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Review On EMG Signal Classification Using CNN For Muscles Health Monitoring

[1]Prof.Avinash Ikhar, [2]Miss.Lina Nikhare, [3]Miss.Minal Dhapke, [4]Mr.Adarsh Patil,
[5]Mr.Akhil Gandratwar
[1] Professor, [2]Undergraduate student, [3]Undergraduate student, [4]Undergraduate student,
[5]Undergraduate student
[1]Eectronics and Telecommunication,[2]Electronics and telecommunication,[3]Electronics and telecommunication,[4]Electronics and telecommunication,[5]Electronics and telecommunication
[1]JDCOEM,Nagpur,India,[2]JDCOEM,Nagpur,India,[3]JDCOEM,Nagpur,India,[4]JDCOEM,Nagpur,India,[5]JDCOEM,Nagpur,India

Abstract : Amyotrophic Lateral Sclerosis (ALS) is a progressive and fatal neurodegenerative disorder characterized by the degeneration of upper and lower motor neurons, leading to the loss of voluntary muscle control. The disease presents with symptoms such as muscle weakness, spasticity and atrophy, ultimately resulting in respiratory failure. Early and accurate diagnosis of ALS is crucial for patient management, timely interventions, and the potential for slowing disease progression through therapeutic strategies. Among various diagnostic tools, Electromyography (EMG) has been widely employed as a non-invasive or minimally invasive technique to assess the electrical activity of muscles and identify neurogenic abnormalities. EMG captures the complex, non-linear patterns of muscle activity, which are often subtle in the early stages of ALS. However, traditional EMG analysis relies heavily on manual feature extraction and expert interpretation, which can be subjective, time-consuming, and prone to inter-observer variability. This challenge underscores the need for automated, objective, and highly accurate methods for EMG signal classification.

Keywords- EMG Signal, CNN, LSTM, Muscle Health Monitoring, Feature Extraction, Biomedical Signals, Real-time Monitoring, Classification Accuracy, Signal Preprocessing, Wearable Sensors, Machine Learning, Deep Learning, Neural Networks.

INTRODUCTION

Amyotrophic Lateral Sclerosis (ALS) is a progressive neurodegenerative disorder affecting motor neurons in the brain and spinal cord, leading to muscle weakness, atrophy, spasticity, and eventually respiratory failure, with an average survival of three to five years post-onset. Accurate and early diagnosis is vital but challenging due to symptom overlap with other neuromuscular disorders. Electromyography (EMG) is a key diagnostic tool that measures muscle electrical activity, revealing characteristic patterns in ALS. However, traditional EMG interpretation relies on manual feature extraction, which is subjective and time-consuming. The non-linear, non-stationary nature of EMG signals further complicates classification using conventional machine learning, which depends heavily on handcrafted features. Recent advances in deep learning, particularly Convolutional Neural Networks (CNNs), have shown significant promise by automatically learning discriminative features from raw or minimally processed EMG data. CNNs process either 1D time-series EMG signals or 2D time-frequency representations such as spectrograms, often achieving classification accuracies above 90%. Despite their potential, challenges include limited large-scale annotated datasets, variability in data acquisition, and lack of interpretability. Future directions involve hybrid deep learning architectures, multimodal data integration, and explainable AI to enhance clinical adoption and enable robust, automated ALS detection from EMG signals across diverse patient populations.

