Remote Monitoring and Detection of Amyotrophic Lateral Sclerosis Disease through 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 helps prevent the disorder from progressing further, thereby improving the quality of life for patients. In this study, we demonstrated a proof-of-concept, point-of-care diagnostics system to measure the surface-EMG signal of a patient. It automatically detects 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 the Internet. The proposed system consists of necessary software modules, machine-learning models, and signal-processing algorithms to detect and classify whether the measured EMG signal from a patient corresponds to the given pathological condition (ALS) or not. The developed framework contains a modified VGG-5 Network, called SpinalNet-VGG, and classifies the Spectrogram of EMG signals to identify the ALS condition. The variations in the spectrogram of the EMG signals form the basis of the proposed framework. The proposed methodology for ALS disease detection involves two major segments: the generation of 2D spectrograms from Raw EMG Signals and the classification of spectrograms using SpinalNet. The performance was evaluated using popular metrics such as overall accuracy, sensitivity, and specificity and was compared with existing methods. The proposed method showed an accuracy of 96.08 %. The proposed system can be used as a point-of-care diagnostic device to help patients monitor by themselves and transmit EMG signals over the Internet to a remote server so that a physician can use the measured data for remote diagnosis.

***Keywords*—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 accessible and affordable. Point-of-care diagnostic devices are 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 study, we developed a prototype for a point-of-care diagnostic system involving Electromyography (EMG) measurements to detect neuro-muscular diseases. 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 helps prevent the relentlessly progressive disorder and improves the quality of life for ALS patients. ALS condition is detected through proper signal analysis of a patient's EMG waveform. We developed a proof-of-concept point-of-care diagnostics system to measure the EMG signal of a patient wirelessly and detect whether the patient is subjected to ALS conditions or not by analyzing the EMG signal on a remote terminal connected through the Internet (Fig. 1(a)).

The hardware of the proposed system consists of sensors, analog front-end signal-processing circuits, and hardware modules to transmit the signals onto a remote server through the Internet. Machine-learning models and signal-processing algorithms were integrated to detect and classify the measured EMG signal from a patient corresponding to ALS conditions. In the remote terminal, machine learning algorithms were included to perform fundamental analysis and predict the results using the EMG signals of the patient. The framework contains a modified VGG-5 Network, called the SpinalNet-VGG to classify the spectrogram of EMG signals and identify ALS conditions (Fig. 1(b)). The variations in parameters related to the time domain of an EMG signal imply the presence of a detectable difference in the frequency domain in the spectrogram of these signals. This change in the spectrogram of the signals forms the basis of the framework. The proposed methodology for the detection of ALS involves two major steps: the generation of 2D spectrograms from raw EMG signals and the classification of spectrograms using SpinalNet (Fig. 1(b)).

The performance was evaluated using accuracy, sensitivity, specificity, and balanced accuracy and was compared with those of existing methods. The proposed method showed an accuracy of 96.08 %. The proposed system offers accessible and affordable medical diagnostics related to neuro-muscular pathological conditions. With its ability to remotely sense and analyze EMG signals, the proposed system allows for the 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 ALS

EMG, a neurophysiological technique, allows for the examination of the 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 motor units 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 change the electrical activity recorded from muscular fibers. The pattern of abnormalities presents the underlying pathology as neuropathic disorders and myopathic disorders [1–6]. Surface EMG (sEMG) is a non-invasive technique that measures the electrical activity of muscles, using surface electrodes placed on the skin. A polyphasic, high amplitude and enlarged MUAP are recorded in chronic neuropathy with reinnervation. On the other hand, myopathic and neuromuscular junction disorders result in MUAPs that are short, small in amplitude, and polyphasic. These variations in the MUAP morphology and parameters provide essential diagnostic information about the underlying neuromuscular condition. The MUAP duration reflects synchrony and fiber density. Short duration is seen in disorders with fiber loss, whereas Long duration in chronic neuropathies/polymyositis and the mixed pattern shows rapidly progressing motor neuron disease/chronic myositis. Morphology of the number of phases reflects firing synchrony, and increased polyphasia is non-specific to myopathic and neuropathic disorders [1,8,9]. The analysis of EMG signals is presented with 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 result shows that the $MEAN_I$ (Mean IPI) parameter differentiates 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) shows that the FPs in ALS patients are generally more unstable (higher SD_I) [2,8–12].

