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Review on the detection of Multiple Neuromuscular Disorder Using Electromyography

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Abstract
Neuromuscular Disorder contains several diseases which can affect the nervous system and they consist of all the motor and sensory nerves. Recently the computer vision system has performed a very essential function in the detection of Neuromuscular disorders. By studying EMG signal patterns, physicians provide their diagnostics; however, guide eye indicators study contains an excessive error percentage. EMG signal is the smallest electrical contemporary created by way of muscle fibers. It's hard to find a detailed review study so our research work is to provide a detailed review of detecting the Neuromuscular disorders by using Electromyography signals through segmentation, machine learning, and deep learning methods. Our research offers valuable insights and publicly available dataset information that will prove highly beneficial for future researchers.

Keywords: Neuromuscular Disorders (NMDs), Diabetic, Electromyography (EMG), Segmentation, Deep Learning, Machine Learning

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1. Introduction

Neuromuscular Disorders (NMD) contain several diseases which can affect the nervous system and they consist of all the motor and sensory nerves. It is used to interlink the brain and spinal cord with the whole body. When the growth of neurons responds unhealthy a result connection breaks between the nervous system and muscle mask. So, in the end, muscle groups get extremely weak and get wasted. Detection of the disease at the right time may decrease the number of deaths caused by NMDs. Nowadays including many developed experts training we have. But unfortunately, these traits didn't aid the expert in the diagnosis of NMDs. Thus, no device may want to grant a definitive diagnosis of this deadly disorder. However recently many scientific tools are developed to discover NMDs like Myopathy, Neuropathy and Amyotrophic Lateral Sclerosis (ALS).

Recently the signals processing system has performed a very essential function in the detection of neuromuscular disorders. Thus, no device could supply a certain analysis of this deadly disorder. However, currently, much clinical equipment is being developed to discover neuromuscular diseases like Myopathy, Neuropathy, and ALS. One of these devices is Electromyography. This tool endorses the analysis of NDMs successfully and can observe anomalies in muscular tissues by recording its signals. EMG signals are typically recorded using surface electrodes or needle electrodes inserted into the muscles. The recorded signals are then analyzed to evaluate muscle activation patterns, motor unit recruitment, and the integrity of nerve-muscle communication. It's important to note that while EMG is a valuable diagnostic tool, the interpretation of results requires expertise from a healthcare professional, such as a neurologist or physiatrist, who can accurately interpret the data and correlate it with clinical findings.

Electromyography (EMG) signals play a crucial role in the detection and diagnosis of various disorders related to the muscular and neuromuscular systems. EMG is a technique used to measure and record the electrical activity generated by muscle fibers during contraction and relaxation. By studying EMG signal patterns, physicians provide their diagnostics; however, guide eye indicators study contains an excessive error percentage. EMG signal is the smallest electrical contemporary created by way of muscle cells. For medical detection, these signals processing is the most necessary situation for researchers due to the fact quite several neuromuscular disorders can be decided by examining the frequency domain and time domain from the EMG signals and their properties.

This research study proposes a detailed review of detecting the Neuromuscular disorder by using EMG signals which include signal pre-processing techniques, feature extraction, segmentation, machine learning, and using deep learning methods. In the next section, we discuss Neuromuscular Disorders and electromyography. In a later section related to the Literature review the classifier by segmentation, machine learning, and deep learning methods. Our research provides valuable guidance and publicly available dataset information, which can be highly beneficial for future researchers in the field.

Background

The detection of Neuromuscular Disorders (NMDs) by using EMG Signals which measure the electrical potential generated by muscular cells. The detection of neuromuscular disorders through electromyography (EMG) signals is heavily dependent on the precise measurement of Motor Unit Action Potentials (MUAP).

Neuromuscular Disorder

Neuromuscular issues affect the nerves that manage voluntary muscular tissues and the nerves that talk sensory data back to the brain. Nerve cells (neurons) ship and obtain electric messages to and from the frame to assist manage voluntary muscle mass. When the neurons turn out to be bad or die, conversation among the apprehensive machine and muscle mass breaks down. As a result, muscle groups weaken and waste away. The EMG sign is an electrical sign that measures electric currents generated in muscle tissue at some stage in their contraction

representing neuromuscular activities. Neuromuscular disorders (NMD) can disrupt the normal transmission of electrical impulses from the brain to specific areas of the body via the peripheral nervous system, thereby affecting the coordination and control of muscle movements.

NMD has a lot of types of diseases like Amyotrophic Lateral Sclerosis (ALS), Myopathy Neuropathy, etc.

- Amyotrophic Lateral Sclerosis (ALS) is a major disease of neuromuscular disorders that directly affects the nerve cell which controls the movement of muscles.
- Myopathy is the disease of muscle fiber skin that affects voluntary muscle movement.
- Neuropathy disease affects the nerves that are the source of communication between the brain and spinal cord.

