Title:

Hardware Implementation for Lower Limb abnormality detection using Surface EMG with various Deep Learning Techniques

Abstract:

Knee problems are a big issue for older adults. Doctors use MRI or X-ray to diagnose them. X rays are good for first checks, but MRIs are better for finding problems, though they cost more.This study looked at muscle signals (sEMG) from 22 people (11 healthy and 11 with knee abnormalities) during three different lower limb activities: Gait, Standing, and Sitting. The raw sEMG signals were first denoised using an appropriate filter. Feature selection was then carried out based on importance gain, focusing on the most relevant features. These features were used to train a Long Short-Term Memory (LSTM) model, which was subsequently tested with data collected directly from a clinic.

The base model achieved an accuracy of (96%), F1 score of (98%), and AUC of (90)[1]. In contrast, our proposed model reached an accuracy of (98), F1 score of (98), and AUC of (98)[1]. Overall, our model outperformed the base model across all metrics, with a 64% accuracy on our collected data.

Introduction :

In this present generation, Knee pain is the most common health issue in elder people. The reason for this knee abnormality is due to aging, injuries, and working hard which stress the joints repeatedly and may affect the knee. These are some of the conditions which can lead to knee abnormality. *The Knee joint is one of the main joints which keeps our body stable. It is constructed mainly of three bones and consists of ligaments and muscles. The tibia, femur, and patella are the three major bones that form the knee joint*. To detect whether the knee is normal or abnormal we use so many images. For getting these images of the knee joint we have so many techniques such as Magnetic resonance imaging (MRI), X-ray, Computer Tomography scans (CT), etc. Some doctors use X-rays to detect knee abnormalities but the problem with these is they will produce low-resolution images leading to difficulty in the detection time.MRI scans produce somewhat better images compared to X-ray images.

However, MRI scanning is very expensive. Some studies say that we can also identify knee abnormalities during daily activities like sitting, walking, standing, and jumping by using wearable sensors like the Muscle Bio amp candy sensor . These sensors are mainly used to recognize human activities.

Electromyography (EMG) is a technique that is used to measure the electrical activity produced by the muscles. We have two types of EMGs one is surface EMG where electrodes are placed on the skin above the muscle where the contraction and expansion happen and another one is the Inter muscular EMG where we will insert the needle electrodes into the muscle tissue. The intermuscular EMG will provide more detailed information compared to the surface EMG but patients will feel uncomfortable due to inserting that needle into the tissue which will cause more pain. The EMG signals are the electrical signals produced whenever we want to move our muscles our brain will produce some electrical signals through nerves so that muscles can contract or be in a state of rest.

Dataset:

We used a dataset with the surface EMG signals acquired during three different movements: standing, walking and sitting, performed by 22 subjects. All of the subjects were more than 18 years old, and eleven of the individuals were healthy and the remaining were suffering from knee abnormalities. The healthy individuals did not have any record of a knee injury while the unhealthy individuals had suffered any knee abnormality already diagnosed by professionals. A DataLog MWX8 and a goniometer were used to collect the data. The surface EMG data were collected around four distinct muscles: rectus femoris (RF), biceps femoris (BF), vastus medialis (VM) and semitendinosus (ST). The goniometer was attached to the external side of the knee joint. All the acquired data were stored on the computer. We utilized a Muscle Bio-amp sensor interfaced with an ESP32 module. The ESP32 was further connected to the ThingSpeak cloud platform, enabling real-time observation and storage of sensor data. To collecting those data with the help of these hardware kit (Esp32 +)and software(arduino + thinkspeak).We also collected the data from (3 subjects from abnormal people by doctor consultation and 10 subjects from normal people)

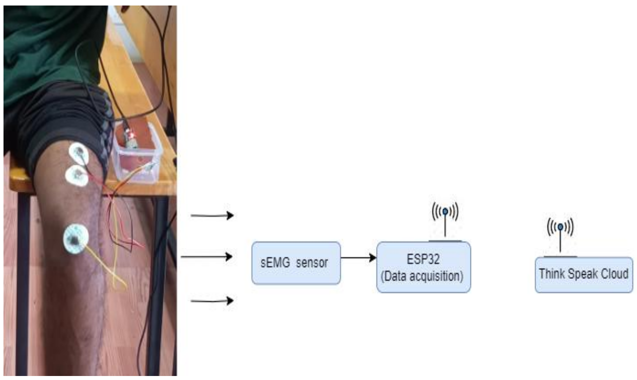
Dataset link : https://archive.ics.uci.edu/dataset/278/emg+dataset+in+lower+limb

