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RESEARCH ARTICLE

Intelligent Technique for Neuromuscular Disorders Prediction Based on Stockwell Transform

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Abstract: Electromyography (EMG) signals, which reflect the electrical activity of skeletal muscles, serve as a fundamental tool in diagnosing neuromuscular disorders. Yet, due to their inherently nonstationary characteristics, extracting meaningful features from these signals remains a persistent challenge in the field. To address this, the present study introduces a hybrid methodological framework. Initially, EMG signals are transformed into time–frequency representations using the Stockwell transform (ST), effectively converting complex signal data into image-like formats amenable to advanced analysis. Subsequently, the framework leverages the power of five pretrained deep convolutional neural networks (CNNs)—namely, VGG16, ResNet50, DenseNet201, InceptionV3, and InceptionResNetV2—as automated feature extractors. This approach reduces dependence on traditional handcrafted features and exploits the capacity of CNNs to uncover intricate signal patterns. The investigation utilizes the publicly available EMGLAB database, encompassing EMG data from individuals diagnosed with amyotrophic lateral sclerosis, myopathy, and healthy controls. The signals are segmented and transformed into Stockwell-based images prior to feature extraction. For classification, features derived from the CNNs are evaluated using conventional machine learning algorithms, including support vector machine (SVM), random forest, k-nearest neighbor, and naïve Bayes. Empirical results reveal that the combination of VGG16 and SVM produces the most accurate classification, with achieved accuracies ranging between 97.0% and 98.5% across five distinct classification tasks. These findings underscore the efficacy and potential of the ST combined with CNN-based strategies for robust and accurate classification of neuromuscular disorders, establishing a valuable benchmark for future EMG research.

Keywords: artificial intelligence, medical informatics, machine learning, signal processing, convolutional neural networks

1. Introduction

Neuromuscular disorders refer to various diseases that cause disruption in communication between nerves and muscles that can ultimately culminate in gradual weakness, loss of mobility, and a decrease in quality of life. Supportive means such as physiotherapy can help facilitate muscular strength; however, successful clinical management relies upon timely and accurate diagnosis [1, 2].

Electromyography (EMG) is a common associated method of diagnosis for neuromuscular disorders, assessing muscle function, as well as assisting with prosthesis control [3–6]. EMG signals, created by action potentials that occur in the motor units, produce signals that are nonstationary and complex and therefore are not trivial to interpret. As such, more advanced signal processing techniques are typically required to extract relevant and discriminative features that may be classified in a reliable manner.

Time–frequency (T–F) methods have been commonly used as processing methods in EMG analysis because they provide localized information in the time domain and in the frequency domain [7, 8]. The short-time Fourier transform (STFT) is a type of T–F approach (or analysis) that provides the earliest T–F methods, and therefore, it is assumed that there is a fixed window size, which leads to a leads to a trade-off between time resolution and frequency resolution. The wavelet transform (WT) provides greater flexibility in windowing and thereby adaptability; however, it can be susceptible to noise [9]. The Stockwell transform (ST) was developed as a merger of STFT and WT, which employs adaptive resolution and is also improved to rise to the challenge of noise susceptibility [10]. Models developed using features extracted from the ST are particularly suitable for biomedical signal analysis, as the enhanced spectral representation and improved resolution enable more effective interpretation of signal characteristics and support reliable decision-making by providing additional contextual information across multiple signal samples.

Researchers have assessed numerous signal processing and machine learning methods for EMG-based neuromuscular disorder classification over the last twenty years. Hubers et al. [11] developed a two-stage ANN framework. In the first stage, the EMG segments are classified into rest, contraction, or artifacts with an accuracy of 96%. In the second stage, the system

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classified motor unit action potential durations into prolonged, normal, and shortened categories, achieving between 67% and 83% accuracies. Yoo et al. [12] utilized a residual one-dimensional convolutional neural network (CNN) for classifying neuromuscular disorders directly from raw needle EMG signals. They used a divide-and-vote strategy for subject-level diagnosis, and the model achieved an accuracy of 83.69%. Bose et al. [13] proposed a weighted visibility graph framework and achieved 99.05% accuracy. Subasi [14] utilized dual-tree complex WT features that achieved the highest classification accuracy of 99.6% using a support vector machine (SVM), while Subasi and Yaman [15] used an ensemble Random Subspace classifier, and tunable Q-factor wavelet transform (TQWT) was utilized and strongly performed based on k-fold cross-validation.

Recent works have explored different decomposition approaches and hybrid approaches. Samanta et al. [16] outlined the robust hyperbolic ST with a genetic algorithm for parameter selection, while classifying healthy, myopathy (MYO), and ALS signals, using SVM. Recently, Khan et al. [17] provided useful feature extraction by combining empirical mode decomposition (EMD) with cepstral coefficients, which achieved an accuracy of 91.1%. Furthermore, Dubey et al. [18] also used EMD features but instead used a feedforward neural network, reporting an accuracy of 99.53%.

Abdennaji et al. [19] presented a hybrid technique that incorporated multi-resolution analysis, fast WT, and wavelet networks, followed by the encoding and classification step with AdaBoost, by way of reference, achieving an accuracy of 100%. Other studies [20] used higher-order statistics with discrete WTs and ensemble classifiers and determined that optimized hyperparameters can generate robust classification.

