. It is widely used in the diagnosis of neuromuscular disorders such as amyotrophic lateral sclerosis (ALS) and myopathies, which are characterized by distinct alterations in muscle fiber or motor unit potentials. In myopathic conditions, EMG recordings typically show short-duration and low-amplitude motor unit potentials, whereas neuropathic disorders such as ALS are associated with prolonged and high-amplitude waveforms due to motor unit loss and collateral reinnervation[1]. While expert neurologists can often identify these differences visually, manual interpretation is time-consuming and subject to variability across observers. Consequently, there has been a strong motivation to develop automated, objective, and reproducible systems for EMG signal classification.

Early computational approaches to EMG analysis primarily relied on hand-crafted time-domain features such as mean absolute value, zero-crossing rate, waveform length, and variance, coupled with simple classifiers including multilayer perceptrons (MLP), support vector machines (SVM), and k-nearest neighbors (KNN). However, these early methods typically achieved only 69–73% accuracy when distinguishing between normal, myopathic, and ALS EMG signals [1, 2]. The limited discriminative power of basic statistical features highlighted the need for richer representations that capture the non-linear and non-stationary nature of EMG signals. Over the past decade, the integration of advanced signal processing and machine learning has substantially improved diagnostic accuracy, often exceeding 95–99% across multiple studies [3-6].

One of the most impactful methodological developments was the introduction of wavelet transform (WT) based analysis[7, 8]. Wavelets provide a time–frequency representation capable of isolating localized transient patterns in EMG, which traditional Fourier-based approaches fail to capture effectively. Gokgoz and Subasi (2015) applied discrete wavelet transform (DWT) features combined with decision-tree classifiers and reported accuracies approaching 96% for three-class (normal, ALS, myopathy) classification[1]. Subsequent extensions using wavelet packet transforms and ensemble learning further improved robustness. Yaman and Subasi (2019) demonstrated that an AdaBoost ensemble of decision trees using wavelet features reached 99.08% accuracy, outperforming bagging and random forest methods [4]. These results established wavelet-domain features as a strong baseline for EMG pattern recognition.

Beyond classical wavelets, researchers began exploring nonlinear and higher-order descriptors to capture the complex temporal structure of EMG. Mishra et al. (2016) proposed a combination of bispectrum features (e.g., mean phase entropy) and fractal dimensions analyzed via an Extreme Learning Machine (ELM) classifier, achieving marked improvements over traditional wavelet features [2]. Similarly, Artameeyanant et al. (2016) employed a normalized weight vertical visibility algorithm (NWVVA) to map EMG time series into graph representations, from which topological features were extracted. This approach achieved 98.36% accuracy, showing that structural complexity measures can effectively distinguish between myopathic and neuropathic EMG signals[3]. These studies emphasized the diagnostic potential of incorporating non-linear dynamics and graph-based representations into EMG feature extraction pipelines.

Another major advancement has been the application of Empirical Mode Decomposition (EMD) for adaptive feature generation. Unlike fixed-basis transforms, EMD decomposes EMG signals into intrinsic mode functions (IMFs) that naturally adapt to non-stationary oscillations. Dubey et al. (2022) introduced an EMD-based approach that extracted geometric features (area and circumference) from selected IMFs, achieving 99.53% accuracy with a feed-forward neural network (FFNN) classifier[9]. This study demonstrated that EMD provides a data-driven and highly discriminative basis for EMG analysis, capable of matching or exceeding the performance of traditional wavelet approaches.

Complementary work explored time–frequency distributions such as the Stockwell transform (ST), which integrates advantages of both Fourier and wavelet methods. Chatterjee et al. (2019) employed a modified windowed Stockwell transform to generate spectrogram-like representations and achieved high accuracy in distinguishing myopathy from ALS[5]. The diversity of these method wavelet, EMD, Stockwell, and fractal-based approaches reflects a broader trend toward multi-domain analysis of EMG signals, where each technique captures distinct aspects of signal morphology and variability.