III. Proposed Methodology

We developed a point-of-care diagnostics system to measure the EMG signal of a patient and transmit it through wireless mode to detect ALS conditions. By analyzing the EMG signal on remote terminals connected through the internet, remote monitoring of patients at home from hospitals and health-care centers is enabled (Fig. 1(a)).

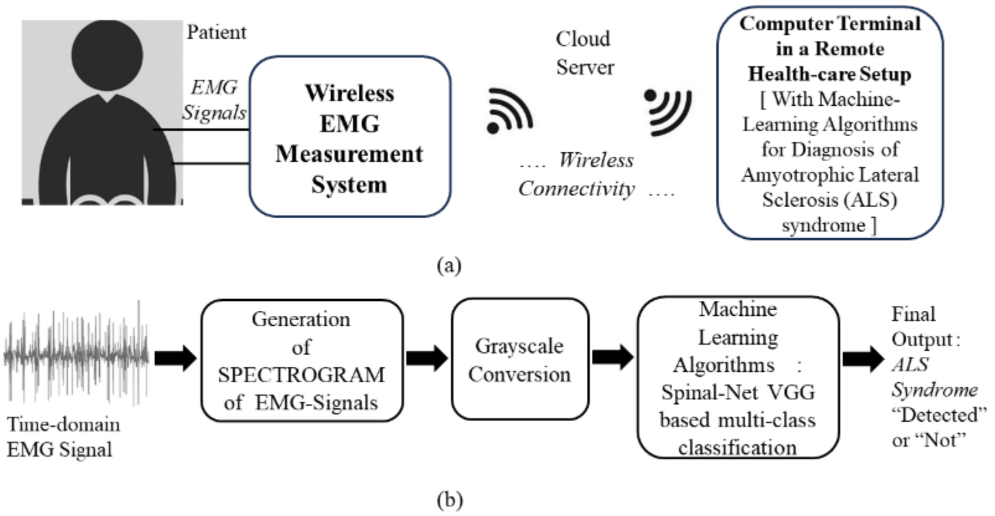

Fig. 1. Structure of proposed system.

In the receiving end, machine learning algorithms are used for analysis and predictions on these received EMG signals from the patient. In this research, the framework contains a modified VGG-5 Network, called the Spinal-Net VGG for the classification of the spectogram of EMG signals to identify ALS. The difference in parameters related to the time domain signal implies the presence of a detectable difference in the frequency domain in the spectrogram of these signals [12–16]. This change in the spectrum of the signals forms the basis of our proposed framework. The proposed methodology for ALS detection involves the generation of 2D spectrograms from raw EMG signals and the classification of spectrograms using SpinalNet.

IV. Hardware

Surface electrodes were placed on the muscle of interest to capture the electrical signals generated by muscle activity. The recorded EMG signals were processed using a custom-designed analog front-end circuit. The processed signals were transmitted to a cloud server using a Wireless Microcontroller Unit (Fig. 2(a)). A Node-MCU (ESP-8266) microcontroller was used for digitizing the processed analog signal using its ADC unit and transmitting the digitized signals to a remote computer through the Internet. The analog front-end block was custom-designed with an instrumentation amplifier, frequency selective filters, differential amplifier, and full-wave rectifier (Fig. 2(b)).