Several research gaps remain in existing methods. Most studies depend on handcrafted features, which are difficult to generalize across datasets from different clinical sources. These studies also use a small number of feature transformations, limiting robustness. Although T–F techniques such as the ST, TQWT, and EMD can enhance feature quality, they are rarely combined with deep learning models. As a result, the ability of deep networks to automatically learn complex feature representations is underused.

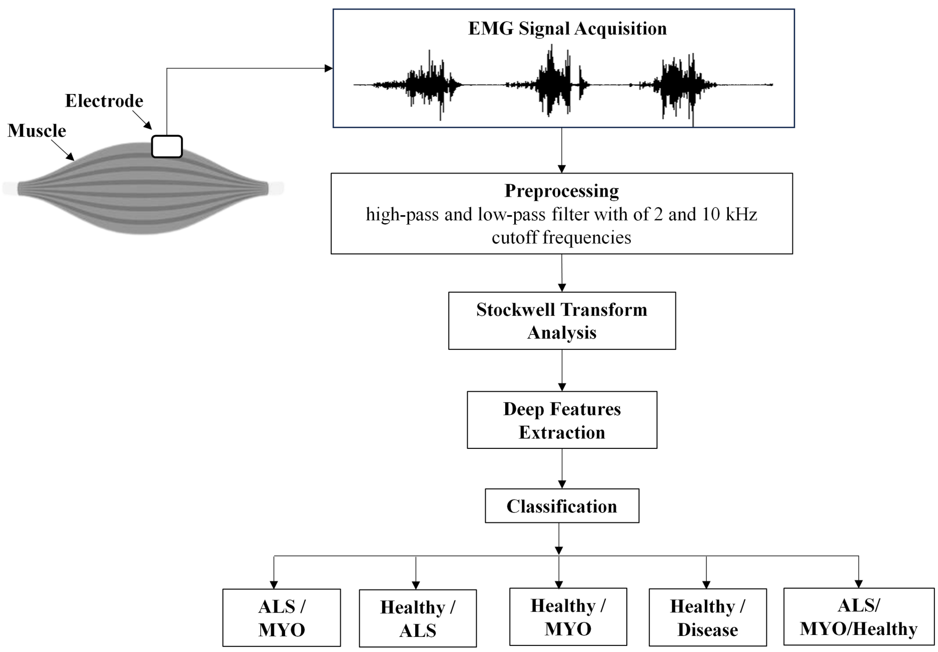
To address these limitations, this study proposes an intelligent diagnostic framework for EMG-based neuromuscular disorder classification based on deep feature extraction using ST and VGG16 and classification using SVM. The novelty of this work lies in converting EMG signals into ST images and using pretrained VGG16 for feature extraction. Furthermore, the study conducts a comprehensive comparative analysis with other established pretrained CNN architectures, such as ResNet50, DenseNet201, InceptionV3, and InceptionResNetV2, as well as multiple classifiers, including SVM, RF, k-nearest neighbor (kNN), and naïve Bayes (NB). This provides a systematic evaluation of model performance and demonstrates the efficiency and scalability of the proposed approach for clinical applications. The approach is described in detail in Sections 2 and 3, and its performance is evaluated via extensive experiments provided in Section 4.

2. Research Methodology

The methodology of this study was designed to develop and evaluate an effective approach for the classification of neuromuscular disorders using EMG signals. The proposed method integrates deep feature extraction using the VGG16 CNN model with classification based on SVM. Figure 1 illustrates the whole methodology proposed for the diagnosis of EMG signals. The overall pipeline consists of five main phases: data collection from the publicly available EMGLAB database, followed by segmentation into equal-length frames and transformation into T–F images using the ST.

For feature extraction, the CNN model was first fine-tuned using the training set and validated using the validation set, with hyperparameters adjusted based on validation accuracy to achieve

Figure 1
An overview of the proposed method for classifying EMG signals



optimal weights. After the training and validation, the optimized model was employed to extract deep feature representations from EMG signal ST images. The extracted training features were then used to train the SVM classifier, while the validation features supported hyperparameter selection.

Finally, the independent test set was used for feature extraction based on a CNN model and classified using the optimized SVM to evaluate performance.

2.1. Signal transformation using Stockwell transform (ST)

In this phase, EMG signals are transformed into T–F images using ST. The ST advantage is that it combines the benefits of STFT and WT. In the ST, a Gaussian window, with a variable width based on frequency, gives ST a high resolution in time and frequency, making ST also capable of filtering noise. For a signal g(t), the ST is defined in the article by Stockwell [21] as:

$$ST(\tau, d) = \int_{-\infty}^{\infty} g(t)\, \frac{|f|}{\sqrt{2\pi}} e^{-\frac{t^2 f^2}{2}} e^{-i2\pi f t}\, dt \tag{1}$$

where τ is the time shift and f is the frequency. The output is a two-dimensional T–F representation that forms the input for CNN-based feature extraction.

ST was applied to EMG signals sampled at 1000 Hz with 4096 points, over a frequency range of 0–500 Hz, yielding 2048 frequency bins and a resolution of ~0.244 Hz. The Gaussian window standard deviation was proportional to frequency ($\sigma = f/(2\pi)$), resulting in a wide window of ~80 samples at 1 Hz for precise frequency localization and a narrow window of ~80 samples at 500 Hz for high temporal precision. No temporal downsampling was applied, preserving full time resolution. Compared to conventional STFT or wavelet transforms, this adaptive windowing provides superior T–F localization, enabling more precise feature extraction for EMG classification. The raw EMG signals from ALS, MYO, and healthy subjects with their corresponding ST spectrograms are illustrated in Figure 2.