1.2.2 EMG Signals

The electromyogram (EMG) is used to measure electrical interest going on in a muscle. It plays a necessary role in the analysis of neuromuscular issues that consist of myopathy and neuropathy, but we prefer the clinical evaluation of electromyograms. Computer technology helps scientists to put their efforts into the evaluation of EMG in a new way to build up the evaluation of neuromuscular problems. Computer technology has saved a lot of time in the area, keeps proper standards of measurement, and allows the feature extraction of EMG indicators that need to not be calculated manually.

EMG is a vital method to keep a check on the circumstances of muscle tissues and the nervous system which is used to control them. EMG signal is known as kind of a complex one that depends on anatomical and physiological muscles. EMG signals kind of produce sounds while tissues go through them. In clinical EMG It was said that signal evaluation of motor unit action potential (MUAP) is a diagnostic device.

Our nervous system is continuously busy controlling muscle activity through contraction and relaxation. EMG is a complex signal that the nervous system is used to manage.

Here are some of the disorders where EMG signals are commonly used for detection:

Neuromuscular Disorders: EMG can help diagnose conditions such as muscular dystrophy, myasthenia gravis, amyotrophic lateral sclerosis (ALS), and peripheral neuropathy. By assessing the electrical activity in the muscles, EMG can identify abnormalities in nerve conduction and muscle response.

Nerve Entrapment Syndromes: EMG is valuable in diagnosing conditions like carpal tunnel syndrome, cubital tunnel syndrome, and sciatica. It can identify the location and severity of nerve compression or entrapment, aiding in treatment decisions. **Spinal Cord Injuries:** EMG can provide information about the extent and location of spinal cord injuries by assessing muscle activity below the level of injury. It helps determine the severity of damage and the potential for recovery. **Movement Disorders:** EMG is utilized in the evaluation of movement disorders like tremors, dystonia, and myoclonus. It helps differentiate between different types of abnormal movements and assess the underlying muscular activity. **Muscle Pathologies:** EMG can aid in diagnosing various muscle disorders, including myopathies and inflammatory conditions. It detects abnormal muscle electrical activity patterns, which can be indicative of specific muscle diseases.

EMG signals are typically recorded using surface electrodes or needle electrodes inserted into the muscles. The recorded signals are then analyzed to evaluate muscle activation patterns, motor unit recruitment, and the integrity of nerve-muscle communication.

Literature Review

A comprehensive literature review on the detection of neuromuscular disorders reveals three prominent categories of research: segmentation techniques and machine learning, as well as the emerging field of deep learning.

Segmentation

segmentation is crucial for localizing abnormalities, enabling quantitative analysis and biomarker identification, facilitating treatment planning and monitoring, as well as supporting automated analysis methods. By accurately segmenting relevant structures or regions, clinicians and researchers can improve the detection, diagnosis, and management of neuromuscular disorders, leading to better patient care and outcomes.

(Voet, et al., 2022) proposed the ergo spirometry cycle test, the ventilatory equivalent method, the V-slope method and the PET method, and Cardiopulmonary Exercise Test (CPET) (Italy). Forty-two healthy and thirty-two patients with neuromuscular disorder used the pre-processing technique like hypothesis, normalized sEMG thresholds, thresholds ventilatory and lower leg muscles of sEMG data also used. The 1st ventilatory was ($p=0.008$), the sEMG threshold was ($p<0.0001$), the 2nd ventilatory was ($p= 0.238$), and sEMG ($p=0.053$). The final result showed that sEMG thresholds were lesser than the ventilatory thresholds.

(Samanta, et al., 2022) used the dataset in which 10 healthy (H) subjects [21-37] years old and EMG recordings from 7 myopathies (M) patients [19-63] years old and 8 ALS patients [35-67] years old for HST matrix of EMG signals by extract the 14 features. The pre-processing techniques used for EMG signals were segmented into frames. From the total 491 EMG signals (106 M, 300 H, and 85 ALS). High-pass filter, first-order Butterworth, zero-phase distortion used for filtration. SVM, k-NN, NB, Hyperbolic Stock well transform, and DescriptionF1Standard deviation method was used. From the HST matrix, the EMG signals show the result that 14 features were extracted.

(S Geo, et. al 2022) in this research paper, various methods including Hidden Markov Models (HMM), Fuzzy Logic (FL), Linear Discriminant Analysis (LDA), Support Vector Machine (SVM), K-Nearest Neighbors, and Deep Learning (DL) were employed. The dataset utilized consisted of surface electromyography (sEMG) signals obtained through electrodes. Pre-processing techniques such as windowing, segmentation, denoising filtering, and rectification were applied. Features were extracted from the time-frequency, frequency, time, and spatial domains. The experimental results demonstrated that the K-Nearest Neighbors method achieved an impressive accuracy of 99.86%.

(Gao, et al., 2022) proposed the Hidden Markov Model (HMM), LDA, K-Nearest Neighbour (K-NN), Fuzzy Logic (FL), and SVM methods, and iEMG Electrodes, sEMG Electrodes dataset. DC, high-low pass filter, windowing, segmentation, filtering for denoising, and rectification were used as pre-processing techniques. Time-Frequency domain, Time domain, Frequency domain, and Spatial domain. Results show that the LDA method was 96.64% accurate. Meanwhile (Chanda P.P. et, al 2018) work on the detection of neuromuscular disorder by using a 1D Local Binary Pattern. A dataset was used in which 10 Healthy, 7 Myopathy, and 8 patients of ALS and 202134 data points per signal. The pre-processing techniques used in high-low filters and segmentation are used for signals. The method in which SVM and classifiers using 1D-LBP feature extraction uniform use. The result was improved in uniform 97.25% than the conventional 96.45%.

