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Lower Limb Activity Prediction Using EMG Signals and Broad Learning

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Abstract: **This article provides an improved lower limb activity prediction system using surface EMG raw data and Broad Learning (BL) classifier. The proposed feature is calculated using three main sequential steps; First, convert EMG raw data to several narrow overlapping segments; Second, apply Kaiser window function and short-time Fourier transform for each segment; Third, find the texture analysis of EMG power spectrum. The public UCI database is used for system evaluation. Experiments show that lower limb activity prediction achieved the highest results of** 96% 94%**, and** 90% **for knee abnormal group, normal group, and both groups together, respectively. Moreover, This study proves the possibility of achieving an acceptable activity prediction results in case of mixing normal and knee abnormal groups together.**

Keywords: Lower Limb, Activity,Broad Learning,Prediction, Power Spectrum.

I. Introduction

With the continuous improvement and usage of computerized machines, Human Computer Interface (HCI) has become an increasingly remarkable sign in our daily life. In HCI technology, it is possible to link computers with human biomedical signals such as Electrooculogram (EOG), Electrocardiogram (ECG), Encephalogram (EEG) and Electromyogram (EMG) for providing tremendous useful applications [1, 2, 3].

In general, Electromyography is the study of muscle functionality depending on the tests and analysis of the generated electrical signals from muscles. Actually, Electromyogram (EMG) signal is related to the physiological changes in muscle state of membranes fiber, and appears as released electrical currents and voltages during muscle contraction process [4, 5]. Hence, interpreting EMG signals may give an important information and further physiological performance dimensions for human body [4].

According to the valuable embedded messages behind EMG data, it could be invested to serve important applications such as motor control in robotics and virtual games, abnormality diagnosis, physical therapy, and limbs activity recognition [3, 6, 7, 8, 9, 10, 11, 12].

In fact, intensive researches are trying to enhance the robustness and reliability of HCI lower limb's applications because their EMG data are noised and distorted by human gravity and normal muscle jitter more than the upper limbs [13].

Consequently, in this paper, a new lower limb motion prediction system is provided depending on the texture analysis of EMG power spectrum and Broad Learning (BL) classifier. EMG spectrogram data are obtained using Kaiser function and Short Time Fourier Transform (STFT). Then, the combination of sequential mathematical steps with local range texture filter is utilised to obtain the final extracted feature.

The novel contributions of the proposed prediction system are listed as follows:

1. An improved feature is extracted from the texture representation of EMG power spectrum. Compared with previous related works which used the same UCI database, it enhanced lower limb motion prediction results.

2. The powerful Broad Learning (BL) classifier is used for feature extraction evaluation. The tested experiments prove the validity of BL classifier among other classifiers in terms of getting the most reliable results and minimum training time which is useful in real time applications.

3. Experiments show that lower limb activity prediction reliability among knee abnormal group is better during only the two movements of walking and standing.

4. This study proves the possibility of achieving an acceptable activity prediction results in case of having a mix of normal and knee abnormal subjects together.

The remainder of paper is organized as follows; Section two provides a description of recent and related literature review. Section three presents the proposed work methodology in detail. Section four illustrates the tested experiments, results with analysis and comparisons, and final section mentions the overall conclusion, and suggests possible directions for future work.

II. Literature Review

Lower limb activity prediction is one of the most challenging and interesting intelligent based application [14]. According to its necessary and important applications in several life domains, researchers are competing to increase the prediction reliability performance by improving the power of extracted features, using new classification techniques, and producing hybrid extraction features [14].

Here, a recent related works description are illustrated and analysed. Many recent researchers used the same UCI public database as in this study, for example, Vijayvargiya et al. [15] used two pre-processing filters: wavelet de-noising filter for removing White Gaussian Noise (WGN), and Ensemble Empirical Mode Decomposition (EEMD) filter for removing Power Line Interference (PLI) and Baseline Wandering (BW) distortions/noises. In feature extraction, a total number of nine different time domain features were extracted. Linear Discriminant Analysis (LDA) classifier was constructed to classify walking, standing and sitting motions, and obtained accuracies of 90.69% and 97.45% for both healthy and knee abnormal groups, respectively.