2.2. VGG16 model

VGG16 Net is a deep learning network that consists of 16 layers. It shows effective classification across thousands of classes; therefore, it is considered one of the most powerful networks in the field of deep learning [22]. VGG16 achieved first place in the ImageNet image localization challenge and second place in the classification task in 2014. To minimize the number of parameters without reducing the receptive field, this model replaces a single large convolution filter with a stack of 3 × 3 convolutional filters. This design allows the network to go deeper, increasing its nonlinear modeling capability and improving feature learning. Furthermore, VGG16 uses 2 × 2 max pooling layers and removes normalization layers to decrease model complexity. The simple and uniform architecture demonstrates strong generalization ability, and its increased depth enables more effective feature extraction. The VGG16 structure diagram is illustrated in Figure 3.

2.3. Support vector machine

SVM is a classification approach that is capable of classifying linear and nonlinear data. The initial training set can be transformed into a higher dimension using nonlinear mapping. This higher-dimensional space is searched for the linear optimum separation hyperplane using margins and support vectors. A decision boundary is a hyperplane that separates one class tuple from the others. This hyperplane is used in classifying data into two classes when using an appropriate nonlinear mapping that provides a high enough dimension. This allows SVMs to accurately represent complex nonlinear decision boundaries. Studies found that SVMs are resistant to overfitting in comparison to other techniques [23]. In this work, one-vs-rest SVM classification was performed using a radial basis function kernel. We employed the grid search strategy combined with tenfold cross-validation to determine the optimal values of the penalty parameter C and the kernel parameter γ. Within the search ranges of $C = [10^{-2}, 10^{-1}, 10, 10^{1}, 10^{2}]$ and $\gamma = [10^{-4}, 10^{-3}, 10^{-2}, 10^{-1}, 10, 10^{1}, 10^{2}]$, we found that the optimal parameters are $C = 10^{-1}$ and $\gamma = 10^{-3}$, respectively, and used them for training the SVM classifier.

3. Experimental Setup

3.1. Dataset

The experiments in this study are performed on EMG signals obtained from the EMGLAB database [24]. The EMGLAB database encompasses:

Figure 2
Samples of (1) raw signal and (2) ST spectrum of (a) ALS, (b) MYO, and (c) healthy subjects

