# Remote Monitoring and Detection of Amyotrophic Lateral Sclerosis Disease through a Wireless EMG Measurement System


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***Abstract*— Amyotrophic Lateral Sclerosis (ALS) is one of the most common neuro-muscular diseases, and it affects both lower and upper motor neurons in human beings. ALS requires periodic monitoring of the patient, and an early diagnosis can be helpful in preventing the disorder to progress further, thereby improving the quality of life for patients. In this work, we have demonstrated a proof-of-concept, point-of-care diagnostics system to measure surface-EMG signal of a patient, thereby automatically detecting whether the patient is subjected to ALS condition or not, by appropriately analyzing the EMG signal. The proposed system consists of required electronics hardware in terms of sensors, front-end signal-processing circuits, and wireless modules to transmit the measured EMG signals onto a remote server through Internet. The proposed system also consists of necessary software modules, in terms of machine-learning models and signal-processing algorithms, to detect and classify whether the measured EMG signal from a patient corresponds to this given pathological condition (ALS) or not. In this research work, a framework containing a modified VGG-5 Network, called SpinalNet-VGG, performing classification on Spectrogram of EMG signals, is proposed for identifying ALS-condition. The variations in spectrogram of the EMG-signals forms the basis of the proposed framework. Our proposed methodology for ALS disease detection involves two major segments, namely: i. Generation of 2D spectrograms from Raw EMG Signals. ii. Classification of spectrograms using SpinalNet. The performance was evaluated using popular metrics such as overall accuracy, sensitivity, specificity, etc., and was also compared with other existing methods. Our proposed method produced an overall accuracy of 96.08 %. The proposed system can be used as a point-of-care diagnostic device to help patients monitor themselves, or also can be used to transmit EMG-signals over internet to a remote server, so that a physician can use the measured data to perform remote diagnosis.**



***Index Terms*—EMG (Electromyography), Neuro-muscular, Amyotrophic Lateral Sclerosis (ALS), Point-of-Care Diagnostics, IoT, Signal Processing, Machine Learning, Wireless System.**


## I. Introduction

The development of point-of-care diagnostic devices has been playing a crucial role in making medical care very accessible and affordable to every individual. Point-of-care diagnostic devices have proven to be very useful for two reasons. Firstly, these devices are efficient in reducing the burden on the healthcare setups, thereby decentralizing the concept of medical diagnostics. Also, point-of-care diagnostic devices are mostly efficient in reducing the cost of medical diagnostics, thereby creating a significant impact on human society as a whole [1] – [9].

In this work, we have proposed a prototype for a point-of-care diagnostic system involving EMG (Electromyography) measurements, and thereby detecting specific neuro-muscular diseases using the system. Amyotrophic Lateral Sclerosis (ALS) is one of the most common neuromuscular diseases which affects both lower and upper motor neurons. ALS requires periodic monitoring of the patient, and an early diagnosis can be helpful in preventing the relentlessly progressive disorder and improving the quality of life for ALS patients. ALS condition can be detected through proper signal analysis of a patient's EMG (Electromyography) waveform. In this work, we demonstrate a proof-of-concept point-of-care diagnostics system to measure the EMG signal of a patient, through wireless mode, and thereby detecting whether the patient is subjected to ALS-condition or not, by appropriately analyzing the EMG signal on another remote terminal connected through the internet (Fig. 1(a)).