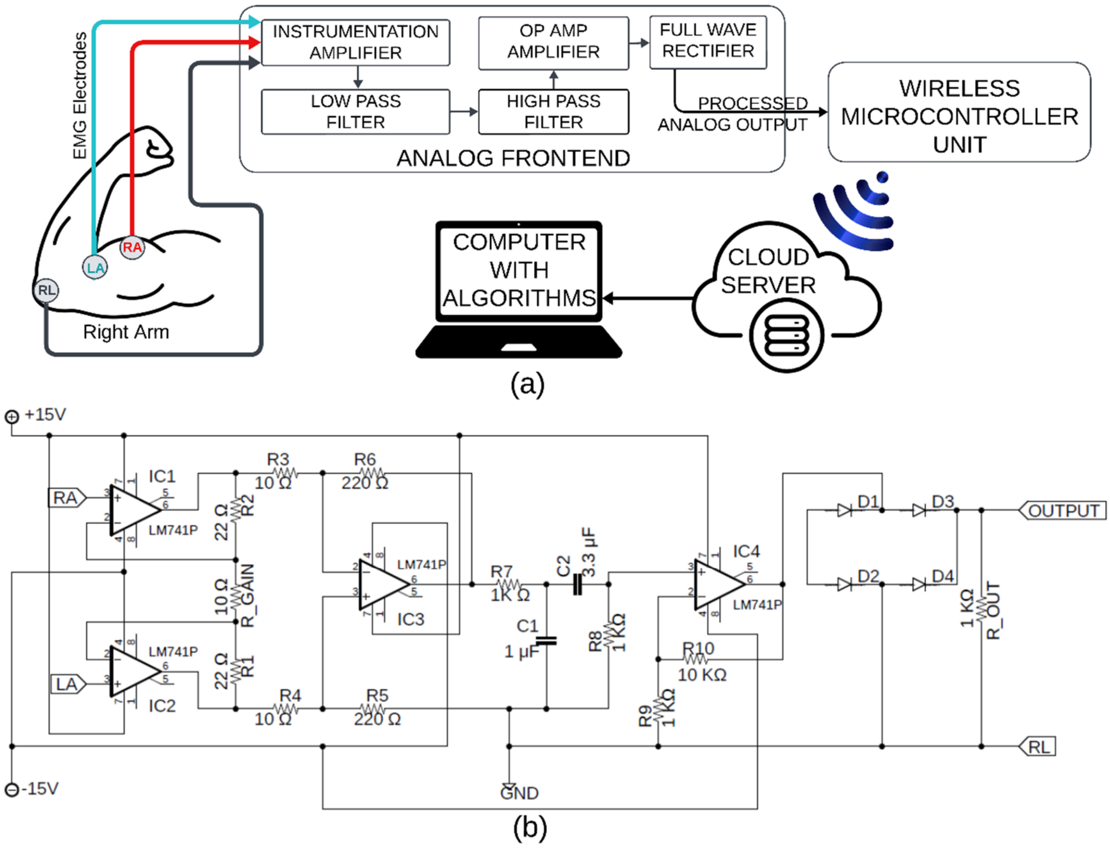

Fig. 2. (a) Block Diagram of Wireless EMG measurement system (b) Analog Front End – Circuit Design