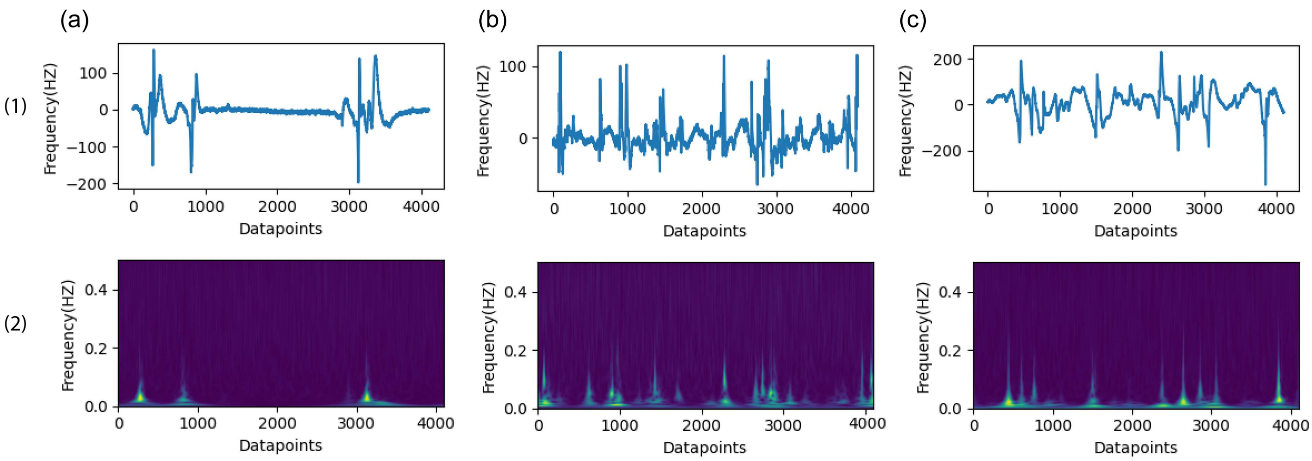


Figure 3
Structure diagram of VGG16

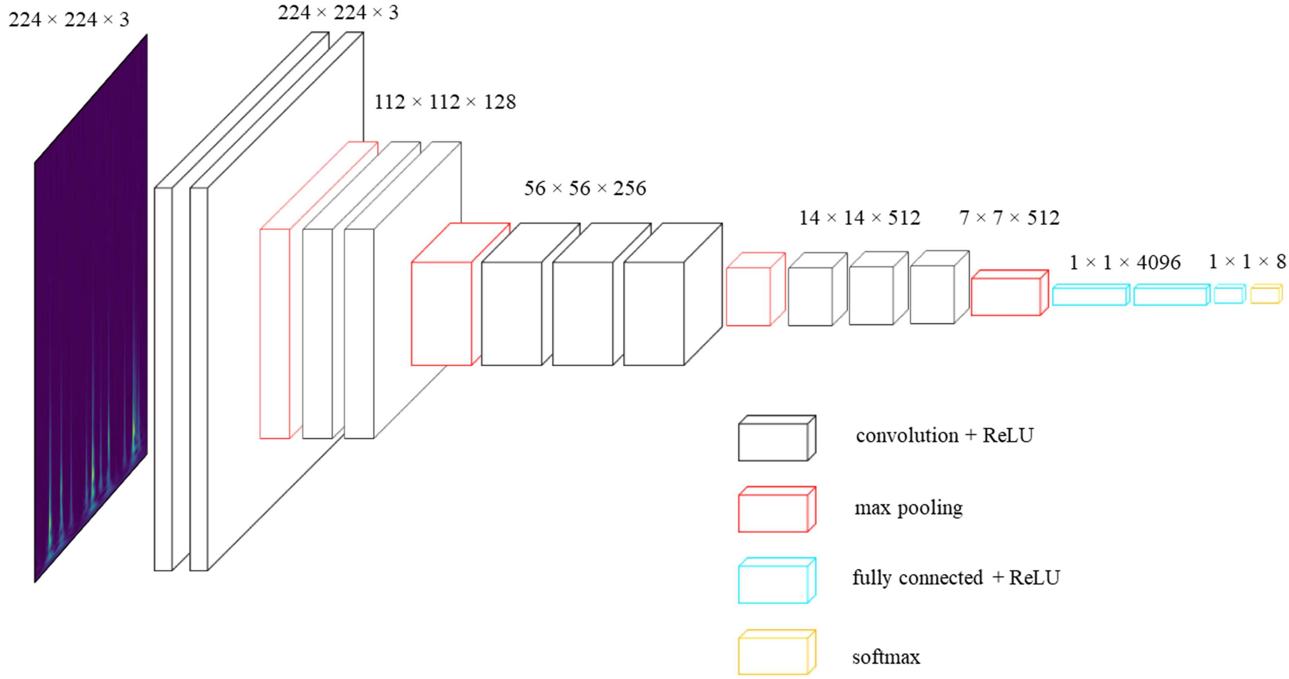
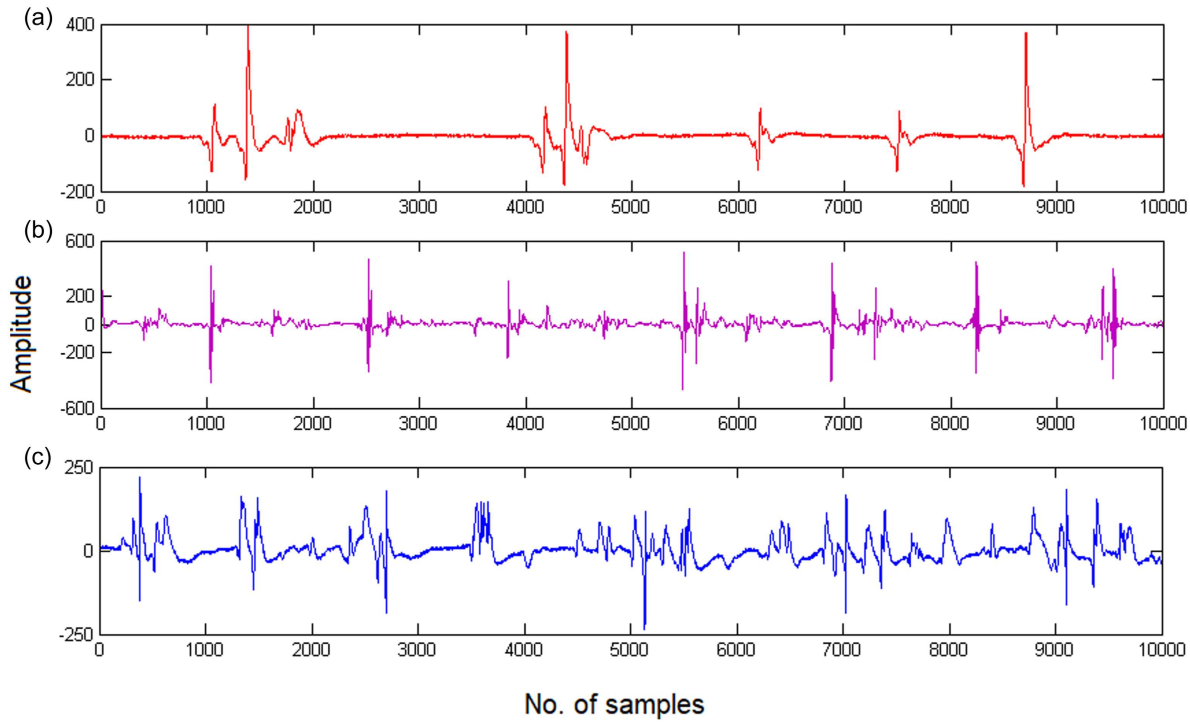


Figure 4
EMG raw patterns of (a) ALS, (b) MYO, and (c) healthy subjects



1) ALS: 8 subjects (4 females, 4 males), ages ranging from 35 to 67 years old
2) MYO: 7 subjects (5 females, 2 males), ages ranging from 19 to 63 years old
3) Healthy: 10 subjects (4 females, 6 males), ages ranging from 21 to 37 years old

Signals are recorded at the biceps brachii muscle using concentric needle electrodes with low voluntary contractions at three depths. The signals are sampled at 23.438 kHz, digitized at 16-bit resolution, and filtered with a Butterworth high-pass filter with cutoff frequencies of 2–10 kHz. Figure 4 depicts typical EMG signals for all three groups.

