ABSTRACT

There is a large number of people around the world suffering from upper limb amputation. A convenient solution to this problem is the use of a prosthetic device. There are two types of prosthetic devices, mechanical (body-powered) and electrical (motor/actuator driven). The biomedical signals of the user, known as Electromyography (EMG), provide the signals that control the electrical type of prosthetic hands. Analysing the characteristics of these signals, which represent the electrical activity of the muscles, reveals that each movement has a different amount of power levels and frequencies.

The user can only control the prosthetic hand with basic functionality (open and close) when relaying on power level differences in the (EMG) signal. This limitation could be overcome by analysing the (EMG) signal and extracting features and patterns associated with each muscle movement. This method is used in more advanced prosthetics and is dependent on the patient's level of amputation.

In recent decades many studies have been made about (EMG) based prostheses. Most of these studies used a complex array of sensors to collect EMG signals and process them in conventional ways of Machine Learning that involve hand-crafted feature extraction. These features are to be fed to classifiers to recognize the patterns of the signal and then classify the movement intended.

These approaches are known to be complex and require knowledge of the characteristics of the signal, which is time and resources expensive.

The objective of this study is to use the simplest hardware of one channel Surface Electromyography (sEMG) dry sensor and rely on Deep Learning approach by using a proposed hybrid model that uses a One Dimension Convolutional Neural Network followed by an enhanced kind of Recurrent Neural Network (1D-CNN-LSTM) to learn the features and patterns of segmented windows of the sEMG recorded signal, and to reduce the hardware cost and software computational power.

A Dataset named NTU-sEMG was acquired and recorded from 14 healthy subject whom volunteered to participate in the process of

recording (sEMG) signals from their arms while performing a set of hand movements.

After training on the dataset, the model was tested using a separate test set and it was capable of achieving relatively high accuracy of (98.59 %), (99.38 %), and (99.63%) in classifying 8, 5, and 4 classes of different hand movements respectively.

A real-time mode of the model was deployed to Raspberry Pi 4 computer to make the system portable and easy to use for controlling a 3D printed hand prototype to help people with disability. It was able to achieve accuracy of (60.75 %), (86.80 %), and (91.75%) in classifying 8, 5, and 4 classes of different hand movements respectively.