In Gautam et al. [16] study, EMG signals were end-to-end trained to classify walking, standing, and sitting motions using Transfer Learning based on deep Long-term Recurrent Convolution Network (LRCN). Good results of 98.1% and 92.4% were obtained for both healthy and knee abnormal groups, respectively.

In Zhang et al. [17] research, EMG data were segmented, and then decomposed using three different approaches of Empirical Mode Decomposition (EMD), Multivariate EMD (MEMD), and Noise-Assisted MEMD (NA-MEMD). The decomposed Intrinsic Mode Functions (IMFs) were obtained and normalized in each approach, and then, estimated using the spectra analysis. Finally, the number of IMFs, mode-alignment, and mode-mixing criterions were evaluated. The experiments show that NA-EMD approach achieved the better results among the healthy group with accuracies of 79%, 83% and 83% for walking, sitting, and standing motions, respectively.

Herrera et al. [18] extracted time-frequency domain features from EMG signals using wavelet transform and spectrogram. In classification, Multilayer Perceptron-Artificial Neural Networks (MP-ANN) was used among knee abnormality group and got accuracies of 88%, 94%, and 92% for classifying walking, sitting, and standing motions, respectively.

Naik et al. [19] decomposed EMG signals using both Independent Component Analysis with Entropy Bound Minimization (ICA-EBM) technique, extracted several time domain features, and applied Fisher score with statistical models for feature selection. Linear Discriminant Analysis (LDA) classifier was constructed and got a good accuracy of 96.1% and 86.2% for healthy and knee-abnormality subjects, respectively.

Recently, Issa et al. [20] also depended on UCI public database. they derived texture characteristics for EMG spectrum during walking, sitting, and standing movements using Short Time Fourier Transform (STFT) and Convolutional Neural Network (CNN). Their experiments achieved an accuracy of 92% for classifying three motions among normal group, and 95% for classifying only two motions among abnormal group.

Additionally, several studies used other EMG database sources. For example, Ai et al. [13] extracted distinct time domain features with wavelet coefficients. Two ordinary machine learning of Linear Discriminant Analysis (LDA) and Support Vector Machine (SVM) were implemented to predict five different motions, and got an accuracy of 95%.

Laudansk et al.[21] used a collection of time domain and frequency domain features, and neighborhood component analysis for dimension reduction. K Nearest Neighbor (KNN) was constructed to predict different knee flexion postures and produce an acceptable accuracy of 80.1%.

Zhang et al. [22] presented an extraction feature using both Wavelet Transform (WT) and Singular Value Decomposition (SVD). Their system achieved an accuracy of 91.85% for classifying four different motions.

Nazmi et al.[23] worked on five time domain features and Artificial Neural Network (ANN) classifier. They obtained an accuracy of 87.4% for predicting two movements.

Due to the above literature description, it is obvious that it still needs more improvement and enhancement [14]. Most related works depended on extracting a huge dimension of feature extractions, used complicated feature extraction methods, and/or hybrid features to obtain reliable models [13, 15, 18, 19, 21, 22, 23].

III. The Proposed Prediction System

Any prediction system consists of the following stages: Data Acquisition, pre-processing, feature extraction, and classification. Figure 1 illustrates the flow chart of the proposed prediction system. In this section, lower limb prediction system stages will be discussed in detail.

A. Data Acquisition and Pre-Processing

In this study, the public UCI EMG surface database is chosen for evaluating the proposed feature extraction. UCI datast includes EMG recordings for 22 subjects (50% of subjects have knee abnormality). Healthy subjects do not have any preceding case history for knee problems [24].