The dataset contains 343 recordings in total. Of these, 150 signals are collected from healthy subjects, 101 from patients diagnosed with MYO, and 92 from patients with amyotrophic lateral sclerosis (ALS). Each EMG signal was segmented into 64 equal frames, with each frame consisting of 4096 data points to ensure an adequate balance between temporal resolution and frequency-domain representation. This preprocessing resulted in 7500 frames for the healthy class, 2650 for MYO, and 2125 for ALS. This segment length captures sufficient motor unit activity while preserving diagnostically relevant spectral characteristics. Preliminary experiments were conducted using alternative segment lengths (2048 and 8192 samples); however, 4096-point segments yielded superior classification performance with reduced computational overhead. Similar segmentation strategies have been reported as effective in prior EMG-based neuromuscular disorder studies.

To ensure balanced representation across the three classes, 2000 frames are randomly selected from each class, yielding a total of 6000 segments. The dataset is then partitioned into three subsets: 60% for training, 20% for validation, and 20% for testing. The training set is used to optimize the CNN models, the validation set is used to tune hyperparameters and retain the best-performing weights, and the test set is reserved for final evaluation. In addition, features extracted from the CNNs are used to train the classifiers on the training set, while their performance was assessed using the independent test set.

3.2. Parameter configuration

All the experiments in this paper are implemented in Python 3.9 using Python Keras and TensorFlow libraries and conducted on a computer with the following specifications: a Core i7 processor with 16 GB RAM.

The following experiments include a comparison between five pretrained CNN models, including VGG16, ResNet50, DenseNet201, InceptionV3, and InceptionResNetV2. To ensure a fair comparison, all networks in the experiments are evaluated under the same conditions. Key hyperparameters, including batch size, learning rate, number of training epochs, and initial weight configuration, are kept consistent across all models. Each network processes input images with dimensions of 224 × 224 × 3. Training is conducted using the Adam optimizer and the CrossEntropyLoss function. All models are trained on the EMGLAB dataset with a learning rate of 0.00005, a batch size of 32, and 50 epochs. To eliminate any bias from pretrained weights, all network parameters are initialized randomly. After deep feature extraction, another comparison is performed for the classification using standard classifiers, including SVM (linear kernel), random forest (RF) (100 trees) [25], kNN (k = 5), and NB [26].

3.3. Evaluation

All classification tasks are evaluated using tenfold cross-validation across four binary problems (ALS vs MYO, ALS vs Healthy, MYO vs Healthy, and Healthy vs Disease) and one multiclass problem (ALS vs MYO vs Healthy). To evaluate the performance of the proposed method, multiple metrics are employed, including accuracy, sensitivity, and specificity. These metrics are defined based on four possible prediction outcomes: true positive (TP), true negative (TN), false positive (FP), and false negative (FN). In this study, TP refers to positive samples correctly classified as positive, TN represents negative samples correctly classified as negative, FP denotes negative samples incorrectly classified as positive, and FN indicates positive samples incorrectly classified as negative. Higher values in these metrics indicate better model performance.

1) Accuracy:

Accuracy measures the proportion of correctly classified samples out of the total number of test samples. A higher accuracy value indicates better overall classification performance.

$$Accuracy = \frac{(TP + TN)}{(TP + FN + TN + FP)} \tag{2}$$

2) Sensitivity (Se):

Also known as the true positive rate or recall, sensitivity measures the proportion of actual positive samples that are correctly identified by the model. It reflects the model's ability to detect positive cases.

$$sensitivity = recall = \frac{TP}{(TP + FN)} \tag{3}$$

3) Specificity:

Specificity measures the proportion of actual negative samples correctly identified as negative. It evaluates the model's ability to avoid false alarms by correctly rejecting negative cases.

$$specificity = \frac{TN}{(TN + FP)} \tag{4}$$

4) F1-score:

This measure represents the consistent mean of precision and recall, providing a balanced measure of classification performance. The F1-score ranges from 0 to 1, where a value of 1 indicates optimal performance and 0 indicates the poorest performance.

$$precision = \frac{TP}{(TP + FP)} \tag{5}$$

$$F1 - score = 2 \times \frac{precision \times recall}{precision + recall} \tag{6}$$

4. Results and Discussions

In this section, we present the results of our proposed approach that combines ST with the VGG16 deep learning model and SVM classifier. To evaluate its performance, two complementary analyses were performed: (i) a comparison of different pretrained CNN models for feature extraction and (ii) a comparative study on the choice of classifiers across the binary and multiclass classification tasks.

4.1. Performance of the proposed methodology

The classification results presented in Table 1 demonstrate that VGG16 features can effectively differentiate between ALS, MYO, and healthy EMG signals when used with different classifiers. For all tasks, SVM produced the best accuracy, sensitivity, and specificity, confirming that it performed the best due to its robustness to high-dimensional deep features. In the binary classification task ALS vs MYO, SVM achieved an accuracy of 98.5%, which is significantly better than RF (97.3%), kNN (97%), and NB (96%). The high performance of SVM highlights its ability to classify the high-dimensional EMG signals.