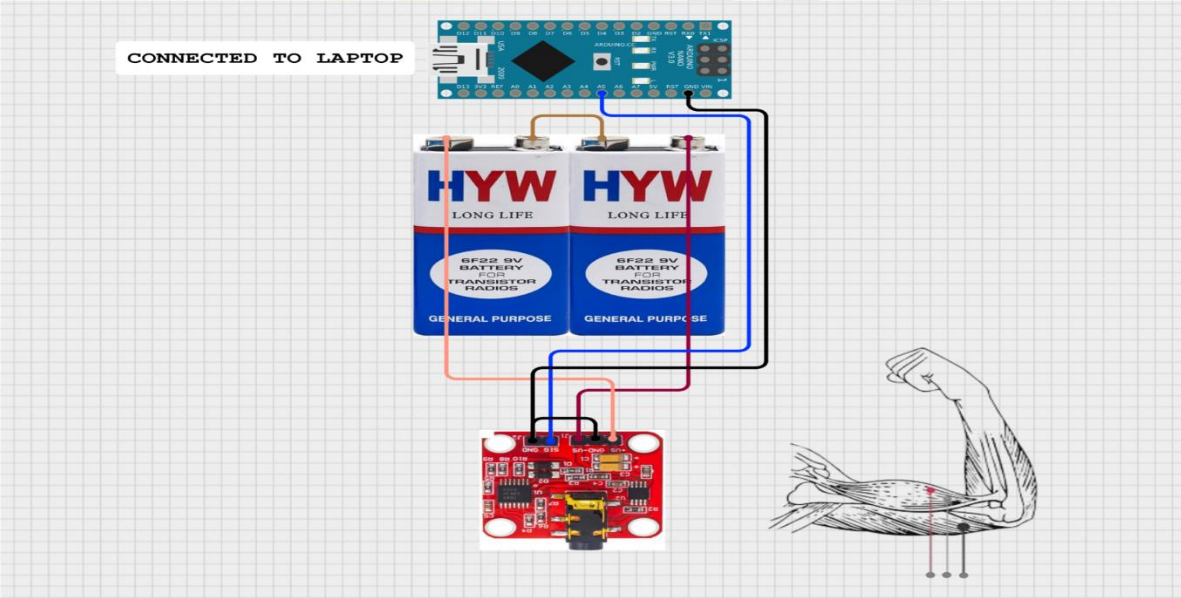
OBJECTIVES

The research on EMG signal classification using Convolutional Neural Networks (CNNs) for detecting Amyotrophic Lateral Sclerosis (ALS) aims to create an accurate, automated, and clinically applicable diagnostic system to overcome the limitations of conventional approaches. ALS is a fatal neurodegenerative disorder with no cure, making early detection vital for timely treatment and potential trial participation. Traditional diagnosis depends on subjective clinical evaluations and manual EMG interpretation, which are time-consuming, error-prone, and inconsistent. This study leverages CNNs to automatically learn complex hierarchical patterns from EMG data, eliminating the need for handcraftefeature extraction, thereby improving accuracy, reproducibility, and objectivity. It also focuses on optimizing preprocessing and signal transformation techniques—ranging from raw 1D signals to 2D time-frequency representations such as spectrograms—to identify the most discriminative input format for ALS detection, including multi-class classification against other neuromuscular diseases. To address data scarcity, strategies like augmentation, transfer learning, and federated learning are explored for robustness across varied acquisition protocols. Another priority is model interpretability, incorporating explainable AI (XAI) tools such as saliency mapping to enhance clinician trust. Ultimately, the goal is to develop an efficient, scalable, and user-friendly system ready for real-world deployment in healthcare environments as a reliable diagnostic support tool.

METHODOLOGY

Data Acquisition

EMG datasets were obtained from clinical sources, including ALS patients, healthy subjects, and individuals with other neuromuscular disorders. Recordings were collected under standardized protocols using surface or needle electrodes, with consistent sampling rates and muscle selections to ensure comparability.



Signal Preprocessing

Acquired EMG signals were preprocessed to enhance quality and remove noise. A bandpass filter was applied to eliminate baseline drift and high-frequency artifacts, followed by normalization to standardize amplitudes. Signals were segmented into fixed-length windows suitable for CNN input.