The hardware of our proposed system consists of the required sensors, associated analog front-end signal-processing circuits, and hardware blocks to transmit the signals onto a remote server through Internet. Our proposed system also consists of the necessary software, in terms of machine-learning models and signal-processing algorithms, to detect and classify whether the measured EMG signal from a patient corresponds to ALS-condition or not. The software-code present in this remote terminal involves machine learning algorithms to perform fundamental analysis and predictions on these received EMG-signals from the patient. In this research work, a framework containing a modified VGG-5 Network, called the SpinalNet-VGG, performing classification on the Spectrogram of EMG signals, is proposed for identifying ALS-condition (Fig. 1(b)). The variations in parameters related to time domain of an EMG signal also implies the presence of a detectable difference in frequency domain, ie., in the spectrogram of these signals. This change in spectrogram of the signals forms the basis of the framework. Our proposed methodology for detection of Amyotrophic Lateral Sclerosis (ALS) disease involves two major steps, namely: i. Generation

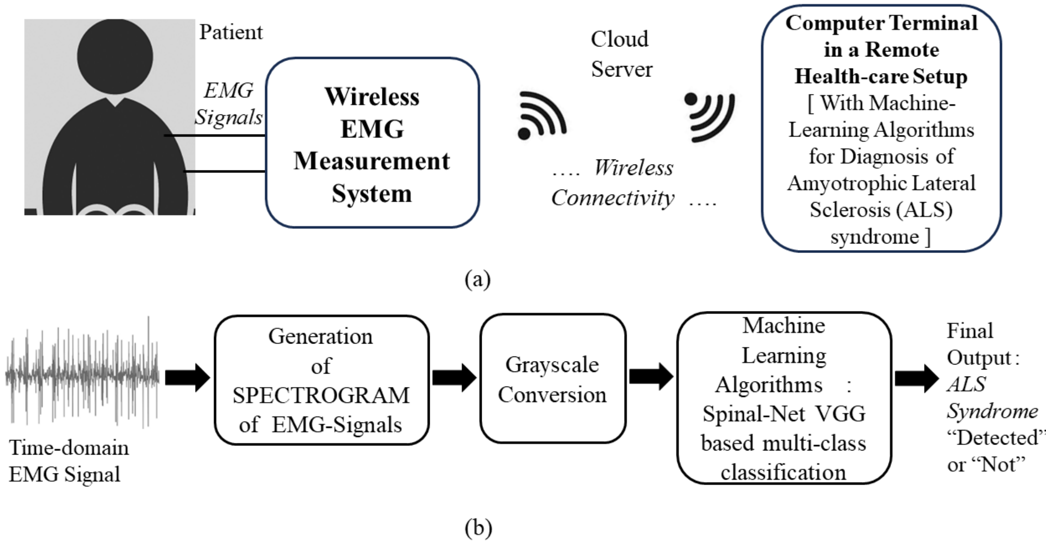


Fig.1 . (a) Overall block diagram of the proposed system (b) Proposed Methodology to detect ALS disease – Machine Learning based approach

of 2D spectrograms from Raw EMG Signals. ii. Classification of spectrograms using SpinalNet (Fig. 1(b)). The performance was evaluated using popular metrics such as overall accuracy, sensitivity, specificity and balanced accuracy, and also compared with other existing methods. The proposed method produced an overall accuracy of 96.08 %. The proposed system has the potential to produce a significant impact in making medical diagnostics more accessible and affordable, with regard to neuro-muscular pathological conditions. With its ability to remotely sense and analyze EMG signals, the proposed system can be extended to allow for a more comprehensive diagnosis of various neurological disorders, such as neuropathies, muscular dystrophies, and motor neuron diseases. The use of machine-learning algorithms also enables the system to provide real-time monitoring and feedback to patients, enabling them to manage their conditions better.

## II. EMG BASED DIAGNOSIS OF AMYOTROHIC LATERAL SCLEROSIS

EMG, a neurophysiological technique, allows the examination of electrical activity of skeletal muscles, by detecting the muscular membrane potential. Muscle fibers innervated by axonal branches of a motor neuron form a motor unit. Their intermingling with fibers of other MUs results in the summation of action potentials, known as Motor Unit Action Potential (MUAP). The bio-signal recorded from a muscle, or its fibers, reflects the anatomical and physiological properties of the motor system. Most of the primary neuro-muscular diseases result in changes in the electrical activity recorded from muscular fibers. The pattern of abnormalities can usually mark the underlying pathology as neuropathic disorders, myopathic disorders, etc [1]–[6].

