Brain-Computer Interface (BCI) systems present many advantages for their use in the fields of robotics and prosthetics. BCIs enable the control of electronic systems using only the central nervous system, allowing, for example, patients with motor neuron disease to control prosthetic limbs or electronic devices. In this study, an electroencephalographic (EEG) signal gesture recognition process for BCI applications is described. The gesture recognition process receives a raw EEG signal as an input and classifies the received input into its corresponding gesture.

The gesture data was acquired from different subjects using the EMOTIV\textsuperscript{R} EPOC, a 14-channel EEG headset. 402 samples of 6 different gestures were recorded. The gesture recognition process consists of two main stages: feature extraction and classification. The feature extraction stage consists of a 4-level wavelet decomposition of the filtered EEG signal using a db2 wavelet. The wavelet decomposition of the signal allows for each EEG frequency band (delta, theta, alpha and beta) to be analyzed individually. Statistical data is then taken from each frequency band of the EEG signal individually and is placed into the input layer of the ANN. The ANN’s input layer is made up of 336 elements, consisting of 6 statistical values of 4 frequency bands from 14 EEG channels. The ANN consists of input layer, 50 hidden layers, and an output layer. The ANN uses a backpropagation algorithm, a type of supervised learning where the neural network is fed a set of labeled training data prior to testing and a gradient descent algorithm is used to adjust the weights and biases on each of the hidden layers to effectively produce the desired output. The output layer consists of 6 different targets, each representing a gesture (smile, look left, look right, raise eyebrows, blink, and hard blink). During tests, the gesture recognition algorithm exhibits about 86% accuracy, which indicates positive results.