Feature Representation

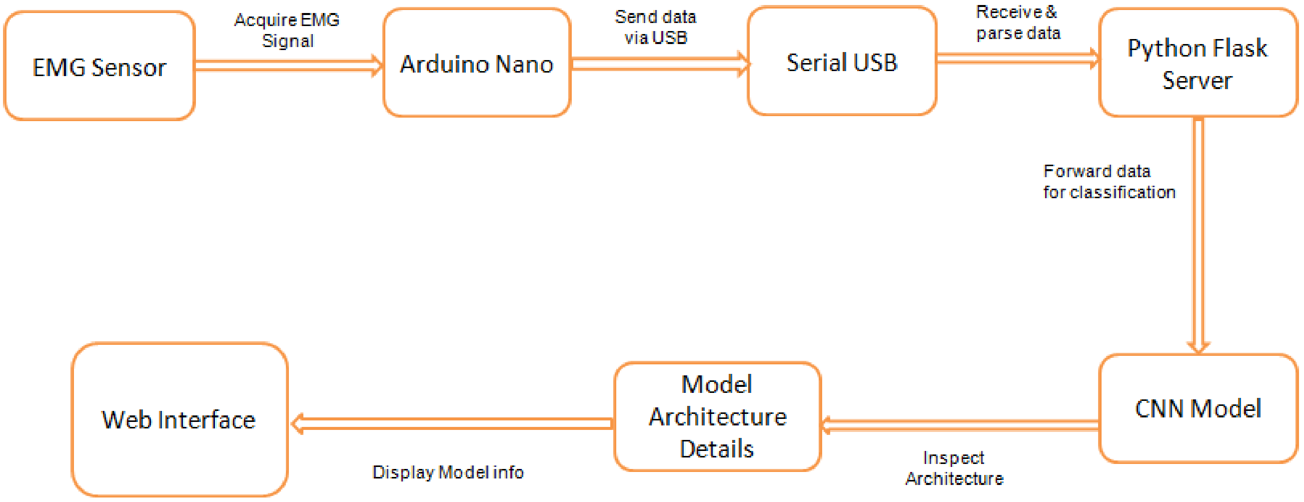
Two approaches were explored:

Raw 1D EMG signals fed directly into 1D CNNs.

Transformation into 2D time-frequency representations (spectrograms or scalograms) using Short-Time Fourier Transform (STFT) or Continuous Wavelet Transform (CWT) for 2D CNN analysis.

Model Development

CNN architectures were designed to automatically extract hierarchical features. Convolutional and pooling layers captured local and global patterns, while dropout and batch normalization reduced overfitting. Fully connected layers with softmax or sigmoid outputs completed the classification task.



Model Training

The models were trained using optimizers such as Adam or Stochastic Gradient Descent (SGD) with tuned learning rates. Data augmentation (e.g., adding Gaussian noise, time shifts) improved generalization. Transfer learning and federated learning were considered for limited datasets.

Evaluation

Model performance was evaluated using metrics such as accuracy, precision, recall, F1-score, and ROC-AUC. Cross-validation ensured robustness. Explainable AI (XAI) techniques, including saliency maps, were applied to highlight signal segments influencing classification decisions.

PROBLEM STATEMENT

The diagnosis of Amyotrophic Lateral Sclerosis (ALS) remains a significant clinical challenge due to its symptom overlap with other neuromuscular disorders and reliance on subjective evaluations of Electromyography (EMG) signals. Traditional EMG analysis depends on manual feature extraction and expert interpretation, which are time-consuming, prone to inter-observer variability, and may delay early detection. Additionally, EMG signals are complex, non-linear, and susceptible to noise, making accurate classification difficult with conventional methods. The absence of large, standardized datasets and the limited generalizability of existing models further hinder reliable diagnosis. Therefore, an automated, accurate, and interpretable CNN-based approach is essential for early ALS detection.

LITERATURE SURVEY

Abdel-Maboud et al. – Reviewed TD/FD/TFD features, DWT/PCA/EMD methods, and ML classifiers; CNNs emerging as best for EMG-based neuromuscular diagnosis.