Table 1
Classification results of VGG16 features

Task	Classifier	Accuracy (%)	Specificity (%)	Sensitivity (%)	F1-score (%)
ALS vs MYO	SVM	98.5	98.0	98.6	98.3
	RF	97.3	97.1	97.5	97.3
	kNN	97.0	97.3	97.6	97.4
	NB	96.0	96.5	96.2	96.1
ALS vs Healthy	SVM	98.2	98.6	97.8	98.2
	RF	97.2	97.1	97.3	97.2
	kNN	96.8	96.5	97.0	96.8
	NB	95.0	95.5	94.5	95.0
MYO vs Healthy	SVM	97.7	97.5	97.5	97.5
	RF	97.0	97.2	97.5	97.3
	kNN	96.5	96.3	97.2	96.8
	NB	95.8	97.0	94.6	95.8
Healthy vs Disease	SVM	98.0	96.2	97.5	96.8
	RF	97.0	95	97.8	96.4
	kNN	96.7	96.5	96.9	96.7
	NB	95.1	94.5	95.4	95.0
ALS vs MYO vs Healthy	SVM	97.0	96.6	97.0	96.8
	RF	96.5	96.1	96.7	96.4
	kNN	96.5	96.2	96.2	96.2
	NB	94.8	94.9	94.8	94.8

The categorization of ALS and healthy subjects indicated high accuracy, with SVM again leading at 98.2%. A small drop in performance was seen when classifying MYO form healthy subjects, with the SVM showing an accuracy of 97.7%. The MYO signal likely shares a few similarities with healthy EMG patterns, likely making it not as straightforward a classification task as healthy versus ALS. In the Healthy vs Disease task, SVM had an accuracy of (98.0%) despite the sensitivity being lower at 96.2%, indicating that some diseased cases were misclassified. This could mean that while some VGG16 features are useful, it could be beneficial to optimize some features to improve sensitivity for disease detection.

The multiclass classification task (ALS vs MYO vs Healthy) was the most difficult task, with SVM's accuracy being 97.0%. RF and kNN provided similar performance (although lower relative to SVM), while NB consistently fell behind in all tasks, indicating its limited ability to model the feature distributions of EMG signals.

4.2. Comparison of CNN pretrained models

The comparative evaluation of the pretrained CNN models combined with an SVM classifier demonstrates that VGG16 consistently outperforms other pretrained models on both binary and multiclass classification tasks. As presented in Table 2, VGG16 achieved the highest accuracy, specificity, and sensitivity in the ALS vs MYO (98.5%, 98.0%, and 98.6%), ALS vs Healthy (98.2%, 98.6%, and 97.8%), and MYO vs Healthy (97.7%, 97.5%, and 97.5%) tasks, which reflects its capability to distinguish between highly similar neuromuscular disorder classes. Similarly, in the Disease vs Healthy and the three-class (ALS vs MYO vs Healthy) classification tasks, VGG16 again produced high performance (98.0% and 97.0% accuracy, respectively), which confirms its efficiency for clinical decision-making. While DenseNet201 and ResNet50 produced competitive results in single tasks, their performance was less than that of VGG16, and InceptionResNetV2 was the worst in all tasks. These findings indicate that VGG16 features yield the most discriminative representations for EMG spectrogram classification when integrated with SVM, providing the best-performing model among those examined.

Feature extraction times for VGG16, ResNet50, InceptionV3, DenseNet201, and InceptionResNetV2 were 983, 1188, 1106, 2901, and 6775 s, respectively. VGG16 achieved the highest accuracy with the fastest computation, making it most suitable for time-sensitive clinical applications. While DenseNet201 is accurate, it consumes more time, limiting its practicality. ResNet50 and InceptionV3 provided a balanced trade-off between accuracy and speed, whereas InceptionResNetV2, despite satisfactory performance, was the slowest and therefore less suitable than other models for frequent clinical usage. The findings illustrate the importance of considering both diagnostic accuracy and computational efficiency in model selection.

The mean accuracies obtained using SVM for all models and classification tasks are illustrated in Figure 5. We observe that DenseNet201 follows VGG16 in terms of classification accuracy, followed by ResNet50, InceptionV3, and finally InceptionResNetV2.

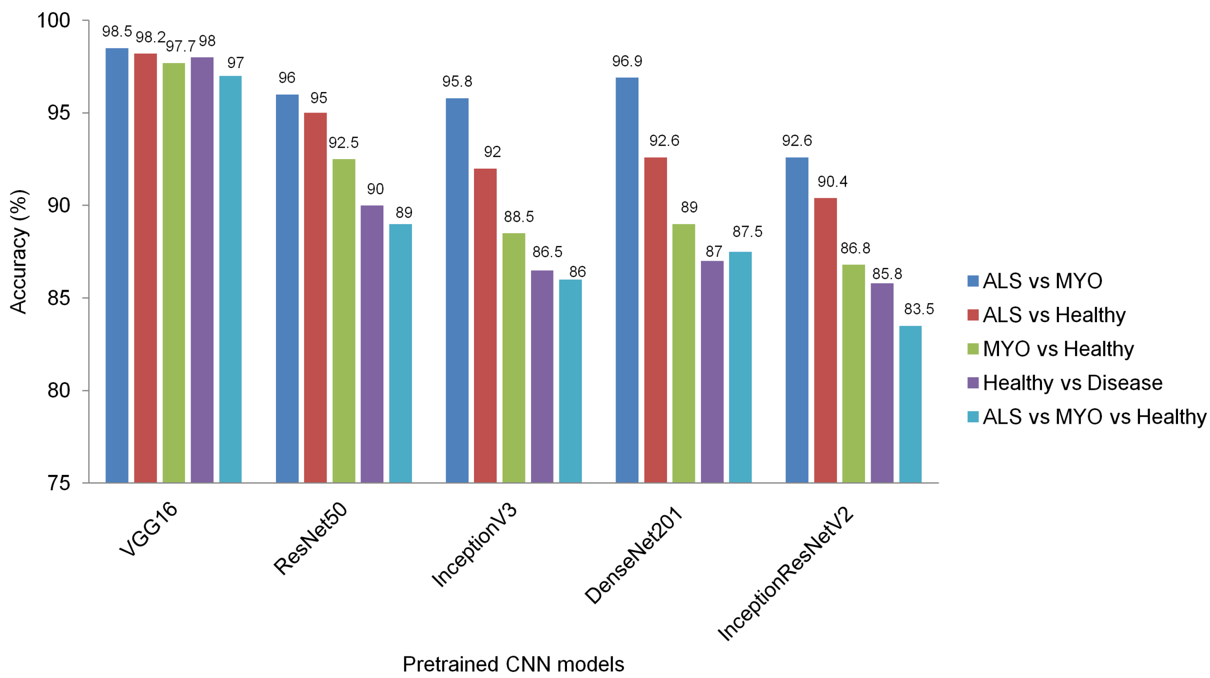
Thus, integrating the ST with deep feature extraction via pretrained CNNs demonstrates significant potential for neuromuscular disorder prediction. Within the models evaluated, VGG16 consistently achieved an optimal balance between classification accuracy and computational efficiency, positioning it as the most effective feature extractor among the options considered.