(R Bose, et.al 2020) work on Augmenting neuromuscular disease using a Weight Visibility Graph (WVG) to convert time series into undirected graphs. Dataset used in which normal=10(4F,6M) age 21 to 37 years, Myopathy=7(5M,2F) age 19 to 63 years, ALS=8(4M,4F) age 37 to 67 years. The segmentation of signals was pre-processed and clustering, efficiency, and Naïve Bayes were used for feature extraction. The high classification accuracy of SVM, KNN, and LAD show comparative performance.

(Harriet Mary James, et.al 2019) work on the review of classification and feature extraction of a neuromuscular disorder. Dataset used in which normal=10[4F,6M] age 21 to 37 years, Myopathy=7[5M,2F] age 19 to 63 years, ALS=8(4M,4F) age 35 to 67 years. The segmentation is based on the Root Means Square (RMS) and time-frequency, time domain, and MUAP (Motor Unit Action Potential) used for feature extraction. The methods of which Artificial Neural Networks(ANN), K-Nearest Neighbor(KNN), and Support Vector Machine(SVM), were used. For neuromuscular disorder, the K-Nearest Neighbor was the best classifier with 99% accuracy when feature extraction was performed on MUAPs of signals.

(Hanife Kucuk, et, al 2020) work on the classification of neuromuscular disorders with the Artificial Intelligence method. Division and clustering (Hybrid clustering) are used for pre-processing. The feature extraction by a vector in the time and frequency domain with Multiple Feature vectors (A total of 25 features) was used. The methods used were Discriminant Analysis (DA), K-Nearest Neighbor (KNN), and Support Vector Machine (SVM). As a result, Support Vector Machine had shown higher accuracy than K-NN and DA classifiers with 97.39% for ALS, and 86.74% for myogenic.

(Gongfa Li, et.al 2019) used a dataset in which Neuromuscular disorder has eight males and one female of age between 20 to 30 years and has high-pass, butter worth filters, and comb filters for signals in per-processing. The feature extraction in which Slope Sign Changes (SSC), Mean Absolute Value (MAV), Zero Crossing (ZC), Time-Domain (TD), Waveform Length (WL), and AMR. The results show the average classification errors of MAV, WL, AMR, SSC, and ZC 19%,26%,13%, 24%, and 22%.

(Gurmanik et al 2009) proposed the analysis of Electromyography (EMG) signals by the motor unit action potentials (MNAP) that were used for the better diagnosis of neuromuscular disorder. For extraction of EMG, signal segmentation is required to discover the MUAPs composed. 5 myopathic (MYO),12 EMG signals from three normal (NOR) subjects, and four motor neuron disease (MND) subjects as datasets were analyzed. Three methods for segmentation were used in this research work of EMG signals presented: 1). By using a way of coming across the binging extraction point (BEP), 2) Segmentation by the manner of identifying the peaks of the MUAPs and ending extraction factor (EEP) of MUAPs and 3) with the aid of the use of discrete wavelet remodel (DWT). The result of the method that used MUAPs was 95.90%, for the method that used EEPs and BEPs was once 75.39% and for the technique that used DWT was once 66.64%.

Table 1

Reference	Authors	Dataset	Preprocessing Techniques	Features Extraction	Methodology	Accuracy
1	Voet, N.B.,,2022	24 healthy and 32 patients	hypothesis, normalized thresholds	EMG data of lower leg muscles, ventilatory and sEMG thresholds	ergo spirometry cycle test (CPET)	sEMG threshold less than ventilatory thresholds.
2	Samanta,Bose, R. (2022).	21 healthy,EMG Signals 10 myopathy(M) patients 8 ALS patients	Segmentation	First order Butterworth, high-pass filter	SVM,kNN, NB, Hyperbolic Stockwell transform. DescriptionF1Standard deviation	14 new features were extracted and used for HST.
3	S Geo, J Gong, B Zhang,2022	EMG Signals using electrodes.	signal windowing of signal segmentation, signal filtering for denoising, and signal rectification	TD, FD, TFD, SD	LDA,KNN,HMM,SVM ,FL,DL	KNN has an accuracy of 99.86%.
4	S Gao, J Gong, B Zhang,2022	EMG signals iEMG Electrodes,sEMG Electrodes	low-high-pass filter, signal windowing of signal segmentation, signal filtering for denoising, and signal rectification.	TD, FD, TFD, SD	LDA, KNN ,HMM, FL, and SVM	LDA method accuracy was 96.64%
5	Roh, it Bose,2020	N=10,7M,8AL	Segmentation	Clustering Coefficient,Efficiency,Naïve Bayes Classifier	WVG	SVM, LDA, and KNN
6	Hassiet Mary,2019	10 normal,8 ALS, Myopathy 262134 samples on	Segmentation is based on Root Mean Square	Time-Frequency, Time domain	Artificial Neural Network(ANN),KNN,SVM	For the Neuromuscular Discorde K-NN classifier