More recent studies have combined multiple feature sets or employed ensemble and hybrid frameworks. Jose et al. (2020) fused fractal and texture features derived from lifting wavelet transform sub-bands, using a multilayer perceptron (MLP) combined with a majority voting mechanism, achieving 99.87% accuracy across 250 EMG recordings [6]. Such hybrid systems demonstrate that complementary feature spaces, when aggregated through robust classifiers, can provide nearly perfect discrimination among neuromuscular conditions. However, as reported in the same study and others, excessively high accuracy scores often reflect small datasets or potential subject overlap, underscoring the need for careful validation on independent cohorts.

In parallel, the past five years have witnessed the increasing application of deep learning architectures. Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Long Short-Term Memory (LSTM) models have been adapted to learn EMG representations directly from either raw signals or transformed domains. Bakiya et al. (2022) combined traditional feature extraction with a Bat algorithm optimized Deep Neural Network (DNN), reporting 100% accuracy in differentiating ALS and myopathy (though later retracted due to methodological issues) [10]. Their follow-up study (2024) applied a fractional-order Bat-optimized CNN on time–frequency images, confirming that optimized deep architectures can outperform standard CNNs on EMG datasets [11]. Similarly, Tuncer and Doğru Bolat (2023) implemented an LSTM-based sequential model on Coiflet-5 wavelet sub-bands and achieved 100% accuracy in classifying normal versus myopathy cases[12]. These approaches illustrate that deep neural models are effective when applied to well-preprocessed EMG representations but still depend heavily on feature extraction and careful regularization to avoid overfitting on limited data.

Despite the remarkable performance of deep learning, shallow models integrated with robust feature extraction remain highly competitive, particularly when data are limited or computational efficiency is critical. The Wavelet Scattering Transform (WST) represents a principled evolution of wavelet analysis, providing translation-invariant and deformation-stable representations that are both mathematically grounded and well-suited for biomedical signals. WST retains the interpretability of wavelet features while producing standardized coefficients that can feed into conventional classifiers without the need tuning. Compared to handcrafted features, scattering coefficients encode hierarchical signal structures, making them ideal for analyzing EMG signals that exhibit complex transient patterns.

Building on these insights, the present study introduces a MATLAB-based framework for automated EMG classification at the epoch level using WST features combined with a K-Nearest Neighbor (KNN) classifier. The proposed system preprocesses raw EMG signals through resampling, baseline correction, and band-pass filtering between 20–2500 Hz, followed by segmentation into one-second epochs. For each epoch, WST coefficients are extracted and statistically summarized, yielding compact and noise-robust feature vectors. Multiple supervised classifiers were trained and evaluated, including neural network architectures and KNN variants, to determine the optimal balance between accuracy and computational cost. Experimental results demonstrated that the Fine KNN model achieved a validation accuracy of 93.36% and a test accuracy of 95.98%, outperforming neural network models while requiring significantly less training time.

Unlike patient level studies, the present work adopts an epoch level analysis, focusing on the discriminative power of short signal segments. While this setup does not enforce subject independence, it provides valuable insight into the intra-signal consistency and classification feasibility across short temporal windows an essential step toward real time EMG analysis systems. The proposed framework, therefore, contributes a transparent, reproducible, and computationally efficient approach that complements recent literature emphasizing deep architectures and complex optimization. In contrast to over parameterized models requiring large datasets, the WST + KNN pipeline demonstrates that high accuracy can be achieved through careful signal processing and feature design.

In summary, this study extends the ongoing progression in automated EMG analysis by integrating wavelet scattering with classical machine learning. The results reaffirm that shallow learning frameworks, when combined with robust time–frequency representations, can yield performance comparable to advanced deep networks while maintaining simplicity and interpretability. This balance between analytical rigor and computational efficiency aligns with the broader goals of biomedical engineering developing reliable, and accessible diagnostic tools for neuromuscular disease assessment.

The primary objective of this work is to develop an efficient and transparent framework for automated classification of EMG signals at the epoch level using wavelet scattering features and K-Nearest Neighbor (KNN) classification. Unlike many recent deep-learning-based approaches, this study emphasizes algorithmic simplicity, reproducibility, and computational efficiency while maintaining high accuracy. By leveraging the Wavelet Scattering Transform, the proposed method captures multiscale and shift-invariant representations of EMG activity, enabling robust discrimination among ALS, myopathy, and healthy control signals. The use of epoch-level segmentation provides fine-grained temporal resolution and facilitates the design of lightweight models suitable for real-time implementation. Overall, the study contributes a validated and open methodological pipeline that bridges the gap between advanced feature extraction and practical biomedical diagnostic systems.