Surface EMG (sEMG) is a non-invasive technique that measures electrical activity of muscles, using surface electrodes placed on the skin. A polyphasic, high amplitude and enlarged MUAP may be recorded in chronic neuropathy with reinnervation. On the other hand, some myopathic and neuromuscular junction disorders can result in MUAPs that are short, small in amplitude and polyphasic. These variations in MUAP morphology and parameters provide essential diagnostic information about the underlying neuromuscular condition. MUAP duration reflects synchrony and fiber density; short-duration is seen in disorders with fiber loss, whereas long-duration in generally seen in chronic neuropathies/polymyositis, and mixed pattern in rapidly progressing motor neuron disease/chronic myositis. Morphology (number of phases) reflects firing synchrony; and also, increased polyphasia is non-specific to myopathic and neuropathic disorders [1], [8], [9]. Analysis of EMG Signals, by Nicolic et.al., describes the mean and standard deviation of the Inter Potential Interval (IPI) [2]. The inter–potential interval (IPI) is the time between two consecutive discharges from the same MU. The analysis shows that the $MEAN_I$ (Mean IPI) parameter is able to differentiate between healthy individuals, patients with myopathy, and patients with ALS. The mean IPI is lower for firing patterns (FPs) from patients with myopathy, and higher for patients with ALS compared to healthy individuals. Also, the $SD_I$ (Standard Deviation of IPI) parameter showed that the FPs in ALS patients are generally more unstable (higher $SD_I$) [2], [8]–[12].

## III. PROPOSED METHODOLOGY

In this work, we demonstrate a point-of- care diagnostics system to measure the EMG signal of a patient, and transmit it through wireless mode, and thereby detect whether the patient is subjected to ALS-condition or not, by appropriately analyzing the EMG signal on another remote terminal connected through the internet. Such a wireless EMG system would be useful for remote monitoring of patients located at their homes, from hospitals and health-care setups situated far away (Fig. 1(a)).