		11.184 sec				
7	Hanife Kucunk,Ilyas Eminoglis,2019	Verification is done by cross-validation	Division, clustering (Hybrid Clustering)	Vectors in time and Frequency domains with Multiple feature vectors (A total of 25 features Vectors) were used.	SVM, K-Nearest Neighbour (KNN), and Discriminant Analysis	97.39%for ALS,86.74% for myogenic
8	Gongfa Li1 ,Jiahan Li, Z. Ju, Y.Sun, et.al,2019	ND=(8M,1F) aged (20-30)years	Worth filter, high-low pass filter, comb filter	(AMR),(MAV),(WL),(ZC),(SSC) and (ARV).		Active Muscle Region (AMR) obtain (Avg 13%)
9	Gurmanik et al 2009	5 myopathic (MYO),12 EMG signals from three normal (NOR) subjects, and four motor neuron disease (MND) subjects	Segmentation	EEPs and BEPs	DWT	MUAPs was 95.90%, for the method that used EEPs and BEPs was once 75.39%, and for the technique that used DWT was once 66.64%.

Machine Learning

Machine learning's ability to classify, predict, detect early signs, enable non-invasive diagnostics, facilitate personalized medicine, and provide decision support makes it a powerful tool in the detection of neuromuscular disorders. By leveraging machine learning algorithms, healthcare professionals can enhance their diagnostic capabilities, improve patient outcomes, and optimize treatment strategies.

(Bakiya, A, et. al,2022) used bat algorithm on EMG Signals using features extraction like Time Domine (TD) and Wigner-Ville Transform (WVT), time-frequency, and results showing deep neural network models (neurons = 2 and 4) and EMG signals have 100% accuracy. While (Usman Munawar, et. al,2022) used the methods MS-FHWN and AdaBoost and the dataset used 3 categories: 10 healthy subjects,6 Myopathy patients,8 ALS patients, and 329 total recordings (107 from Myopathy, 89 from ALS, and 133 from

Normal). Other methods used were AdaBoost and Random Forest. Features Extraction used in this research paper novel multi-scale fast hybrid wavelet network technically, Fast wavelet Transform, and wavelet network. The result shows that MS-FHWN plus AdaBoost has 100% accuracy.

(Margarida Antunes, et. al,2022) in which the data divide into two subjects: patients diagnosed with ALS and healthy controls (HCs). Out of forty-one patients, 3592 contractions were detected, with 46% occurring in pathological samples and 54% occurring in healthy samples. The pre-processing used a Butterworth filter (3rd order), and Teager–Kaiser Energy Operator (TKEO). Features Extraction used peak-related and MUAP morphology. The results show the subject classification approval (83.6 ± 6.9) and F1 score (81.9 ± 5.7) for the onset classification approval. On the other hand (Dubey, et al., 2022) have a dataset in which 900 EMG signals of three classifier signals were used. Sampling, down-sampling, and high- low-pass filter was proposed for pre-processing. A Feed Forward Neural Network (FFNN), An Intrinsic Mode Function (IMF), An Empirical Mode Decomposition (EMD), and Decision Tree (DT) were used as methods. Results show that feed Forward Neural Network (FFNN) has an accuracy of 99.60%.(Di Nardo, et al., 2022) proposed Support vector machines (SVM) model in which features were extracted LE, RMS, CWT scalogram and have dataset 2880 simulated EMG signals. Features Extraction in which LE and RMS are reliable for the sEMG Signals to the training of Neural networks. The Pre-processing techniques are (RMS), linear envelope (LE), and the wavelet scalogram. low-pass filtering, (2nd-order Butterworth filter). The result shows that DEMANN used the DT algorithm with a higher value ($p<0.05$).

(Ahmed, et al., 2021) proposed ANN, SVM, KNN, and Fine -tree models on the Dataset of EMG signals with Healthy subjects, aged (44y) and Neuropathic patients, aged (62y). Feature extraction used the root mean square value, maximum fractal length, WL, MMAV, EW, DASV, FFT maximum intensity, Variance of FFT, and Variance of neo. Pre-processing techniques used a High-pass filter and low-pass filter. Results show that SVM 70% & ANN 85% have accuracy.

(Ponomarchuk, et al., 2021) used Dataset single-channel EMG data and Features Multilayer perceptron was extracted. Random Forest (RF), Logistic Regression (LR), Support Vector Machine (SVM), and K-nearest neighbor (K-NN) methods were used. Results show that the ADAM Algorithm model Random Forest has 98% accuracy. While (Chandrasekhar, et al., 2020) worked on a real-time portal at a low cost for the neuromuscular disorder with a real-time dataset with EMG Signals. Six different electrodes for various finger and wrist t actions were used and filtration for signal improvement. The method (SVM) Support Vector Machine was used. The result shows 85% accuracy using the Support Vector Machine.