Materıal and Method

The data used in this study were obtained from the publicly available EMG database provided by EMGLAB.net, specifically under the section titled “Clinical Data.” The EMG signals analyzed were originally collected for study [13]. Recordings were obtained from the biceps brachii muscle of 10 healthy subjects, 7 individuals with myopathy, and 8 individuals with ALS (neuropathy group). The healthy group consisted of 4 females and 6 males, aged between 21 and 37 years. The myopathy group included 2 females and 5 males, aged 19 to 63 years. The ALS group comprised 4 females and 4 males, aged 35 to 67 years; the ALS patients passed away within a few years following the recordings. Although the database includes EMG recordings from various muscles, only those acquired from the biceps brachii were used in this study to maintain homogeneity. All EMG signals were recorded using concentric needle electrodes. The EMG acquisition system was configured with a band-pass filter range of 2 Hz to 10 kHz. A total of 270 EMG recordings were obtained from the long head of the biceps brachii muscle in healthy subjects. For the myopathy group, 112 EMG recordings from the same muscle were available. For the ALS group, 98 recordings from the biceps brachii muscle were used, although the specific region of the muscle was not specified in the database. All data were collected during sustained low level voluntary contractions, with a sampling frequency of 23,437.5 Hz.

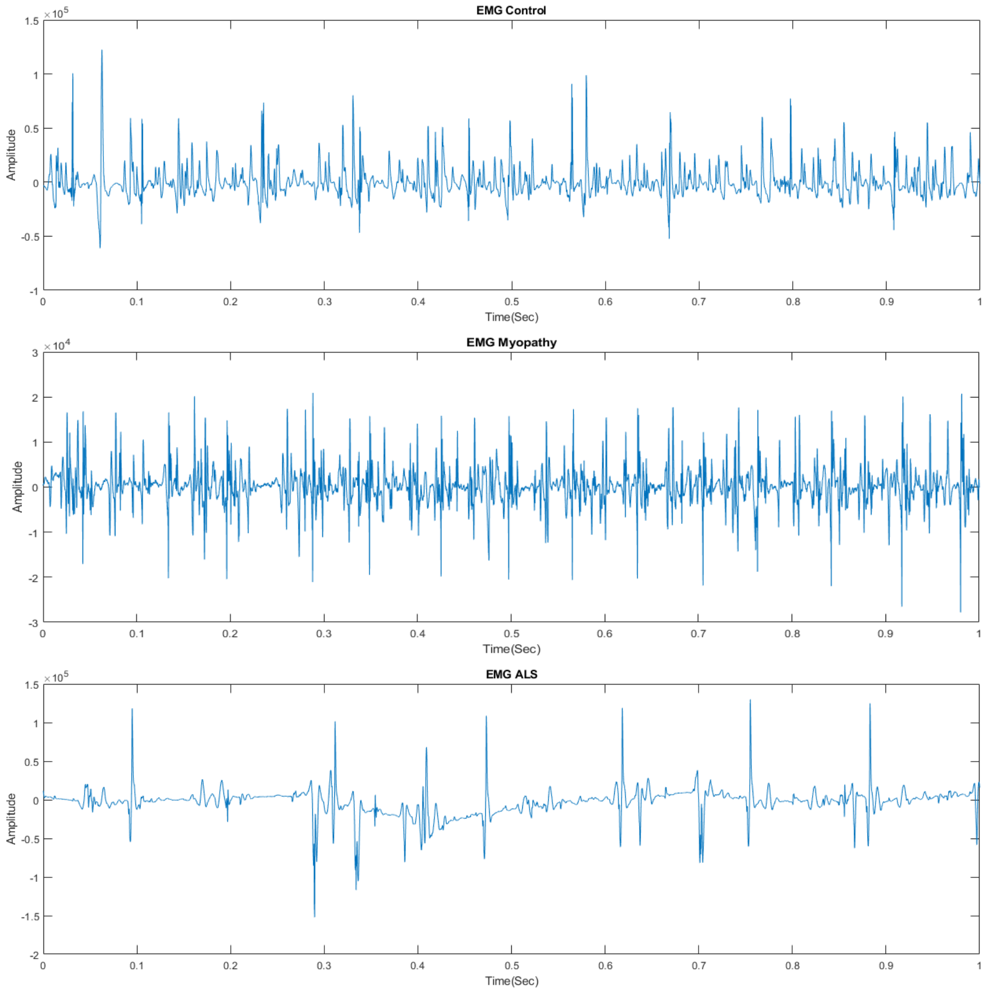

Figure 2.1 1 Seconds of Control, Myopathy and ALS EMG Signals.

Signal Preprocessing

All electromyography (EMG) recordings were processed in MATLAB R2024a using handwritten script. The raw EMG signals, originally sampled at 23,437.5 Hz and stored as 16-bit binary files, were first converted to microvolt units by applying a conversion factor of 13.107 µV per bit which extracted from related header file. To remove the DC offset, each signal's mean amplitude was subtracted, ensuring that subsequent frequency-domain analysis reflected only physiological variations.