All subjects were asked to perform three different motions: walking, sitting, and standing. EMG raw data was measured using only four EMG electrodes around the following muscles: Recto Femoral (RF), Femoral Biceps (FB), Vastus Medialis (VM), and Semitendinosus (ST). Additionally, goniometer was attached to the external side of the knee joint [24].

DataLOG MWX8 device of 8 digital channels and 4 analog channels were used for EMG data measuring and recording. A real-time datalog software of Bluetooth technology was implemented to save EMG signals in a computer. Then, data was sampled at 1000 Hz and 14 bit resolution [24].

Pre-processing is necessary before extracting feature stage, hence, a band pass filter of range 10-250 Hz was applied.

Table 1 summarises the public UCI database.

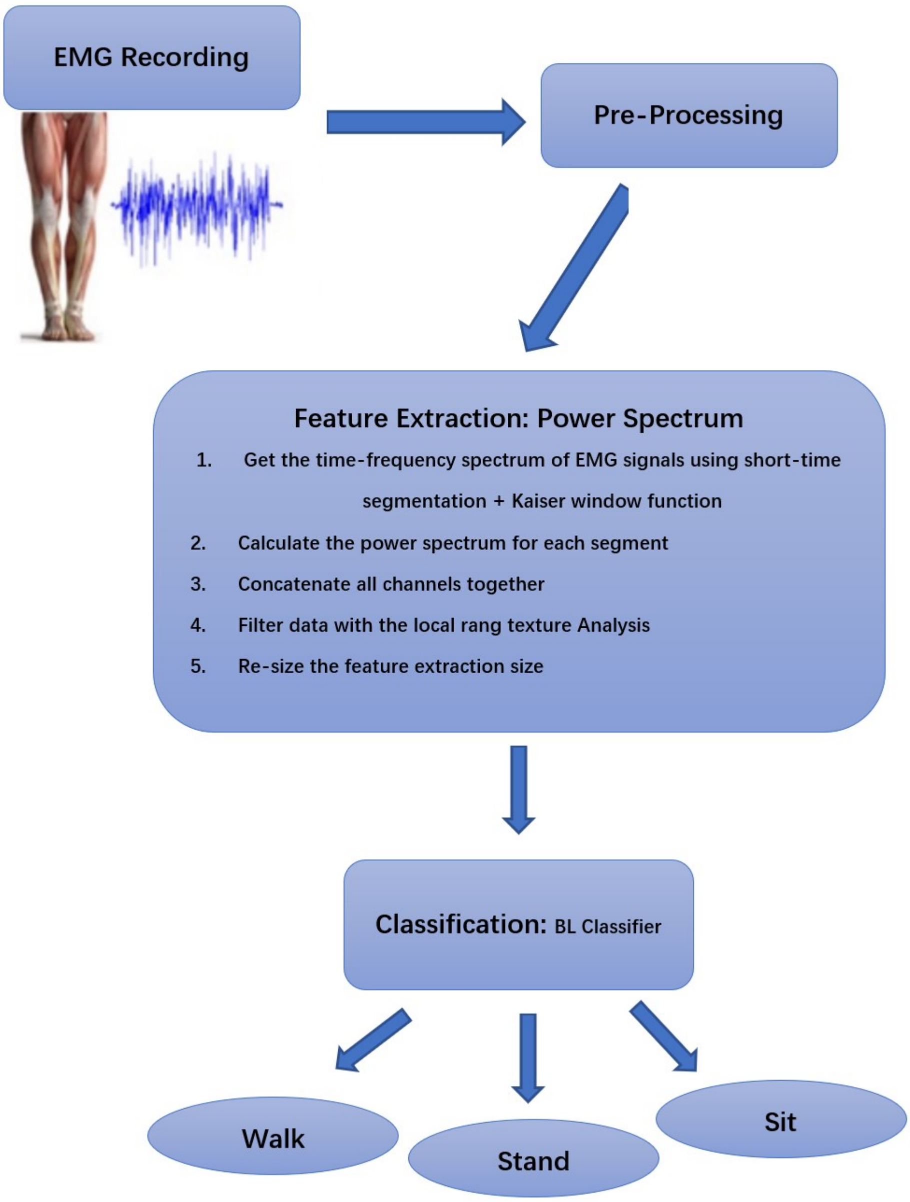


Figure. 1: The Proposed Prediction System

Table 1: UCI Database Summary.