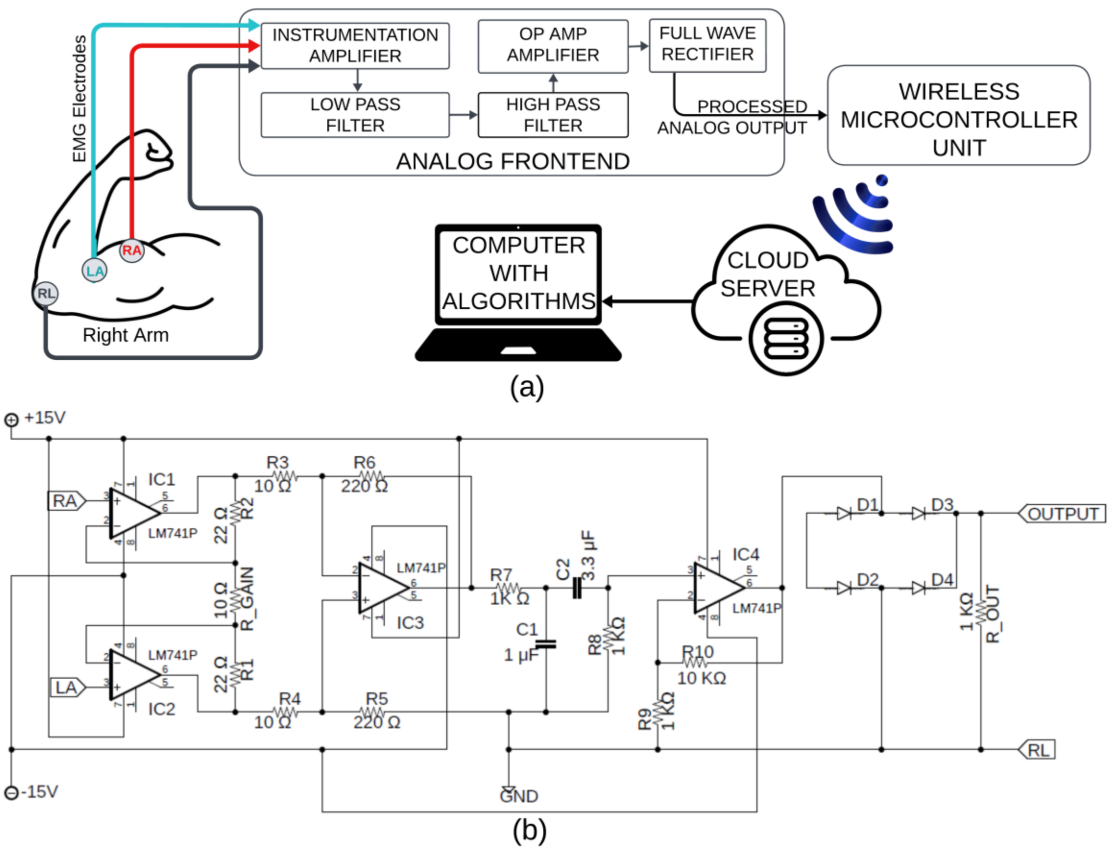

Fig. 2. (a) Block Diagram of Wireless EMG measurement system (b) Analog Front End – Circuit Design

The software-code present in the receiving-end employs machine learning algorithms to perform fundamental analysis and predictions on these received EMG-signals from the patient. In this research work, a framework containing a modified VGG-5 Network, called the Spinal-Net VGG, performing classification on the Spectogram of EMG signals is proposed for identifying ALS-condition. As discussed above, the difference in parameters related to the time domain signal [12]–[16] implies the presence of a detectable difference in the frequency domain as well, i.e., in the spectrogram of these signals. This change in the spectrogram of the signals forms the basis of our proposed framework. The proposed methodology for ALS-detection involves following two major segments:

(i). Generation of 2D spectrograms from raw EMG Signals
(ii). Classification of these spectrograms using SpinalNet

## IV. WIRELESS EMG – DESIGN OF HARDWARE SYSTEM

In this section, we describe the hardware design of the wireless EMG measurement system (Fig. 2(a)).

Surface electrodes were placed on skin overlying the muscle of interest, to capture the electrical signals generated by muscle activity. The recorded EMG signals were further processed using a custom-designed, analog front-end circuit. The processed signals were then transmitted to a cloud server using a Wireless Microcontroller Unit (Fig. 2(a)). For the hardware design, Node-MCU (ESP-8266) microcontroller unit was used for digitizing the processed analog signal using its inbuilt ADC unit, and also to transmit the digitized signals to a remote computer, through the Internet. The analog front-end block was custom-designed with following circuit modules, namely: Instrumentation amplifier, frequency selective filters, differential amplifier, full-wave rectifier (Fig. 2(b)). The design values used in each of these circuit blocks are given below:

### A. *Instrumentation Amplifier*

An Instrumentation amplifier was designed as shown in Fig. 2(b), with specific resistor values given by: R1, R2 = 22 Ω , $R_{gain}$ = 10 Ω and R3, R4 = 10 Ω, R5, R6 = 220 Ω, where we obtain a gain of 118.8.

### B. *Low Pass Filter*

A low pas filter was designed to remove high-frequency noise from the EMG signal while preserving the lower-frequency components associated with muscle activity. By choosing R = 1k Ω and C = 1μF, we get a cutoff frequency of 150 Hz.

### C. *High Pass Filter*

A high pass filter was designed as shown in Fig. 2(b), by choosing R = 1k Ω and C = 3.3 μF, where we get a cutoff frequency of 48.25 Hz.

### D. *OP-AMP Non-Inverting Amplifier*

This is succeeded by a non-inverting voltage amplifier (gain block) as shown Fig. 2(b). The design values used were: R9 = 1 kΩ and R10 = 10 kΩ, where we get a gain of 11.