All the results show that binary classification between ALS and MYO yielded the highest overall accuracy, indicating that the extracted features successfully differentiated these two conditions. In contrast, multiclass classification—distinguishing among ALS, MYO, and healthy controls—proved considerably more

Table 2
Comparison of several CNN model performance combined with SVM classifier

Task	Pretrained model	Accuracy (%)	Specificity (%)	Sensitivity (%)	F1-score (%)
ALS vs MYO	VGG16	98.5	98.0	98.6	98.3
	ResNet50	96.1	96.0	96.3	96.2
	InceptionV3	95.8	95.5	95.6	95.6
	DenseNet201	96.9	96.4	97.2	96.8
	InceptionResNetV2	92.6	93.3	91.8	92.6
ALS vs Healthy	VGG16	98.2	98.6	97.8	98.2
	ResNet50	95.0	95.2	95.2	95.2
	InceptionV3	92.3	92.8	92.1	92.4
	DeneNet201	92.6	92.2	93.0	92.6
	InceptionResNetV2	90.4	93.1	90.7	91.8
MYO vs Healthy	VGG16	97.7	97.5	97.5	97.5
	RestNet50	92.5	91.3	93.2	92.3
	InceptionV3	88.5	88.2	88.8	88.5
	DeneNet201	89.3	89.3	89.3	89.3
	InceptionRestNetV2	86.8	85.0	88.0	86.5
Healthy vs Disease	VGG16	98.0	96.2	97.5	96.8
	RestNet50	90.0	92.5	89.5	90.9
	InceptionV3	86.5	86.2	86.8	86.5
	DeneNet201	87.2	91.3	87.5	89.4
	InceptionRestNetV2	85.8	90.1	82.0	85.8
ALS vs MYO vs Healthy	VGG16	97.0	96.6	97.0	96.8
	RestNet50	89.1	91.1	88.5	89.0
	InceptionV3	86.0	90.2	86.3	86.2
	DeneNet201	87.5	93.7	87.4	90.4
	InceptionRestNetV2	83.5	84.1	83.3	83.5

Figure 5
Performance analysis of the pretrained models using SVM



challenging, underscoring the complexity inherent in this broader diagnostic task.

Among the classifiers tested, SVM reliably outperformed alternatives such as RF, kNN, and NB in terms of accuracy, sensitivity, and specificity. Although DenseNet201 and ResNet50 also delivered competitive performance metrics, their computational requirements were substantially higher than those of VGG16. InceptionV3 offered a moderate compromise between accuracy and efficiency, while InceptionResNetV2, despite yielding reasonable results, required the longest execution time.

The integration of ST features with VGG16 and SVM classification emerged as the most robust framework for accurate neuromuscular disorder prediction in this study.

4.3. Comparison between pretrained and randomly initialized models

This section examines the impact of transfer learning by comparing CNN architectures initialized with ImageNet pretrained weights to the same architectures trained from scratch under identical experimental conditions.

As shown in Table 3, pretrained models consistently outperform randomly initialized networks across all tasks, confirming the effectiveness of transfer learning for neuromuscular disorder classification. The level of improvement varies across tasks, with smaller gains observed for simpler binary classifications and larger gains for more complex and multiclass problems. This variation is expected and reflects differences in task complexity, class separability, and architectural characteristics. In particular, VGG16 and ResNet50 show larger improvements in complex tasks, while DenseNet201 demonstrates stable gains across all scenarios. Overall, the results indicate that pretrained CNNs provide more discriminative representations and are especially beneficial for challenging classification settings.