Subjects	22 persons above 18 11 Normal persons 11 Abnormal persons
Number of Channels	4 Channels RF, BF, VM, and ST Muscle
Sample Rate	1k Hz
Acquisition Task	3 motions (Walk, Stand, Sit)
Frequency Range	1-500 Hz
Recorded Device	DataLOG MWX8

B. Feature Extraction

The statistical local range texture for Power Spectrum (PS) magnitudes of EMG raw data is implemented as an extracted feature for the proposed prediction system. Feature calculation can be summarized in the following stages:

1. Split EMG signal into equally and overlapping segments.

2. Calculate the spectrum for each segment using Kaiser window function to get the Short Time Fourier Transform (STFT). The main equation of STFT is given by [25]:

$$STFTx[n](m,\omega) = \sum_{n=-\infty}^{\infty} x[n]\omega[n-m]e^{-j\omega n} \quad (1)$$

   where x(n) is the EMG time domain signal; ω(m) is Kaiser window function, and m is the number of segments. Kaiser window function is defined below [26]:

$$\omega(m) = \frac{M}{I_o\beta}\frac{\sin(\sqrt{(\frac{M\omega}{2})^2-\beta^2})}{\sqrt{(\frac{M\omega}{2})^2-\beta^2}} \quad (2)$$

   where β parameter is the convenient continuous control between side lobe level and main lobe width; and I_o is the zero order modified Bessel function of the first kind.

3. Calculate the signal Power Spectral (PS) for all segments [27].

$$PS = \frac{1}{N^2}|X(f)|^2, f = 0 : N-1 \quad (3)$$

   where PS is the power spectrum; and $X(f)$ is the two sided spectrum of EMG data.

4. Apply the statistical local texture filter to the concatenated power spectrum matrix of the four EMG channels. Eq.4 below describes the statistical local range texture calculation.

$$\begin{aligned} PS[r][c] &= \max(Nhood(PS[r][c],3)) \\ &- \min(Nhood(PS[r][c],3)) \end{aligned} \quad (4)$$

   where r row represents the channel number; c column represents the power spectrum distribution; and Nhood is the neighborhood matrix of size 3×3.

5. Reduce the feature extracted dimension to 4×50 by dividing each power spectrum vector to 50 batches.

$$\forall c \in C[PS' = \max PS(R,c)] \quad (5)$$

   where R row represents the channel number (1-4); c column represents the power spectrum distribution; and C represents the batch number (1-50).

Algorithm 1 below presents the pseudocode of feature extraction calculation.

Algorithm 1 Feature extraction Method

```
procedure FEATURE(EMG)
    X(n) ← EMG
    for m segments do
        Σ_{n=-∞}^{∞} x[n]ω[n − m]e^{−jωn}          ▷ STFT transform Eq.1
        ω(m) = M/(I_o β) · sin(√((Mω/2)² − β²)) / √((Mω/2)² − β²)    ▷ Window function Eq.2
    end for
    for f frequencies do
        PS ← (1/N²)|X(f)|²                          ▷ Power Spectrum Eq.3
    end for
    PS[r][c] ← max Nhood(PS[r][c], 3) − min Nhood(PS[r][c], 3)    ▷ Texture Eq. 4
    for c do
        [PS' ← max PS(R, c)]                        ▷ Reduce Dimension Eq.5
    end for
    return PS
end procedure
```

Furthermore, Figures 2 and 3 give examples of power spectrum extracted feature for normal, and knee-abnormal subjects during the three motions of walking, standing, and sitting, respectively.