Each EMG trace was resampled to a uniform rate of 23,437 Hz to standardize temporal resolution. Motion artifacts and power-line interference were attenuated by applying a finite impulse response (FIR) band-pass filter with a Hamming window, order 400, and cut-off frequencies at 20 Hz (high-pass) and 2500 Hz (low-pass). This configuration preserved the main spectral components of motor unit action potentials while removing baseline drift and high-frequency noise Figure (2.2).

After filtering, signals were segmented into nonoverlapping 1 second epochs (23,437 samples each). This segmentation strategy enabled analysis at the epoch level, providing fine temporal granularity and facilitating independent feature extraction from each segment. The resulting segments were stored for subsequent wavelet-based analysis.

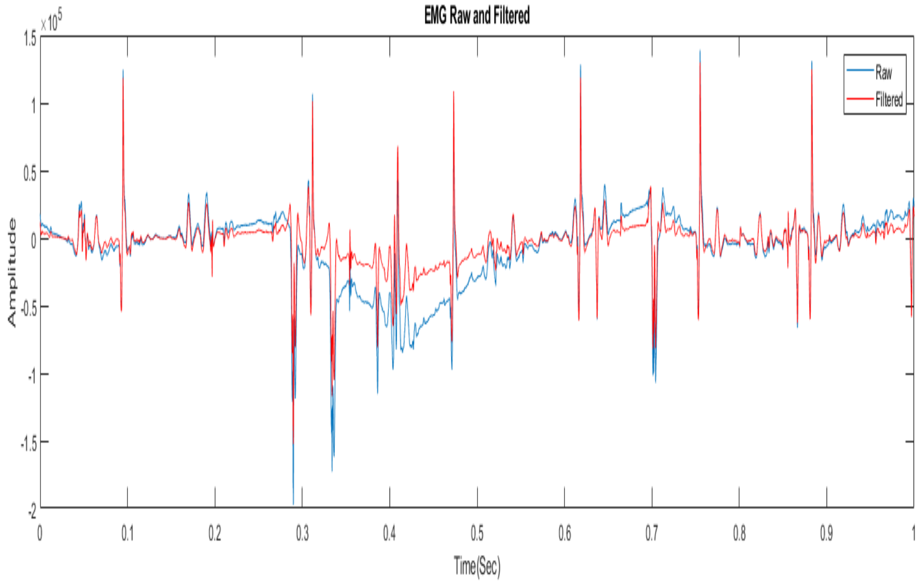

Figure 2.2 1 Seconds of Filtered (Red) and Raw (Blue) Signal

Feature Extraction via Wavelet Scattering Transform (WST)

The Wavelet Scattering Transform (WST) was employed to extract translation-invariant and deformation-stable representations of the EMG signal, preserving essential spectral and temporal structures while minimizing sensitivity to noise and small phase shifts. The WST is a hierarchical convolutional operator introduced by Mallat (2012) that combines the interpretability of wavelet analysis with the robustness of deep feature representations[7, 8]. Unlike conventional discrete wavelet transforms, which rely on explicit coefficient selection and thresholding, WST provides a mathematically stable mapping from the input signal to a set of coefficients whose energy is preserved under translation and small-time deformations properties crucial for biomedical signals such as EMG.