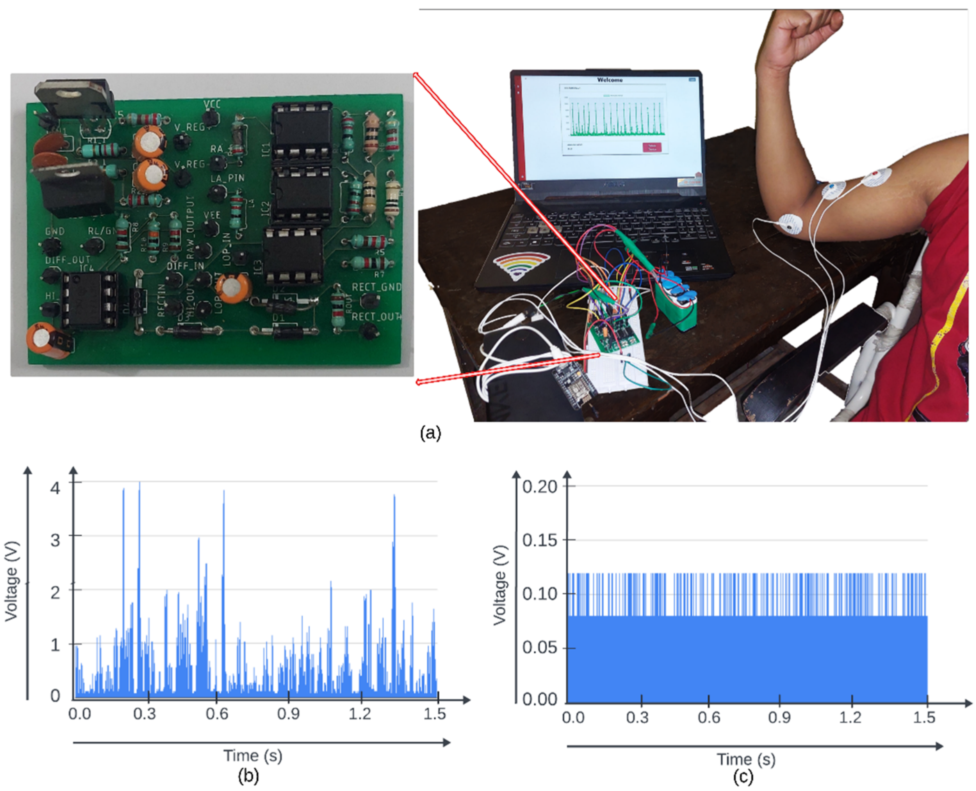

Fig. 3. (a) Wireless EMG measurement system, (b) EMG waveform measured from a flexed arm, and (c) EMG waveform measured from a stationary arm.

A. Amplifier

An amplifier was designed (Fig. 2(b)) with the following resistor values: R1, R2 = 22 Ω, R_{gain} = 10 Ω, R3, R4 = 10 Ω, and R5, R6 = 220 Ω, with a gain of 118.8.

B. Low Pass Filter

A low-pass filter was used to remove high-frequency noise from the EMG signal while preserving the lower-frequency components associated with muscle activity. By choosing R = 1 kΩ and C = 1 µF, a cutoff frequency of 150 Hz was obtained.

C. High Pass Filter

A high pass filter was designed by choosing R = 1 kΩ and C = 3.3 µF with a cutoff frequency of 48.25 Hz.

D. OP-AMP Non-Inverting Amplifier

A non-inverting voltage amplifier (gain block) has the design values of R9 = 1 kΩ and R10 = 10 kΩ with a gain of 11.

E. Full-Wave Rectifier

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

We 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 10 mV (peak-to-peak) from -5 to +5 mV. The processed analog output represents the filtered and amplified signal in a range of 0 to +5 V (Fig. 3(b) and (c)). The signal from the analog front-end was then fed to the analog pin (A0) of the microcontroller development board, NodeMCU, which is an inbuilt Wi-Fi hardware module. The analog signals received were sampled using an inbuilt Analog to Digital Converter block in the microcontroller, at a rate of 1 KHz. The digital signal values were then sent to a Django-based backend server and PostgreSQL Database using API calls using the WiFi Module. The website in the remote terminal end displayed the sampled values using a graph plotter.

V. Machine-Learning Algorithm For ALS Detection

ALS disease detection is performed in the remote terminal by employing machine learning algorithms. Machine learning classifies EMG signals into healthy, ALS, and non-ALS categories by analyzing complex and high-dimensional datasets. EMG signals show the electrical activity of muscles as intricate and valuable information about neuromuscular disorders such as ALS. Traditional methods of signal analysis cannot effectively capture the intricate patterns and variations present in EMG signals.

The proposed framework contains a modified VGG-5 Network, the Spinal-Net VGG and classifies the spectrogram of EMG signals to identify ALS conditions. 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 the proposed framework.

A. Generation

We used 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) and (b)).

B. Classification

The Deep Neural Network (DNN), SpinalNet-VGG was used for the classification of images [15], which is a VGG-5 network with SpinalNet classification layers replacing fully 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 input, intermediate, and output. 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 Analysis

A. Datasets

The clinical EMG signals of the N2001 EMGLAB open-access Dataset were used in the experiment [2]. Each EMG signal was sampled at a frequency of 24 kHz and recorded for 11 s. 302 EMG signals were recorded from the brachial biceps and medial vastus muscles in this experiment. Of the 302 EMG signals, 151 signals were from the normal group, and 151 signals were from the ALS group. Each signal was segmented into 11 segments, where each of the segments had a time duration of 1 s. the size of the dataset used in this experiment was 302 × 11 = 3322 (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 accuracy, precision, recall, and F1- score as shown in Table II. These metrics are the indicators of the framework 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 (Fig. 4(c)) and the evaluated performance metrics (Table II, Fig. 4(d)) highlights the robustness and effectiveness of the proposed framework in accurately classifying EMG signals, from both normal (healthy) and ALS groups.