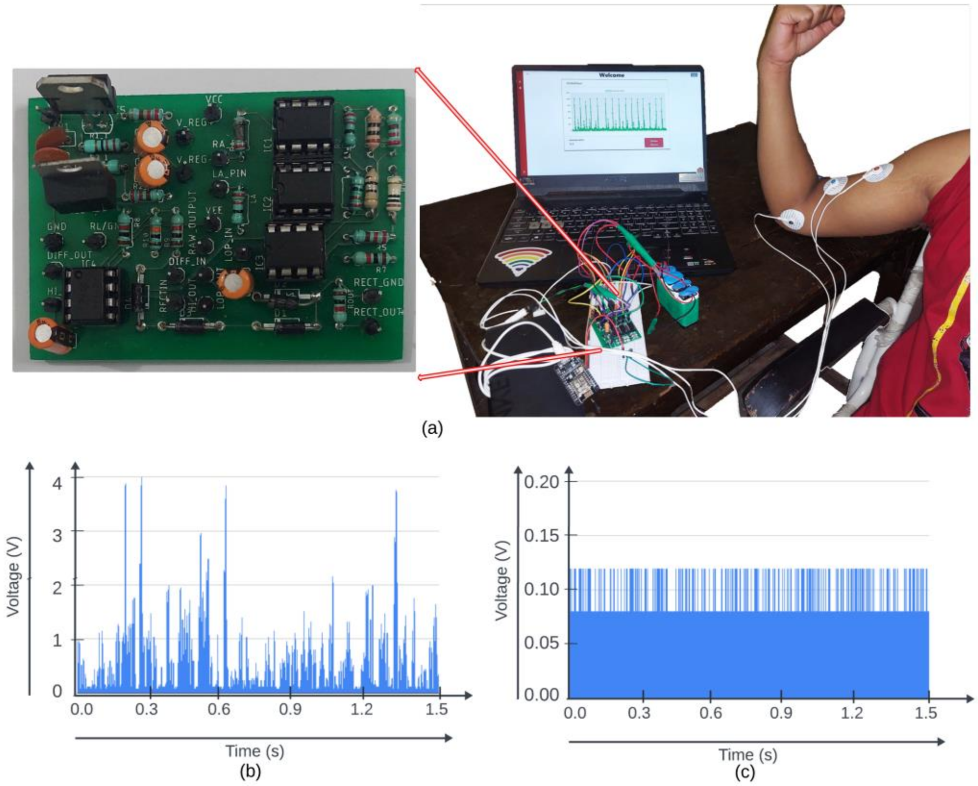

Fig. 3. (a) Wireless EMG Measurement System – Photograph of Hardware prototype, (b) EMG Waveform measured from a flexed arm, (c) EMG waveform measured from a stationary arm

### *E. Full-Wave Rectifier*

A full-wave rectifier was employed as the last block, to obtain a rectified output voltage (Fig. 2(b)).

We have implemented the proposed hardware using a custom-designed PCB, as shown in Fig. 3(a), where the circuit was tested to observe a net gain of 1306.8. The raw EMG signal fed to the instrumentation amplifier had a voltage range of 10mV (peak-to-peak) from -5mV to +5mV. The processed analog output represents the filtered and amplified signal, which had a range of: 0 to +5 V (Fig. 3(b) & 3(c)). The signal from the analog front-end was then fed to the analog pin (A0) of the microcontroller development board, NodeMCU, which has an inbuilt Wi-Fi hardware module. The analog signals received were sampled using an inbuilt Analog to Digital Converter block in the microcontroller, at the rate of 1 KHz. The digital signal values were then sent to a Django-based backend server and PostgreSQL Database using API calls made using the WiFi Module. The website in the remote terminal-end, was made to display the sampled values using a graph-plotter.