Let x(t) denote a 1-second EMG segment with sampling frequency fs=23,437 Hz. The continuous wavelet transform of x(t) using a complex Morlet mother wavelet ψ(t) is defined as:

$$W_x(a,b) = \int x(t)\psi_{a,b}^{*}(t)dt, \qquad \psi_{a,b}(t) = \frac{1}{a}\psi(\frac{t-b}{a})$$

where a and b represent the scale and translation parameters, respectively.

In scattering networks, instead of directly using Wx(a,b) a cascade of modulus and averaging operators is applied to capture higher-order signal modulations:

$$S_0x(t) \;=\; x * \phi_J(t)$$

$$S_1x(t,\lambda_1) \;=\; |x * \psi_{\lambda_1}| * \phi_J(t)$$

$$S_2x(t,\lambda_2) \;=\; \left||x * \psi_{\lambda_1}| * \psi_{\lambda_2}\right| * \phi_J(t)$$

where * denotes convolution, ϕ_J is a low-pass averaging filter at scale 2^J, and λ_i indexes frequency bands.

- The zero-order term S_0x captures the local average energy of the signal.
- The first-order scattering coefficients S_1x encode amplitude envelopes of

high-frequency oscillations (motor unit action potential activity).

- The second-order coefficients S_2xquantify modulations of those envelopes, describing slower variations that often differentiate pathological from normal EMG morphology.

For the chosen configuration (J=8covering frequencies down to ≈ 90 Hz), the scattering network produced a structured coefficient set invariant to translations smaller than ≈11 ms an interval appropriate for EMG bursts and motor-unit discharges.

The scattering coefficients were extracted via the feature Matrix function, resulting in a multidimensional tensor whose mean values across time were computed:

$$\overline{S_m}(\lambda) = \frac{1}{T}\int S_m(t,\lambda)dt$$

producing a fixed-length feature vector per epoch. This averaging compresses the temporal evolution of coefficients while preserving the overall energy distribution of the signal. The resulting features reflect multi-scale amplitude modulations and temporal regularity patterns typical of myopathic or neuropathic EMG activity.

Finally, all scattering feature vectors were concatenated to form a global **feature matrix** (N×PN \times PN×P), where N is the number of epochs and P the number of retained scattering paths. Each column was standardized using **z-score normalization** before classification. This ensured numerical stability, equal weighting across scattering bands, and improved convergence for distance-based classifiers such as KNN.

Classification Using K-Nearest Neighbor (KNN)

Classification was conducted using supervised learning within MATLAB's Classification Learner environment. Among the tested classifiers, the K-Nearest Neighbor (KNN) model was adopted for its simplicity, interpretability, and robust performance on small- to medium-sized biomedical datasets.

In KNN, an unlabeled feature vector is assigned the class most common among its K nearest training samples. The distance metric used was Euclidean distance, defined as:

$$d(x_{i,}x_j) = \sqrt{\sum_{k=1}^{n}(x_{ik} - x_{jk})^2}$$

where xi and xj are feature vectors in an nnn-dimensional space.

Evaluation Metrics

Classification performance was quantified using standard statistical metrics derived from the confusion matrix, including Accuracy, Sensitivity (Recall), Specificity, and F1-Score. These were calculated as follows:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

$$\text{Sensitivity(Recall)} = \frac{TP}{TP + FN}$$

$$\text{Specifty} = \frac{TN}{TN + FP}$$

$$\text{Precision} = \frac{TP}{TP + FP}$$

$$F1 - \text{Score} = 2 * \frac{\text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}}$$

where TP, TN, FP, and FN denote the number of true positives, true negatives, false positives, and false negatives, respectively.

All metrics were computed for each class (ALS, myopathy, control) and averaged via a macro-averaging strategy to provide an overall model performance index. These measures collectively reflect the model's classification accuracy, its ability to correctly identify each pathology, and its resistance to misclassification bias.