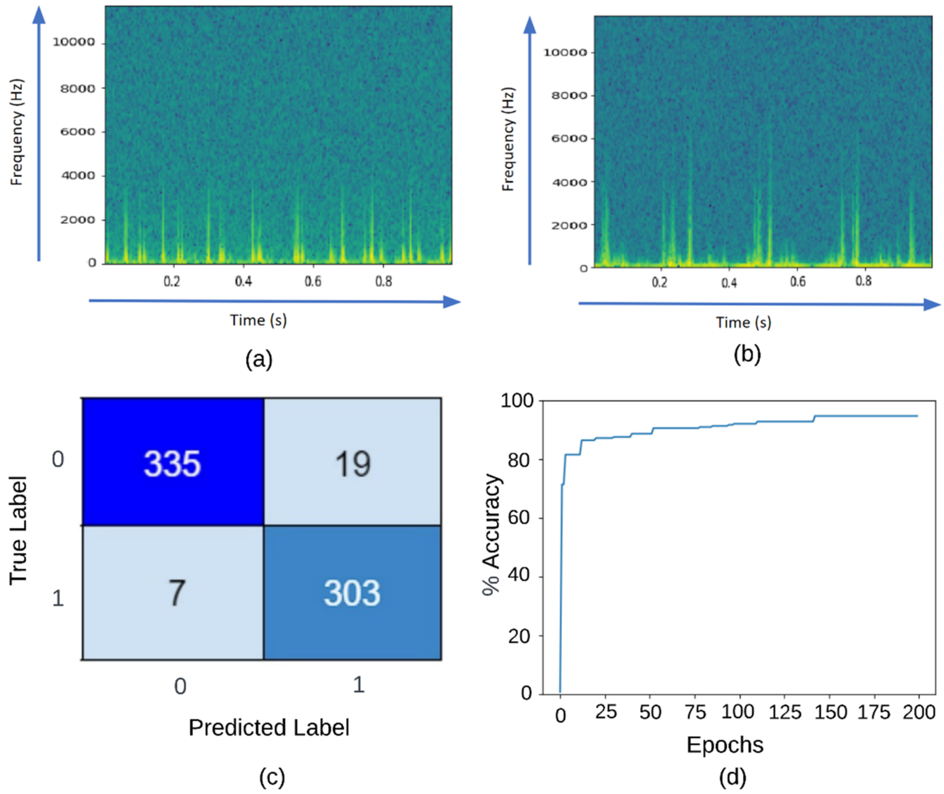

Fig. 4. (a) Sample spectrogram of healthy EMG signal, (b) Spectrogram of EMG signal subject to ALS disease condition, (c) Confustion matrix of the proposed framework , and (d) Accuracy vs Epochs Curve

VII. CONCLUSIONS

The performance of the proposed model was evaluated using popular metrics such as accuracy, sensitivity, specificity, and balanced accuracy. The proposed method showed an accuracy of 96.08 % in the detection of ALS syndrome. The proposed point-of-care diagnostic device is useful to detect ALS disease, and identify the conditions earlier, allowing for prompt and in-time medical treatment and management [16–24]. It also reduces the burden on healthcare systems by identifying cases earlier and the need for intensive treatments later. The machine-learning algorithms allow for real-time monitoring and feedback to patients to manage their conditions better. The proposed system has the potential to significantly impact medical diagnosis procedures for various neuro-muscular pathological conditions in the future. The remote diagnosis ability of the system helps patients in rural areas who cannot access advanced medical facilities. Such a device benefits people with limited access to healthcare facilities as it enables early detection and diagnosis without expensive and complex diagnostic equipment or specialized medical professionals. The proposed methodology can be extended to detect and manage various neurological and muscular disorders in the future. With its ability to remotely sense and analyze EMG signals, the proposed system can be extended to diagnose various neurological disorders, such as neuropathies, muscular dystrophies, and motor neuron diseases, through development of relevant machine learning algorithms.

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