## V. MACHINE-LEARNING ALGORITHM FOR ALS DETECTION

As discussed in the earlier sections, the ALS disease detection is performed in the remote computer terminal, by employing machine learning algorithms. Machine learning is employed for classification of electromyography (EMG) signals into healthy, Amyotrophic Lateral Sclerosis (ALS) and non-ALS categories, by its unparalleled ability to analyze complex and high-dimensional datasets. EMG signals, which record the electrical activity of muscles, are intricate and contain valuable information about neuromuscular disorders like ALS. Traditional methods of signal analysis may struggle to effectively capture the intricate patterns and variations present in EMG signals.

Our proposed framework contains a modified VGG-5 Network, called the Spinal-Net VGG, performing classification on the Spectrogram of EMG signals, for identifying ALS-condition. The difference in parameters related to the time domain signal implies the presence of a detectable difference in the frequency domain as well, i.e., in the spectrogram of these signals. This change in the spectrogram of the signals forms the basis of our proposed framework. The proposed framework consists of two parts: the generation of 2D spectrograms from Raw EMG Signals, and the classification of these spectrograms using SpinalNet [15], as discussed in detail below:

### *A. Generation*

We use the PyLab library to convert the raw EMG signals into a 2D spectrogram, which maps the classification into a Computer Vision Problem. The spectrogram is calculated by dividing the signal into overlapping segments and computing the Fast Fourier Transform for each segment (Fig. 4(a), 4(b)).

### *B. Classification*

The Deep Neural Network (DNN) used for the classification of images is SpinalNet-VGG [15], which is a VGG-5 network with SpinalNet classification layers, in-place of fully

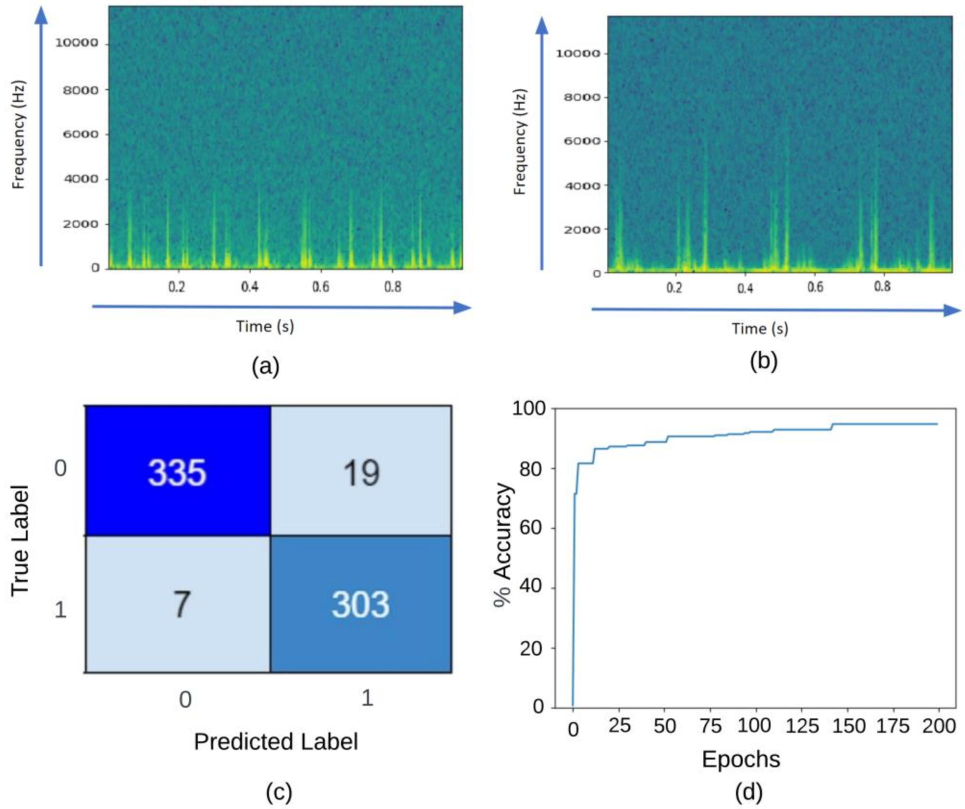


Fig. 4. (a) A sample Spectrogram of healthy EMG signal, (b) A sample Spectrogram of EMG signal subject to ALS disease condition, (c) Confustion matrix of the proposed framework (d) Accuracy vs Epochs Curve