Proposed Methodology :

This methodology section presents which process we followed to Data Acquisition,Noise Filtering and analyze the raw sEmg dataset and also we have trained the Deep Learnig models by these dataset , and tests its performance by giving the EMG signals which we have collected directly from the clinic.

1. **Data Acquisition**
2. **Data Preprocessing**
3. **Model**
4. **Performance metrics**

Data Acquisition:



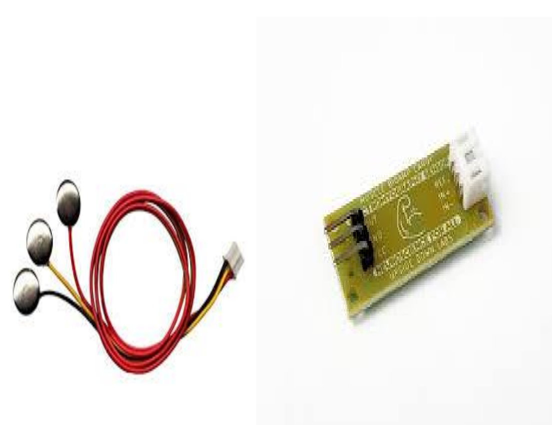
We also collected the data from 3 subjects from abnormal people by doctor consultation and 10 subjects from normal people . We utilized a Muscle Bio-amp sensor interfaced with an ESP32 module. The ESP32 was further connected to the ThingSpeak cloud platform, enabling real-time observation and storage of sensor data.

a) ESP32-S2(Micro Controller):

The ESP32, created by Espressif Systems, features a powerful dual-core Xtensa LX6 processor running at speeds up to 240 MHz. It is widely used in IoT devices, wearables, and industrial automation due to its versatility. Equipped with GPIO pins, UART, I2C, SPI interfaces, ADC, DAC, built-in Wi-Fi, and Bluetooth (supporting Bluetooth 5.0 and BLE), it seamlessly integrates into wireless networks. Memory management is robust, offering up to 520 KB of SRAM and up to 2 MB of flash memory The ESP32 reads data from a Bio-amp sensor connected via its ADC channel. It typically captures about 700 sensor readings per second. However, for precise control, we adjust the sampling rate to 500 samples per second (500 Hz), ensuring accurate and efficient data acquisition from the sensor.

b) BioAmp sensor :

The Muscle BioAmp Candy is a small, affordable muscle sensor for precise EMG (Electromyography) sensing, perfect for projects like controlling robotic hands and prosthetic arms. This candy-sized, single-channel sensor records muscle signals . It uses 3 electrodes and can be connected to various development boards like Arduino and Raspberry Pi. The device operates at 3.3-30V, with an input impedance of 10^11 Ω, a fixed gain of x2420, and a bandpass filter range of 72-720 Hz.



C) ThingSpeak:

ThingSpeak™ is an IoT analytics platform for aggregating, visualizing, and analyzing live data in the cloud. Ideal for prototyping IoT systems, it allows real-time data visualization, uses MATLAB for analysis, and automates actions via schedules or events.

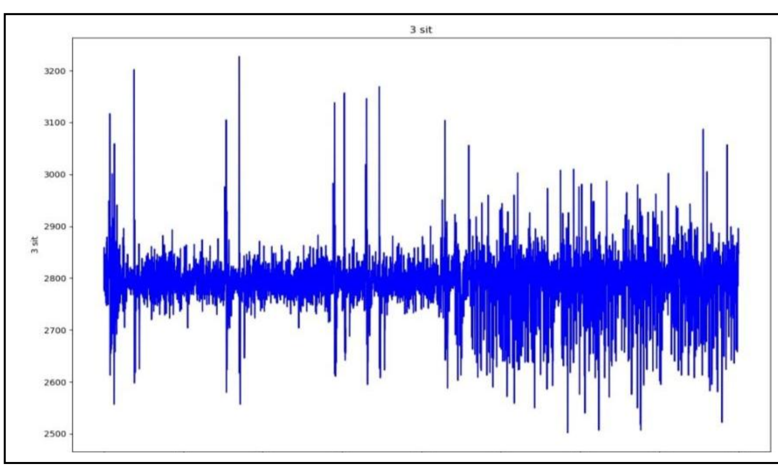
Data Preprocessing :