(Bose, et al., 2020) work on Augmenting neuromuscular disease using a Weight Visibility Graph (WVG) to convert time series into undirected graphs. Dataset used in which normal=10(4F,6M) age 21 to 37 years, Myopathy=7(5M,2F) age 19 to 63 years, ALS=8(4M,4F) age 37 to 67 years. The segmentation of signals was pre-processed and clustering, efficiency, and Naïve Bayes were used for feature extraction. The high classification accuracy of SVM, KNN, and LAD show comparative performance.

(Chandra, et al., 2020) work on Cross-Spectrum Aided used a dataset in which EMG Signals recorded a collection of 10 Healthy, 7 Myopathy, and 8 ALS. The methods were Continuous Waveform Transform, K-Nearest Neighbor, Random Forest (RF), Support Vector Machine (SVM), and Naive Baye (NB). The RestNet50 is used for Feature Extraction. The results show K-Nearest Neighbor (K-NN) has the highest accuracy with 97.25%.

(Aicha, et.al 2020) used dataset normal=10(4F,6M) age 21 to 37 years and ALS=8(4M,4F) age 37 to 67 years for diagnosis of amyotrophic Lateral Sclerosis (ALS). The per-processing technique band-pass filter is used. The time domain and frequency domain are used for feature extraction but the method of Continuous Wavelet Transform (CWT) is applied. The classifier models are used in K-Nearest Neighbor, Support Vector Machine, and LDA. The results show SVM models have the highest accuracy with 95.8%.

(James, et al., 2019) work on the review of classification and feature extraction of a neuromuscular disorder. Dataset used in which normal=10[4F,6M] age 21 to 37 years, Myopathy=7[5M,2F] age 19 to 63 years, ALS=8(4M,4F) age 35 to 67 years. The segmentation is based on the Root Means Square (RMS) and time-frequency, time domain, and MUAP (Motor Unit Action Potential) used for feature extraction. The methods which were K-Nearest Neighbor(K-NN), Support Vector Machine (SVM), and Artificial Neural Networks (ANN), were used. For neuromuscular disorder, the K-Nearest Neighbor classifier was the best classifier with 99% accuracy when feature extraction was performed on MUAPs of signals.

(Khan, et al., 2019) used dataset normal=10(4F,6M) age 21 to 37 years and ALS=8(4M,4F) age 35 to 67 years for the EMG Signals classification. Pre-processing techniques in Empirical mode decomposition, filter, time-scale, bandwidth, and sifting. The Frequency Domain and Time Domain are used in feature extraction. The method LR and SVM. The excellent results show an accuracy of 95% but the actual SVM has 94.10% and LR has 95.10%.

(Ahlem, et.al, 2019) used methods DWT, RF, and K-NN. The dataset used in which Myopathy (50 records), Normal (150 records), and Neuropathy ALS (50 records) and the classification of a dataset in which normal=10(4F,6M) age 21 to 37 years, Myopathy=7(5M,2F) age 19 to 63 years, ALS=8(4M,4F) age 37 to 67 years. The pre-processing techniques in which analog bandpass filters are used. The feature in which the time-frequency domain, frequency domain, and Feature Vector was extracted.

(Verna, et.al 2022) used the method of Tunable-Q dynamics (TQWT). The dataset in which normal=10(4F,6M) age [21-37] years, Myopathy=7(5M,2F) age [19-63] years, ALS=8(4M,4F) age [37-67] years. The pre-processing technique used a high-low pass filter for signals. The features extraction Spectral flatness (SF), Spectral Spread (SS), and spectral decreases entropy ND IQR. The highest accuracy of this result was 99.56%.

(Subasi et.al 2019) used methods RFt and DT-CWT. The pre-processing technique was a low-high pass filter used for signals. The dataset used in which normal=10, Myopathy=7, and ALS=8. The feature in which time-frequency, mean absolute value and skewness, and Kurtosis. The findings indicate that Rotation Forest achieves a remarkable accuracy of 99.7% when applied to Medical EMG Signals. Furthermore, SVM demonstrates an accuracy of 96.6% in classifying EMG Signals when utilizing ANN.

Table 2

Reference	Authors	Dataset	Preprocessing Techniques	Features Extraction	Methodology	Accuracy
10	Bakiya,A., Anitha,A., Sridevi, T.,2022	EMG signals		Wigner-Ville (WV) , time domain, time-frequency	Bat Algorithm	DNN-used EMG signals have 100% accuracy
11	R Dubey, M Kumar, A Upadhyay,2022	900 EMG signals of three classes	Sampling, down-sampling, High-pass filter, low-pass filter	(IMFs), (FFNN), (SVM), and, FFNN	empirical mode decomposition (EMD)	FFNN accuracy is 99.60%.
12	F Di Nardo, A Nocera, A Cusschiarelli,2022	2880 simulated EMG signals)	(LE), (RMS), and the wavelet scalogram, low-pass filtering, (2nd-order Butterworth filter)	CWT, LE, RMS, and RMS are reliable for the sEMG Signals for training Neural networks.	Support vector machines (SVM)	algorithm. Significantly higher values ($p < 0.05$).
13	T Ahmed, MK Islam,2021	EMG signals 44 years = Healthy subjects 62 years = Neuropathic patients	High-pass filter and low-pass filter	RMS, MF, WT, MMAV, EW	ANN, SVM, KNN AND Fine -tree	SVM 70% & ANN 85% have accuracy.