connected layers. Hidden layers in traditional NNs receive inputs in the previous layer, apply activation function, and then transfer the outcomes to the next layer. However, in SpinalNet, each layer is split into three splits: 1) input split, 2) intermediate split, and 3) output split. Input split of each layer receives a part of the inputs. The intermediate split of each layer receives outputs of the intermediate split of the previous layer and outputs of the input split of the current layer. [15]

## VI. ALS DETECTION – QUANTITATIVE RESULTS AND ANALYSIS

### A. *Datasets used:*

The clinical EMG signals of the N2001 EMGLAB open-access Dataset were used in our experiment [2]. Each EMG signal was sampled at 24 kHz frequency and recorded for almost 11 seconds. A total of 302 EMG signals recorded from the brachial biceps and medial vastus muscles were used in this experiment. Of the 302 EMG signals, 151 signals were from the Normal group, and 151 signals were from the ALS group. Each of these signals was segmented into 11 segments, where each of the segments had a time duration of 1s. Size of the dataset used in this experiment is $302 \times 11 = 3322$. Summary of the datset is shown in Table I.

TABLE I
N2001 EMGLAB DATASET

| | Train | Validation | Test |
|---|---|---|---|
| No. of segments | 2125 | 532 | 665 |

### B. *Performance Evaluation:*

The proposed framework was evaluated using a variety of performance metrics, viz., accuracy, precision, recall, and F1-score, as shown in Table II. These metrics serve as crucial indicators of the framework's efficacy in distinguishing between Normal and ALS-based EMG signals.

TABLE II
PERFORMANCE METRICS

| Metric | Value |
|---|---|
| F1-Score | 0. 95886 |
| Accuracy | 0. 96084 |
| Precision | 0. 94099 |
| Recall | 0. 97742 |

The confusion matrix, shown in Fig. 4(c), and the evaluated performance metrics, shown in Table-II & Fig. 4(d), highlight the robustness and effectiveness of the proposed framework in accurately classifying EMG signals, from both normal (healthy) and ALS groups.

## VII. INFERENCES AND CONCLUSIONS

In this work, the performance of the proposed model was evaluated using popular metrics such as overall accuracy, sensitivity, specificity and balanced accuracy. The proposed method produced an overall accuracy of 96.08 %, with regards to the detection of ALS-syndrome. Such a point-of-care diagnostic device, that can detect basic neuropathic disorders, could help identify these conditions earlier, allowing for prompt, in-time medical treatment and management [16] – [24]. It could also reduce the burden on healthcare systems by identifying cases earlier, and thereby reducing the need for more intensive treatments later. The use of machine-learning algorithms enables the system to provide real-time monitoring and feedback to patients, enabling them to manage their conditions better.

The proposed system has the potential to produce a significant impact on medical diagnosis procedures for neuro-muscular pathological conditions. The remote diagnosis ability of the system would be of much help to patients in rural areas, that do not have significant access to advanced medical facilities. Such a device could be much benefit in geographical areas with limited access to healthcare, as it could enable early detection and diagnosis without the need for expensive and complex diagnostic equipment or specialized medical professionals. The proposed methodology can be suitably extended to detect and manage various other neurological and muscular disorders. With its ability to remotely sense and analyze EMG signals, the proposed system can be extended to allow for a more comprehensive diagnosis of various neurological disorders, such as neuropathies, muscular dystrophies, and motor neuron diseases.

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