C. Classification

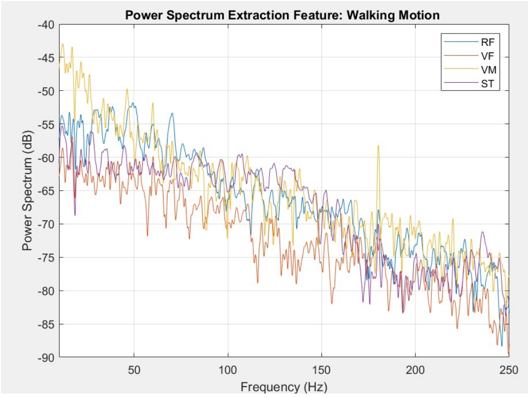
In classification, Broad Learning (BL), deep CNN classifier, and other two ordinary machine learning models were constructed and trained to predict the lower limb movement.

- The new Broad Learning (BL): BL construction is derived from Random Vector Functional Link Neural Network (RVFLNN) [28, 29]. Figure 4 illustrates the flat BL system structure, it contains the following layers: Input layer; Establishment layer; Enhancement layer; and output layer.

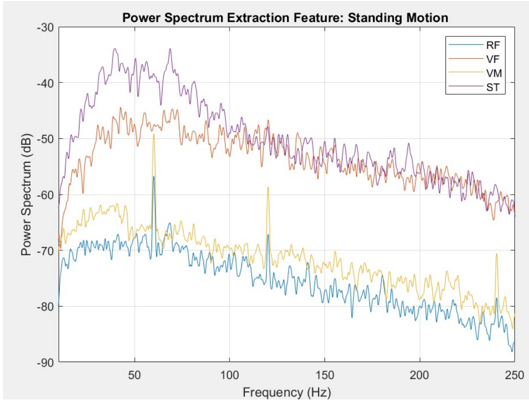
  Input layer X has the size of $N \times M$, where N is the sample size and M is the total features in each sample.

  Establishment layer or Z nodes concatenates and uses the previous input layer according to the following equations [28, 29]:

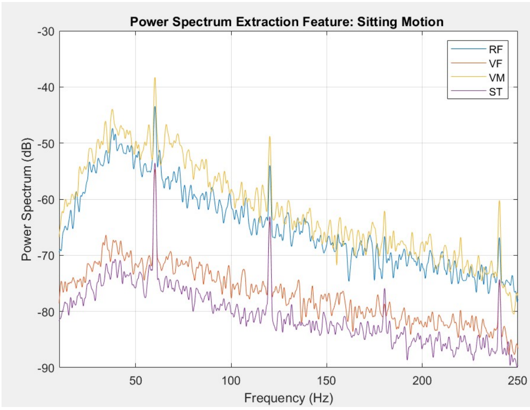
$$Z_i = \phi(XW_ei + \beta_ei), i = 1, ..., n \quad (6)$$