14	Y V Ponomarchuk1 , I V Kuznetsov, 2021	single-channel EMG data		SVM, Multi-Layer perceptron, random forest, (Log. reg), K-NN	ADAM Algorithm	Random forest with 98% accuracy.
15	G FRASCA,2021	EMG Signals 30 hemiplegic children	band-pass 4th order Butterworth filter, linear envelope, K-fold validation, data windowing	Multi-layer Perceptron	Neural network algorithm (Binary cascade classifier, Multiclass classifier)	Winters type I and Winters type II had accuracy 90.5%
16	Vinay Chandrasekhar, Madhav Rao,2020	real-time data with EMS signals, six different electrodes	Filtration	WT	RMS, Waveform, SVM	85%
17	Kaniska Samanta, Roh,it Bose,2020	N=10,7M,8 AL	Segmentation	Clustering Coefficient, Efficiency, Naïve Bayes Classifier	WVG	SVM, LDA, and KNN
18	S. Singha Roy, K.Samanta, S. Modak, S.Chatterjee ,2020	EMG Signals 10H,7 Myopathy, and 8 ALS patient	Filtration	(ANO VA),(FDR) ResNet50	Random Forest, SVM, KNN, NB,	RF=96.40%, SVM=97.08%, KNN=97.25%, NB=95%
19	Aicha MOKDAD a , Amine DEBBALa, 2020	10 Healthy ALS 8 patients	Band-pass Filter	Time and Frequency domain	(CWT) SVM, (LDA), KNN	SVM 95.8% LDA and KNN 91% and 92%

20	Hassiet Mary James.Iqbal ,2019	10 normal,8 ALS, Myopathy 262134 samples on 11.184 sec	Segmentation is based on Root Mean Square	Time-Frequency, Time domain	Artificial Neural Network (ANN), KNN, SVM	For the Neuromuscular Discorde K-NN classifier
21	M.Umar Khan,Suma ir Aziz,2019	10H, ALS has 8 patients	Empirical mode Decomposition	Time and Frequency domain	(LR), SVM	Accuracy of 95.1%, SVM 94.10%, LR 95.10%
22	Ahlem Benazzouz, Rima Guilal,2019	Normal=(150) records, Myopathy=(50) records ,Neuropathy ALS =(50) records	Analog Bandpass Filter	Time-Frequency domain, frequency domain, Feature Vector, Feature selection, Cross Validation.	Discrete Wavelet Transform (DWT), Random Forest (RF), K-NN	RF=88.8%
23	Agya.Ram Verma ,2019	8ASL,7 Myopathy,10 Healthy	High-low pass filters	Spectral uniformity or flatness (SF), Spectral Spread (SS), Spectral decrease Rurtosis, entropy, and IQR	Wavelet transform using Tunable Q dynamics (TQWT)	99.56% ALS-NOR=99.99%, MYO-NOR=98.93%, ALS-MYO-NOR=98.93%
24	Abdulhamit Subasi,2019	1o normal,7 Myopathy, ALS 8 patients	low pass/high pass filter	Time frequency, Mean absolute value, Skewness, Kurtosis	Dual-Tree, Complex WT K-NN, SVM, ANN, LAD	Rotation Forest accuracy 99.7%%

Deep Learning

Deep learning's ability to recognize complex patterns, integrate multimodal data, extract relevant features, scale to large datasets, generalize to unseen cases, and adapt to evolving knowledge makes it a powerful tool for the detection of neuromuscular disorders.

(S Samiei, et. al,2021) proposed GraphTS's new method which used Dataset EMG Signals, and 29 patients were divided into healthy, myopathy, and neuropathy. Pre-processing signal windowing and finding its linear envelope are applied. Features extraction average degree, the average clustering coefficient, transitivity, density, network diameter, global efficiency, the average shortest path, and matrix. Results show that DNN results show 99.30% accuracy.

(Christian MorbidOni et. al,2021) used the dataset EMG signals and 20 patients. Pre-processing techniques were used in which signals segmented & lapping windows of 600 samples. band-pass filtered. Features Extraction used multi-layer perceptron, toe-off (TO) timing, and Models heel-strike (HS), from sEMG signals. Results RNN shows error in which F1-score (0.92±0.07 for TO and 0.95±0.03 for HS) and AMAE (17.6±4.2ms for TO and MAE,14.8±3.2ms for HS).

(G FRASCA et. al,2021) used the dataset EMG Signals in which 30 hemiplegic children (13 Winters' type I and 17 Winters 'type II children) and 30 able-bodied children. Pre-processing techniques applied on signals in which band-pass 4th order Butterworth filter, linear envelope, K-fold validation, data windowing.