Before giving this raw EMG signals directly to the model ,we will preprocess the raw emg signals to enhance the quality of the data . Filtering and the denoising of the signal is done in the data preprocessing.

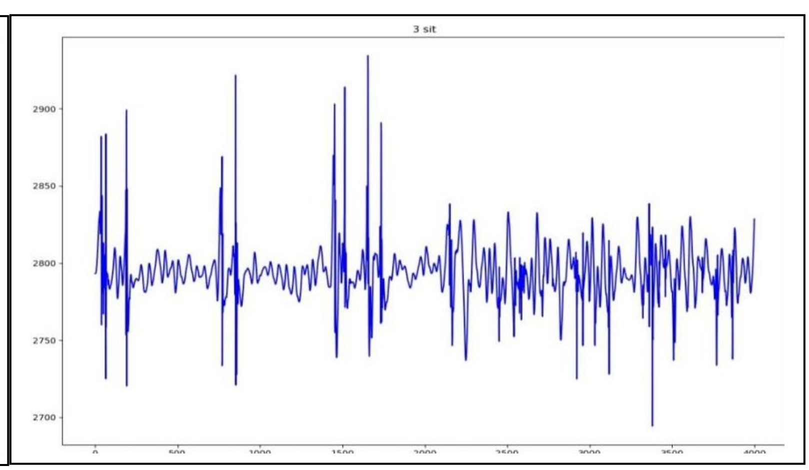
During sEMG signal acquisition, various noises from external and psychological disturbances can obscure the signal's specifics. Traditional filters like high-pass, low-pass, and band-pass are ineffective for removing such noise. Techniques like ICA, DWT, and EMD are used for noise removal. Here, DWT is applied for its minimal signal distortion and dual frequency-time domain information.A sEMG signal can be decomposed into various levels in a discrete wavelet transformation using various wavelets such as Haar, Daubechies, Marlet and Symlet. The transformation can be implemented as a bank of filters which contain low pass filters (approximate coefficients) and high pass filters (detail coefficients). Further, the signal is passed through the next level of low and high pass filters. The number of coefficients depends on the level of decomposition. Fig. 3 shows a wavelet decomposition up to level 4. A wavelet is generated from a mother wavelet (ψt), by scaling (s) and translation (τ).

$$\psi_{s,t} = \frac{1}{\sqrt{s}}\psi\left(\frac{t-T}{s}\right)$$

Sitting Activity:

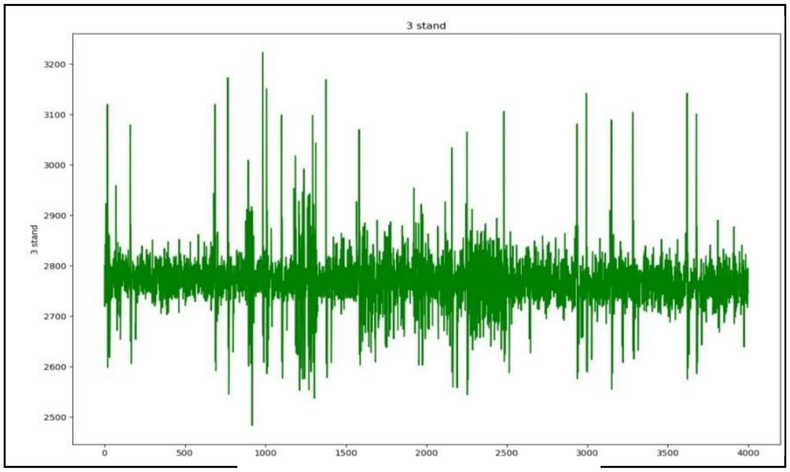


RAW EMG Signal

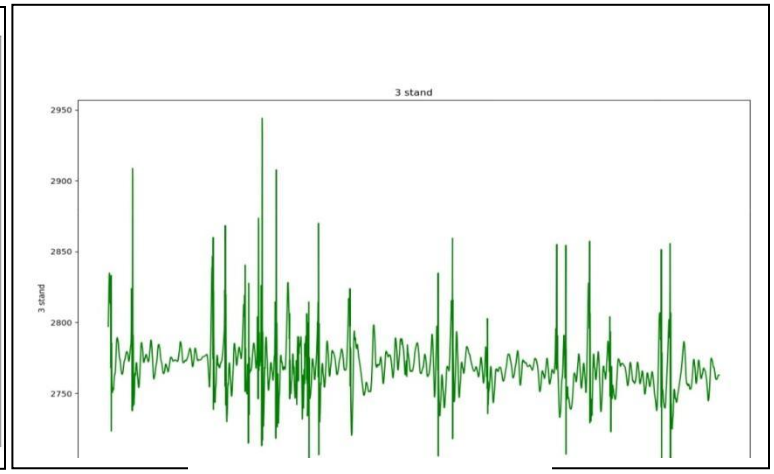


DWT Filtered EMG Signal

Standing Activity:

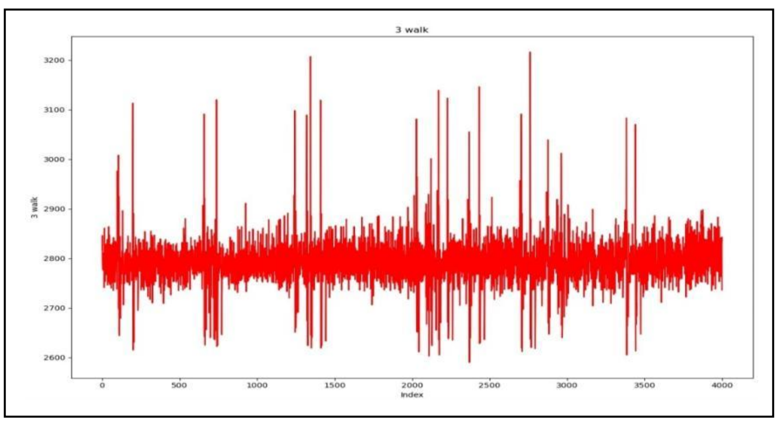


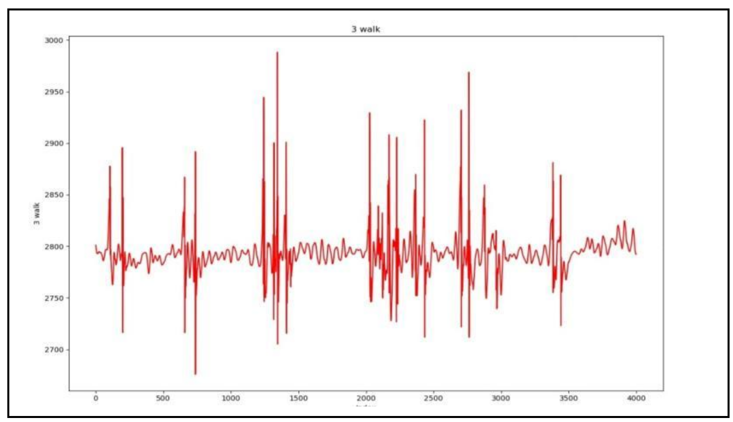
RAW EMG Signal



DWT Filtered EMG Signal

Walking Activity:

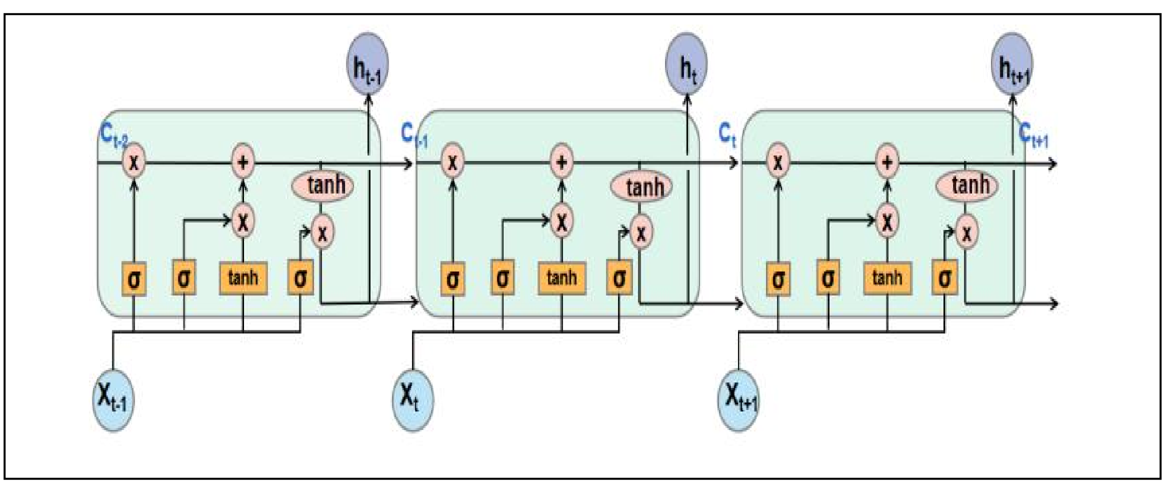




RAW EMG Signal

DWT Filtered EMG Signal

LSTM Model :



Lstm is solve long gterm dependences and ct (cell state) it carries the long term dependences and hidden state carries on short term dependences . It has 3 gtes(input, output and forgot gate

LSTM is a temporal recurrent neural network, which designed to deal with the long-term dependency problems of general recurrent neural networks (RNN). By introducing the For each new moment, the LSTM will receive the recent data input xj and the previous implicit state hi-1 and the memory cell state Ct-1 through the forgetting gate, input gate and output gate. The LSTM computational mechanism is shown below. Through the forgetting gate f t to determine which of the current data messages should be deleted from the memory cell state.

$$f_t = \sigma(W_{fx} X_t + W_{fh} X_{t-1} + b_f) \quad \_\_\_\_\_\_\_\_\_ (1)$$

Using the input gate it to decide the new messages to be stored in the new single page state

$$i_t = \sigma(W_{ix} X_t + W_{ih} h_{t-1} + b_i) \ldots\ldots\ldots\ldots\ldots\ldots\ldots (2)$$

$$g_t = \phi(W_{gx} X_t + W_{gh} h_{t-1} + b_g) \ldots\ldots\ldots\ldots\ldots\ldots\ldots (3)$$

$$C_t = C_{t-1} f_t + g_t f_t \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (4)$$

Where:g t is the candidate value to be added to the new cell state. The effect of Ct−1 ft is to determine how much information will be removed from Ct−1 be forgotten ing ti t,and to determine how many messages will be added

to the new cell state of C t becomes a bitwise multiplication of the elements in the vector. Using the output gate o t to caculate h t:

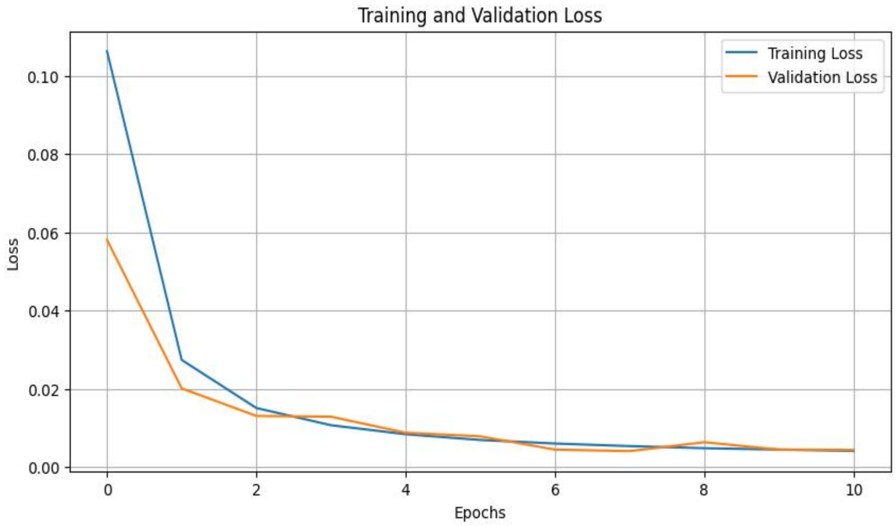
$$O_t = \sigma(W_{ox} X_t + W_{oh} h_{t-1} + b_o) \qquad \ldots\ldots\ldots\ldots (5)$$