Results and Dıscussıon

After applying all preprocessing steps and executing the WST pipeline, a total of 334 features were automatically extracted. The dataset comprised 5,225 EMG segments. These segments were randomly divided into training (70%) and testing (30%) subsets. Consequently, the training matrix had a dimensionality of 3,658 × 335, with one column reserved for class labels, while the test matrix was structured as 1,567 × 335.

Model training was performed using five-fold cross-validation (k = 5). The dataset was partitioned into five equal folds; in each iteration, four folds were used for training and the remaining fold for validation. This procedure was repeated five times to enhance the statistical robustness and generalizability of the model.

Before classification, all feature vectors were shuffled and stratified to preserve class balance across ALS, myopathy, and control segments. The trained classifier then generated predicted labels for each test observation, which were subsequently compared with the corresponding ground-truth labels to assess model performance. Groups labeled as 0,1,2 respectively Control, Myopathy,ALS. Evaluation metrics calculated for validation from confusion matrix shown in Figure 3.1.

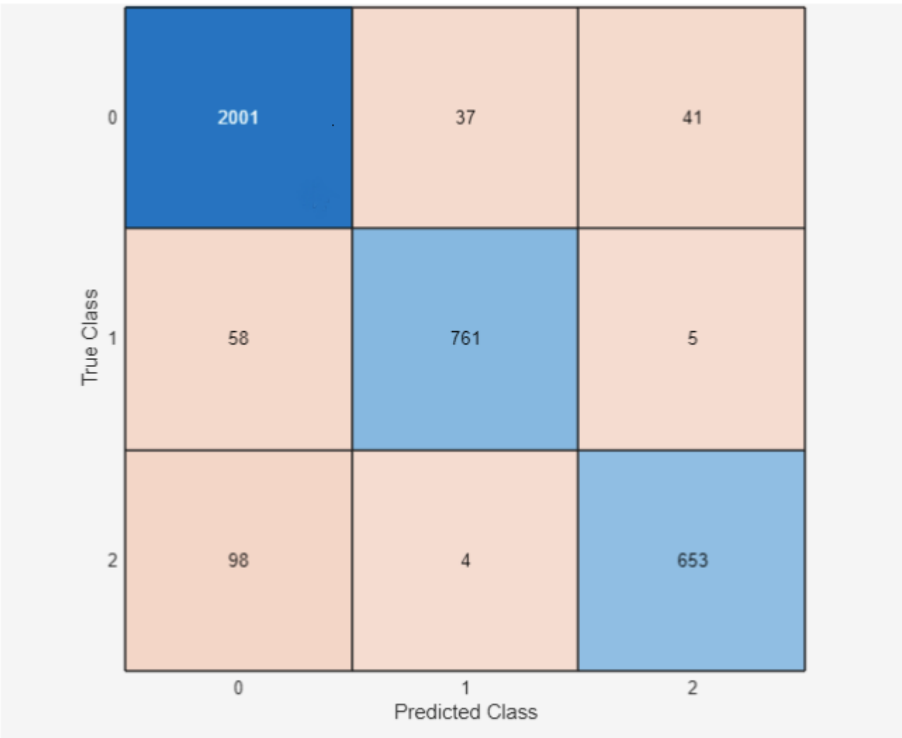

Figure 3.1 Validation Confusion Matrix

As a result the model achieved %93.37 accuracy and other metrics at group level has given in Table 1.

Table 1. Evaluation Metrics for Validation at Group Level

Class	Sensitivity	Specificity	Precision	F1-score
C(0)	0.9625	0.9012	0.928	0.945
M(1)	0.9233	0.9855	0.948	0.935
A(2)	0.8642	0.9841	0.934	0.897

After training and validate the model we use test subset to test model.