Feature Extraction Multi-Layer Perceptron used and model Neural network algorithm (Binary cascade classifier, Multiclass classifier). Results show that Winters type I and Winters type II had an accuracy of 90.5% for learned subjects and 79.2% for unlearned ones

(Y MA, et al. 2021) used a database containing 69 sets of sEMG signals with 5520 samples. Pre-processing techniques epochs and noise removal applied on signals. Feature extraction soft Thresholding applied. Logistic regression model, RF model and CNN, DRSN. Results show that the accuracy of DRSN is 81%.

(Chanda P.P, et. al,2018) work on the detection of neuromuscular disorder by using a 1D Local Binary Pattern. A dataset was used in which 10 Healthy, 7 Myopathy, and 8 patients of ALS and 202134 data points per signal. The pre-processing techniques used in high-low filters and segmentation are used for signals. The method in which SVM and classifiers using 1D-LBP feature extraction uniform use. The result was improved in uniform 97.25% than the conventional 96.45%.

(Kaniska Samanta, et.al 2020) work on EMG signals converted into spectrum images. A dataset in which ten healthy and seven myopathy patients and eight ALS patients. The signals pre-process by sampling and frequency with high and low filtration in which 7500 EMG Signals (2500 for each frame), (2499 for Healthy, 2500 for Myopathy, and 2500 for ALS).

The time-frequency and image scales used for feature extraction and method Cross-Wavelet Transform and RestNet50, SVM, KNN. The results show that multi-classes like XWT+RestNet50+SVM have 99.87% accuracy for healthy vs myopathy and XWT+RestNet50+KNN have 100% accuracy for healthy vs ALS.

(Marcela Valleyo, et.al 2021) proposed the Discrete Wavelet Transform (author={Voet, 2022) (DWT) and fuzzy entropy methods for neuromuscular disorder detection. For this purpose, they collected the dataset from 25 volunteers,10 were healthy (age 21-37) years, Myopathy was seven (age 19-63) years, and ALS patients were eight (age 35-67) years. The deep learning methods ANN used for implementation and the accuracy of ANN was 98.33%.

(A.Bakiya et, al2018) proposed the Deep Neural Network (DNN) approach as a remarkable technique for the detection of neuromuscular problems which classifies Deep learning.

In the pre-processing stage, EMG signals were extracted using four techniques: Short-Time Fourier transform, Synchro-Extracting transform, Stockwell transform, and Wigner-Ville transform.

The dataset consisted of 150 EMG signals recorded from three categories: myopathy (M), Amyotrophic Lateral Sclerosis (ALS), and normal (N). For feature selection Particle Swarm Optimization was utilized with a fractional approach.

The findings revealed that the performance evaluation of the Shallow Neural Network classifier was inferior to that of the Deep Neural Network (DNN) classifier. Consequently, the DNN exhibited higher accuracy in the results.

(Bakiya, et, al 2022) used Electromyograms (EMG) for diagnosing problems related to muscle tissues and nerves.

For sign processing, time domain techniques were used to offer the data of signals with the aid of time. A total of 60 signals were chosen for analysis.

The techniques for feature extraction from these signals were categorized as time domain, frequency domain, and a combination of time and frequency domain methods. When using a deep neural network, the utilization of a bat algorithm outperformed a traditional artificial neural network in terms of speed. The outcome indicates that a CNN utilizing time domain features achieved an accuracy of 83.3%.

(Ilhan Yoo et,al 2023) A novel approach combining a one-dimensional Convolutional Neural Network (CNN) algorithm and a divide-and-vote tool was developed for the diagnosis of subjects. To evaluate its effectiveness, a group of twenty individuals with myopathy underwent an analysis of their EMG signals.

The diagnostic outcomes from the deep learning model were compared to assessments made by six experienced physicians who had expertise in performing and interpreting electromyography.

Remarkably, the deep learning model demonstrated superior accuracy and predictive capability in comparison to the physicians.

The deep learning model achieved an accuracy of 0.875 and a quality predictive rate of 0.820 for diagnosing subjects with myopathy, neuropathy, or normal conditions.

In contrast, the corresponding values for the physicians were 0.694 and 0.524, respectively.

Furthermore, the deep learning model's area under the receiver operating characteristic curves (AUC-ROC) for predicting myopathy, neuropathy, and normal states exceeded the average results of the six physicians.