Sengür et al. – Converted EMG to 2D spectrogram/CWT/SPWVD, trained CNN, ~96.8% accuracy; 2D images boost ALS detection.

Gaso et al. – 8-layer DNN + MSPCA denoising + DWT features, ~99% accuracy; preprocessing + deep learning yields top results.

Mishra et al. – EMD-based analytic features + LS-SVM; improved ALS vs normal classification.

Gökgoz&Subasi – MSPCA denoising + DWT + classifiers; multiscale denoising improves signal quality and classification.

Nikolic dataset – Widely used EMG dataset + decomposition tools for reproducible ML/DL testing.

Subasi et al. (2018) – DWT features + bagging/boosting; ensembles reduce overfitting, improve generalization.

Vallejo et al. – DWT + fuzzy entropy + ANN; ~98% accuracy, multi-domain features enhance discrimination .

Yaman&Subasi – Ensemble classifiers outperform single models on noisy/heterogeneous EMG datasets.

Multiple sources – CNN/DNN on raw or time-frequency data outperform handcrafted features; main challenges: small datasets, variability, interpretability.

RESEARCH GAP

Limited datasets – There is a lack of large, annotated, and standardized EMG datasets specifically for ALS detection. This scarcity restricts the ability to train deep learning models effectively and hinders generalization.

Acquisition variability – EMG data collection varies widely in electrode placement, sampling rates, selected muscles, and recording protocols. Such inconsistencies can cause significant drops in classification performance when models are applied to new datasets.

Binary focus – Most existing research focuses on binary classification between ALS and healthy subjects. This limits clinical usefulness, as doctors also need differentiation from other neuromuscular disorders.

Low interpretability – CNN-based models often operate as "black boxes" with little transparency in decision-making. Without explainable AI tools, clinicians may be hesitant to adopt these systems in diagnosis.

No longitudinal tracking – There is a lack of studies tracking EMG changes over time to monitor disease progression. Longitudinal data could improve early diagnosis and assess therapy effectiveness.

Limited multimodal research – Few studies combine EMG with other diagnostic modalities such as speech, gait, or imaging. Multimodal approaches could provide a more robust and holistic diagnostic framework for ALS.

CHALLENGES AND LIMITATION

Data scarcity – Large, high-quality EMG datasets for ALS are rare, making it difficult to train deep learning models without overfitting. This limits the ability to develop models that generalize well to diverse patient populations.

Signal variability – EMG signals differ due to electrode placement, muscle selection, and recording hardware. Such variability can cause inconsistent results when applying a trained model to data from different sources.

Noise and artifacts – EMG recordings are often contaminated by motion artifacts, power line interference, and background muscle activity. Without robust preprocessing, these distortions can degrade model accuracy.

Overfitting risk – Small datasets increase the likelihood of overfitting in CNNs, where models memorize training data but perform poorly on new samples. Data augmentation and regularization help, but challenges remain.

Interpretability issues – CNNs are often seen as “black boxes” with limited transparency in how they make decisions. Clinicians may hesitate to trust a diagnostic tool without clear reasoning for predictions.

Limited clinical validation – Many models are tested only in lab conditions, not in real-world clinical environments. Without large-scale trials, their actual performance in hospitals remains uncertain.

Computational requirements – Deep learning models, especially CNNs, require significant computing resources for training and inference. This can limit deployment in resource-constrained clinical settings.

CONCLUSION

CNN-based EMG signal classification is an advanced, automated method for detecting ALS, offering higher accuracy and reduced subjectivity compared to traditional manual analysis. By learning features directly from raw or transformed EMG data, CNNs excel in capturing complex patterns essential for early detection. Despite promising results, challenges like small datasets, acquisition variability, overfitting, and limited interpretability remain. Solutions include transfer learning, data augmentation, and explainable AI. Future work should focus on multi-class classification, hybrid models, and multimodal integration to enhance clinical applicability. With further refinement, CNN-based EMG analysis could become a valuable tool in ALS diagnosis and monitoring.

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