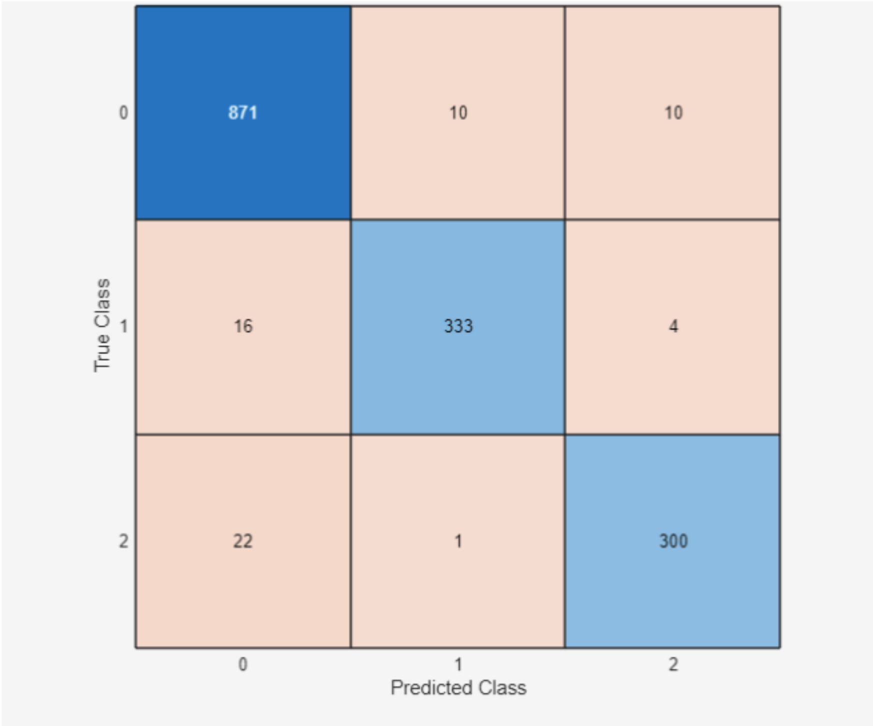

Figure 3.2 Test Confusion Matrix

At test model reached the %96 accuracy and other metrics has given on Table 2.

Table 2. Evaluation Metrics of Test at Group Level

Class	Sensitivity	Specificity	Precision	F1-score
C(0)	0.9776	0.9438	0.9582	0.968
M(1)	0.9430	0.9910	0.9680	0.954
A(2)	0.9280	0.9890	0.9550	0.942

The findings indicate that the wavelet scattering based feature representation enabled the model to learn meaningful temporal,spectral patterns that distinguish ALS, myopathy, and control EMG activity at the epoch level. The consistently high sensitivity and specificity values across classes demonstrate that the classifier was able to capture characteristic differences in motor unit morphology rather than memorizing noise or irrelevant signal components. In particular, the elevated performance in myopathy and control epochs, and the relatively lower recall in ALS, suggest that the WST features predominantly encode amplitude modulation and complexity variations features that are more pronounced in myopathic and normal signals than in neuropathic degeneration patterns, which may appear more heterogeneous.

A key methodological point is that the classification was performed at the epoch level rather than at the patient level. While this approach enables fine-grained analysis and increases the number of training samples, it does not prevent segments from the same individual from appearing in both training and testing subsets. This design improves segment level discrimination but does not fully assess generalizability to unseen subjects. As such, the model demonstrates strong feature learning at the segment level, yet its performance at the patient scale remains unverified. A subject independent evaluation would be required to determine whether the learned features genuinely capture disease specific neuromuscular patterns rather than subject dependent signal characteristics.

Another important aspect is the use of a shallow classifier. The high-test accuracy suggests that the WST feature space is well structured and class separable, allowing a non-parametric model such as KNN to perform effectively without complex optimization. However, the reliance on Euclidean distances also implies that the distribution of scattering features is critical; any deviation in recording conditions, noise characteristics, or electrode placement in future datasets may reduce performance. Consequently, although the framework is computationally efficient and transparent, its robustness to inter-subject and inter-device variability should be examined in future work.

Overall, the results demonstrate that the model successfully learned discriminative EMG patterns at the epoch scale, but they also highlight the need for subject-level validation, variability analysis, and potential integration of temporal decision fusion for clinical applicability.

Conclusion

This study demonstrated that wavelet scattering features combined with a KNN classifier can accurately distinguish myopathy, ALS, and control EMG epochs, achieving 96% test accuracy. The results confirm that the proposed pipeline effectively captures discriminative temporal, spectral characteristics of EMG signals at the segment level. While the method is computationally efficient and delivers high performance, patient-level generalization remains untested; therefore, future work should incorporate subject-independent validation to assess clinical applicability.

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