(a) Walking Motion

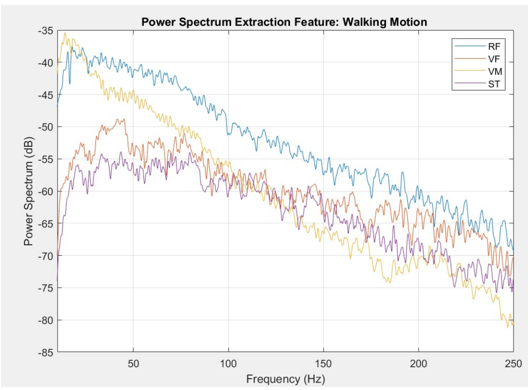


(b) Standing Motion

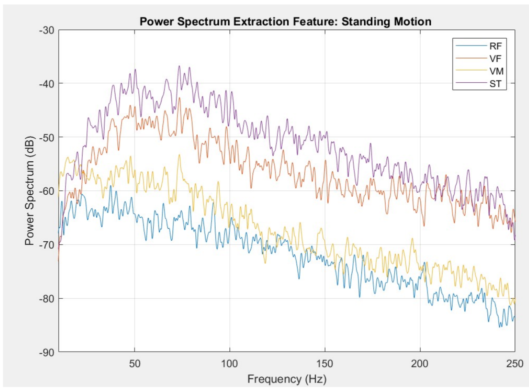


(c) Sitting Motion

Figure. 2: Extraction Feature Example for Normal Group



(a) Walking Motion



(b) Standing Motion

(c) Sitting Motion

Figure. 3: Extraction Feature Example for Knee Abnormal Group

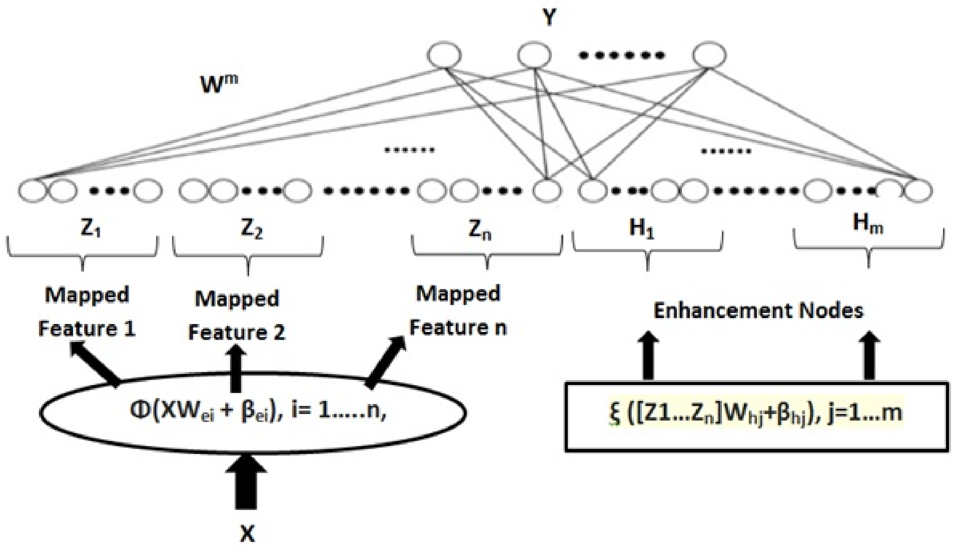


Figure. 4: BL Structure [29]

$$Z^n \equiv [Z_1, ..., Z_n] \tag{7}$$

where ϕ is the transfer function; Wei is a randomly generated weight; β_{ei} is a randomly generated bias; and Z^n is the concatenated Z nodes together.

In enhancement layer or H nodes, a broad concatenation includes the previous layers is calculated using the following equations [28, 29]:

$$H_j \equiv \xi(Z^n W_h j + \beta_h j), j = 1, ..., m \tag{8}$$

$$H^m \equiv [H_1, ..., H_m] \tag{9}$$

where ξ is the sigmoid transfer function; Wei is a randomly generated weight; β_{hj} is a randomly generated bias; and H^m is the concatenated H nodes together.

Finally, output layer Y of size $N \times C$, where C is the class label number [28, 29].

$$\begin{aligned} Y = [Z_1, ..., Z_n \mid \xi(Z^n W_{h1} + \beta_{h1}), ..., \\ ..., \xi(Z^n W_{hm} + \beta_{hm})] W_n^m \\ = [Z_1, ..., Z_n \mid H_1, ..., H_m] W_n^m \\ [Z^n \mid H^m] W_n^m \\ = A_n^m W_n^m \end{aligned} \tag{10}$$

where W_n is the output weight matrix.