4.4. Comparative analysis with existing methods

To further verify the effectiveness of the proposed ST–VGG16–SVM methodology, we compared it with some baseline approaches. In a recent study, an automated time series classification algorithm was developed to discriminate between the EMG signals of healthy controls, ALS patients, and IBM patients with diagnostic accuracy given as AUC 0.834–0.856 and accuracy ranging from 73 to 86% based on muscle-level or patient-level analysis [27]. Handcrafted features (mean, standard deviation, zero-crossing rate, root mean square, variance, the mean absolute value, wavelength, and power spectral density) had an accuracy of 96.7% [28]. An interpretable deep learning framework has been proposed for the multiclass classification of neuromuscular disorders with 95.83% accuracy and 98.61% AUC achieved on various datasets with the Convolutional Neural

Table 3
Comparison of CNN pretrained models and randomly initialized models using SVM in terms of accuracy

Model	Task	Accuracy % (pretrained)	Accuracy % (random)	Accuracy (%)
VGG16	ALS vs MYO	98.5	97.5	+1.0
	ALS vs Healthy	98.2	94.4	+3.8
	MYO vs Healthy	97.7	91.2	+6.5
	Healthy vs Disease	98.0	89.5	+8.5
	ALS vs MYO vs Healthy	97.0	88.7	+8.3
ResNet50	ALS vs MYO	96.1	94.2	+1.9
	ALS vs Healthy	95.0	88.7	+6.3
	MYO vs Healthy	92.5	85.0	+7.5
	Healthy vs Disease	90.0	82.7	+7.3
	ALS vs MYO vs Healthy	89.1	82.2	+6.9
InceptionV3	ALS vs MYO	95.8	90.7	+5.1
	ALS vs Healthy	92.3	89.7	+2.6
	MYO vs Healthy	88.5	85.5	+3.0
	Healthy vs Disease	86.5	80.9	+5.6
	ALS vs MYO vs Healthy	86.0	81.4	+4.6
DenseNet201	ALS vs MYO	96.9	92.7	+4.2
	ALS vs Healthy	92.6	88.7	+3.9
	MYO vs Healthy	89.3	85.4	+3.9
	Healthy vs Disease	87.2	82.5	+4.7
	ALS vs MYO vs Healthy	87.5	82.7	+4.8
InceptionResNetV2	ALS vs MYO	92.6	89.5	+3.1
	ALS vs Healthy	90.4	88.6	+1.8
	MYO vs Healthy	86.8	84.8	+2.0
	Healthy vs Disease	85.8	80.3	+5.5
	ALS vs MYO vs Healthy	83.5	81.4	+2.1

Table 4
Comparison of proposed method vs baseline models for multiclass task

Authors	Features	Classifier	Accuracy	Notes
Tannemaat et al. [27]	Time + Frequency domain	Random forest	36%–84%	Different dataset, 2 classes
Hammachi et al. [28]	Time + Frequency domain	Quantum SVM	96.7%	Same dataset, 2 classes
Ritu et al. [29]	Clinically validated EMG descriptors	CNN–LSTM	95.83%	Different dataset, 3 classes
Dixit et al. [30]	Wavelet synchrosqueezed transform + Histogram of Oriented Gradients	SVM	89.2%	Same dataset, 3 classes
Present work	Stockwell T–F features + VGG16	SVM	97.0%	Highest reported performance, 3 classes

Network with Long Short-Term Memory (CNN-LSTM) model and the use of various explainability tools [29]. Moreover, the use of the wavelet synchrosqueezing transform with histogram of oriented gradients features, and SVM has also reported 89.2% accuracy with Wavelet synchrosqueezed transform (WSST) [30]. The results, shown in Table 4, confirm that ST features used with CNN-based feature extraction significantly outperform traditional methods and other transforms, thus confirming the superiority of the proposed solution.

5. Conclusion

In this study, we presented an automated framework for classifying neuromuscular disorders from EMG signals by transforming them into ST images and utilizing deep learning-based feature extraction. Five pretrained CNN architectures were investigated in combination with traditional classifiers to identify the most effective pipeline. Among the tested approaches, VGG16 features integrated with an SVM classifier consistently provided the best results, with accuracies of 98.5% for ALS vs MYO, 98.2% for ALS vs Healthy, 97.7% for MYO vs Healthy, 98.0% for Healthy vs Disease, and 97.0% for the multi-class task (ALS vs MYO vs Healthy). These findings clearly demonstrate the advantage of ST-based representations and CNN-based feature extraction compared to handcrafted methods, as well as the robustness of SVM for EMG classification.

The main contribution of this work lies in showing how combining image-based signal transformations with pretrained CNNs can enhance automated EMG analysis, offering a more objective and scalable approach for early neuromuscular disorder screening. Although the proposed framework demonstrates strong classification performance, the size of the EMGLAB dataset constitutes a limitation of this study. The dataset includes recordings from a limited number of subjects (8 ALS, 7 MYO, and 10 healthy individuals), which may affect the generalizability of the learned representations. While segmentation increases the number of training samples, it does not substitute for subject-level diversity. To strengthen generalization and clinical applicability, future research should extend this methodology to larger, multi-muscle datasets and additional neuromuscular conditions. Overall, the results provide new benchmarks for EMG-based diagnosis and demonstrate the promise of deep learning in advancing reliable and automated tools for neuromuscular disease detection.

Ethical Statement

This study does not contain any studies with human or animal subjects performed by any of the authors.

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

The data that support the findings of this study are openly available in dataset N2001 at http://www.emglab.net.

Author Contribution Statement

Nahla F. Abdel-Maboud: Conceptualization, Methodology, Software, Investigation, Resources, Data curation, Writing – original draft, Visualization. **Marco Alfonse:** Validation, Formal analysis, Investigation, Writing – review & editing, Visualization. **Silvia Stoyanova Parusheva:** Validation, Writing – review & editing, Visualization, Supervision. **Abdel-Badeeh M. Salem:** Validation, Writing – review & editing, Visualization, Supervision, Project administration.

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