Table 3

Reference	Authors	Dataset	Preprocessing Techniques	Features Extraction	Methodology	Accuracy
25	S Samiei, N Ghadiri,2021	EMG Signals,29 patients	signal to the window and finding its linear envelope	average degree, average clustering, transitivity, density, network diameter, global efficiency, the average shortest-path, matrix	Graphs new method	Deep neural network results show 99.30% accuracy
26	Christian Morbidoni , Cucchiarelli,2021	EMG Signals. 20 hemiplegic effective children	segmented & lapping windows of 600 samples, a Band-pass filter, an FIR filter	multi-layer perceptron model	HS, TO	MAE, 14.8±3.2 ms in HS F1-score in HS 0.95±0.03
27	G FRASCA,2021	EMG Signals 30 hemiplegic children	band-pass 4th order Butterworth filter, linear envelope-fold validation, data windowing	Multi-layer Perceptron	Neural network algorithm (Binary cascade classifier, Multiclass classifier)	Winters type I and Winters typeII had an accuracy of 90.5%
28	Y MA, C Wang, Zli,2021	69 sets of sEMG signals have 5520 samples	epochs and noise remove	soft Thresholding	(CNN), DRS, RGM, FM	accuracy of 81% in DRSN
29	K. Samanta, S. Singha Roy, Sudip,2020	Healthy=10, Myopathy=7 ALS=7	sampling frequency, high-low filter	time-frequency frame, time scale	cross-wavelet, transform, RestNet50, SVM, KNN	RestNet50 gives 49 Convolutional layers
30	Marcela Valleyo, et.al 2021	10 healthy years, Myopathy=7	-	Discrete Wavelet Transform, fuzzy entropy	ANN	ANN 98.33%

		, and ALS=8				
31	A.Bakiya et, al2018	with 150 EMG Signals myopathy (M), Amyotrophic Lateral Sclerosis (ALS), and normal (N)	Short-Time Fourier transform, Synchro-Extracting transform, Stock well transforms, and Wigner-Ville transform	Particle Swarm Optimization		DNN higher accuracy
32	Bakiya, et, al 2022	60 signals	Time Domain	A combination of time and frequency domain, time domain, frequency domain	bat algorithm	CNN= 83%
33	Ilhan Yoo et, al 2023	20 patients with myopathy and EMG signals were analyzed			Convolutional Neural Network and divide-and-vote	(AUC-ROC) shows higher accuracy than six physician expert results.

Available Dataset: research.

Ref	**Available**	**Link**
4	**Yes**	https://www.mdpi.com/article/10.3390/s22093507/s1
7	**yes**	https://www.mdpi.com/article/10.3390/s22093507/s1
	Yes	https://github.com/TenanATC/EMG

12	**Yes**	https://www.sciencedirect.com/science/article/pii/S0169260722004606
14	**Yes**	**https://github.com/TenanATC/EMG**,
18	**Yes**	Seoul National University Hospital and underwent EMG between June 2015 and July 2020
20	**Yes**	Laboratory of Gait Analysis, Ospedale Santa Croce, Moncalieri (TO), Italy
22	**Yes**	Laboratory of Gait Analysis, Ospedale Santa Croce, Moncalieri (TO), Italy
23	**yes**	Institutional Review Board (IRB) at the North Carolina State University (IRB approval number: 20602). (R2017a, MathWorks, MA, USA (Speedgoat Inc., Liebefeld Switzerland
24	**Yes**	GitHub - aljazfrancic/myo-readings-dataset: Myo armband electromyographic readings dataset for various wrist gestures.
26,28, 29,30	**Yes**	M. Nikolic, Detailed analysis of clinical electromyography signals: EMG decomposition, findings and firing pattern analysis in controls and patients with myopathy and amyotrophic lateral sclerosis, 2001.
32	**Yes**	Department of the University of Gaziantep. public satisfying Institutional Review Board (IRB) practices of EMGlab and local IRB
33	**Yes**	EMGLAB (http://www.EMGlab.net.)

Discussion

In this work, we evaluate Neuromuscular Disorder (NMD) detection by using Electromyography (EMG) signals. Hybrid models based on machine learning and deep learning are needed to leverage the strengths of both approaches and improve the accuracy and interpretability of complex tasks in neuromuscular disorder detection. The presence of biased data can significantly impact the fairness and reliability of machine-learning models used in neuromuscular disorder detection. Machine learning models utilizing electromyography (EMG) data can effectively identify and differentiate multiple neuromuscular disorders, providing valuable diagnostic capabilities in a non-invasive manner. The development of an automated detection system based on machine learning and deep learning techniques offers the potential to improve the efficiency and accuracy of neuromuscular disorder identification, facilitating early intervention and personalized treatment strategies.

Conclusions

Neuromuscular disorder (NMD) is a very massive time encompassing a variety of conditions that impair the functioning of the muscles, each directly, being a pathology of the voluntary muscle, or indirectly, being a pathology of the peripheral nervous system or neuromuscular junctions. From the study of the literature review, we conclude that it's hard to detect Neuromuscular disorder automatically in diabetic patients through EMG signals so we will use deep learning methods to detect this disease in diabetes patients. In conclusion, our research provides a detailed review addressing the scarcity of comprehensive studies on the detection of neuromuscular disorders using Electromyography (EMG) signals. Through our analysis, we explored the application of segmentation techniques, machine learning, and deep learning methods in this field. Our work contributes to the existing knowledge by shedding light on the effective utilization of EMG signals for the accurate detection and diagnosis of neuromuscular disorders. The findings from our research offer valuable insights and pave the way for future advancements in this area of study. Our research provides significant insights and openly accessible dataset information that will greatly benefit future researchers. The valuable findings from our study offer a valuable resource for those in the research community.

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