After rearranging Eq.10 we get the following one [28, 29]:

$$W_n^m = [Z^n \mid H^m]^+ Y = (A_n^m)^+ Y \tag{11}$$

In this study, the ridge regression of the pseudoinverse [28, 29] technique is used to find the output weight matrix as seen in Eq.12.

$$W_n^m = (\lambda I + AA^T)^{-1} A^T Y \tag{12}$$

$$\arg\min_{\hat{W}} :\| Z\hat{W} - M \|_v^{\sigma_1} + \lambda \| \hat{W} \|_u^{\sigma_2} \tag{13}$$

where $\sigma_2 = 1$, $\sigma_1 = 2$, v and u are norm regularizations; $\hat{W}$ is the sparse autoencoder solution; and Z is the outcome of the linear equation.

Then, the iterative steps in Eq.14 could be used for the proximal problem [28, 29]:

$$\begin{cases} w_{k+1} := (Z^T Z + \rho I)^{-1}(Z^T x + \rho(o^k - u^k)) \\ o_{k+1} := S_{\frac{\lambda}{\rho}}(w_{k+1} + u_k) \\ u_{k+1} := u_k + (w_{k+1} - o_{k+1}) \end{cases} \tag{14}$$

where $\rho > 0$, and S is the soft threshold value which is defined in the below equation [28, 29]:

$$S_k(a) = \begin{cases} a - k, & a > k \\ 0, & \mid a \mid \leq k \\ a + k, & a < -k \end{cases} \tag{15}$$

According to Gaussian elimination method, the complexity computation of BLS training and sparse autoencoder processes are $O(MNC)$ and $O(MN)$, respectively, where N is the number of training sample; M is the number of features in each sample; and C is the number of classes in output layer.

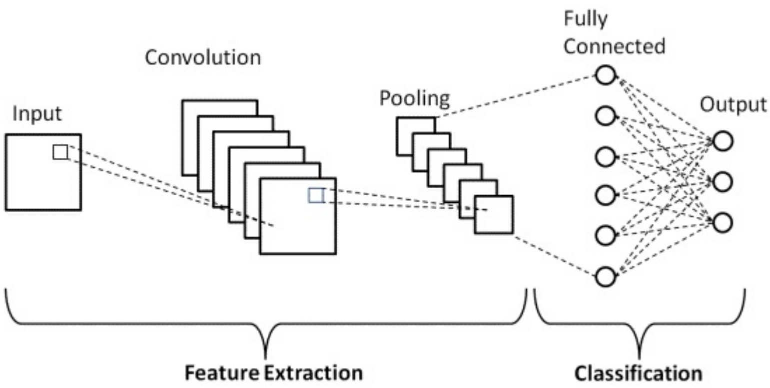


Figure. 5: CNN Structure

- Convolutional Neural Network (CNN): It is organized in a deep three dimensions. Figure 5 illustrates CNN basic structure [30, 31].

  It contains input layer; a basic convolution layer for calculating the neurons which are related to the local parts of previouslayer; pool layer for down sampling the spatial dimension; and fully connected layer for providing the final category or class label [30, 31].

- Support Vector Machine (SVM): It is a common supervised learning classifier in machine learning [32].

  Suppose that X is the training sets or features where X = x1, x2, ..., xi, and Y is the corresponding class labels of X where Y = y1, y2, ..., yi, therefore, Eq.16 should be solved [32].

$$sgn(\omega^T\phi(x_i)+b) = sgn(\sum_{i=1}^{l} y_i\alpha_i K(x_i,x)+b) \quad (16)$$

  where $K(x_i, x)$ represents the kernel function; and $\phi(x_i)$ manipulates with x_i in a higher dimensional space.

- Linear Discriminant Analysis (LDA): It is a generalization of Fisher's linear discriminant [33].