$$h_t = O_t \, \phi(C_t) \qquad \ldots\ldots\ldots\ldots (6)$$

Where : σ and ϕ are respectively functioned by the sigmoid and tanh activation. Wfx, Wfh, Wix , Wih, Wgx, Wgh, Wox, Woh are respectively the oblivion gate, input gate, input node, output gate and input Xt and the previously implied state ht−1 the matrix of weights multiplied by each other.bf, bt, bg, bo are the corresponding bias coefficients; and f t, i t, g t, ot , C t, h t are respectively the output results of forgetting gate, input gate, input node, output gate, memory cell state and implicit state.

Metrics Calculation on Every Epoch:

Epoch	Loss	Accuracy	Precision	Recall	AUC	Val Loss	Val Accuracy	Val Precision	Val Recall	Val AUC
1/15	0.1063	0.9575	0.9143	0.8552	0.9870	0.0581	0.9782	0.9863	0.8977	0.9960
2/15	0.0274	0.9899	0.9757	0.9705	0.9987	0.0202	0.9928	0.9771	0.9853	0.9991
3/15	0.0151	0.9946	0.9866	0.9849	0.9993	0.0131	0.9954	0.9837	0.9920	0.9996
4/15	0.0107	0.9963	0.9907	0.9899	0.9995	0.0129	0.9957	0.9964	0.9808	0.9990
5/15	0.0084	0.9972	0.9928	0.9923	0.9996	0.0088	0.9972	0.9923	0.9928	0.9995
6/15	0.0070	0.9977	0.9941	0.9938	0.9997	0.0079	0.9975	0.9913	0.9957	0.9997
7/15	0.0061	0.9980	0.9949	0.9947	0.9997	0.0045	0.9986	0.9962	0.9964	0.9998
8/15	0.0054	0.9982	0.9955	0.9952	0.9997	0.0041	0.9987	0.9964	0.9969	0.9998
9/15	0.0049	0.9984	0.9959	0.9959	0.9997	0.0064	0.9980	0.9986	0.9911	0.9995
10/15	0.0045	0.9986	0.9962	0.9962	0.9998	0.0045	0.9986	0.9959	0.9968	0.9998
11/15	0.0042	0.9987	0.9966	0.9965	0.9998	0.0044	0.9987	0.9974	0.9956	0.9998



Dataset	True Negative	False Positive	False Negative	True Positive
Training Data	679898	301	229	15840
Testing Data	169777	145	122	39663
Generalisation Data	63, 023	77, 069	10, 980	100, 058

Dataset	Recall	Precision	F1 Score	Accuracy
Training Data	0.985	0.981	0.983	0.997
Testing Data	0.997	0.996	0.996	0.999
Generalisation Data	0. 4494	0. 8630	0. 6032	0. 6497

Conclusion:

In this study, we employed a cost-effective and non-invasive method to diagnose knee abnormalities in elderly individuals by collecting surface EMG (sEMG) signals from healthy and abnormal individuals during gait, standing, and sitting. Our comprehensive approach involved data collection, preprocessing, feature selection and model training. We denoised the raw sEMG signals and trained a Long Short-Term Memory (LSTM) model on a dataset from 22 subjects, subsequently testing it with additional clinical data. The results indicate that the LSTM model effectively detects knee abnormalities, with clinical data confirming its accuracy, precision, and generalizability, thereby offering a promising, reliable, and non-invasive alternative to expensive MRI scans.To acheving the best Generalization accuracy is 64.9% aquracy