  Its solution principle depends on assuming that the conditional probability density functions of $P(\vec{x}, c) = 0$ and $P(\vec{x}, c) = 1$ are normally distributed, where $\vec{x}$ is the sample features; and c is the corresponding class of $\vec{x}$. As shown in Eq.17 [33],

$$\sum b = \frac{1}{c}\sum_{i=1}^{c}(\mu_i-\mu)(\mu_i-\mu)^T \quad (17)$$

  where μ is the class mean.

IV. Results and Discussion

Power Spectrum (PS) feature matrix of EMG signals was calculated, and has the size of 240x4, 240 is related to to the frequency spectrum range, and 4 is related to the four muscle channels. The proposed feature is down sampled to reduce the dimension to 50x4 by dividing each power spectrum vector to 50 batches.

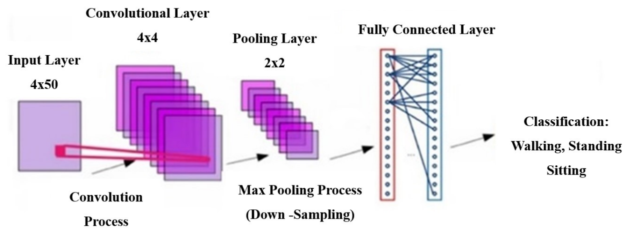


Figure. 6: The Constructed CNN

Ten-fold cross-validation was utilized. Then, Broad Learning (BL), Convolutional Neural Networks (CNN), Support Vector Machine (SVM), and Linear Discriminant Analysis (LDA) were constructed for classification and evaluation purposes.
The parameters for the constructed classifiers are summarized below:

1. BL classifier : Feature nodes are five with ten batches for each feature node. Enhancement nodes number is 3000, sigmoid transfer function is used, and randomly generated weights within the normal distribution of [1, 1] interval.

2. CNN classifier: The specification and parameters are provided in Figure 6.

   It comprises the following layers; Input Layer of size 4×50; Convoloutional layer with filter size of 4×4 and a stride motion of two steps; Pooling layer with filter of size 2×2 and a stride motion of only one step; Softmax lose function in the fully connected layer; and output layer to predict the class category.

3. SVM classifier: Polynomial kernel function

4. LDA classifier: PseudoLinear discriminant.

The evaluation motion prediction system includes three experiments: Motion prediction among Normal group; Abnormal group; and finally, among normal and abnormal groups together.

Tables 2 and 3 provide the experimental accuracy results for normal group, and knee abnormal groups, respectively. Tables 4 and 5 provide the experimental accuracy results for both groups together in case of two and three motions, respectively.
Figures 7 and 8 present the average accuracy of the constructed classifiers in normal and abnormal subject groups, respectively. While, Figures 9 and 10 present the average accuracy of the constructed classifiers in both groups together in case of three and two motions, respectively.

Table 2: Accuracy Results for Muscles in Normal Group

Classifier	RF	BF	VM	ST	All Musc.
BL	85	90	85	80	**90**
CNN	85	85	80	86	85
SVM	70	72	70	70	75
LDA	71	65	66	66	73

Table 3: Accuracy Results for Muscles in Abnormal Group

Classifier	RF	BF	VM	ST	All Musc.
BL	90	85	90	85	**96**
CNN	80	82	88	83	88
SVM	77	70	68	60	80
LDA	70	75	66	67	70

Table 4: Accuracy Results for Muscles in Both Normal and Abnormal Groups: Three Motions

Classifier	RF	BF	VM	ST	All Musc.
BL	81	80	84	81	**85**
CNN	75	75	77	80	80
SVM	60	60	66	60	55
LDA	66	58	55	60	50

Table 5: Accuracy Results for Muscles in Both Normal and Abnormal Groups: Two Motions

Classifier	RF	BF	VM	ST	All Musc.
BL	80.2	80.2	80.2	83.5	**94**
CNN	85	80	75	80	85
SVM	71	72	75	73	70
LDA	65	64	70	69	70

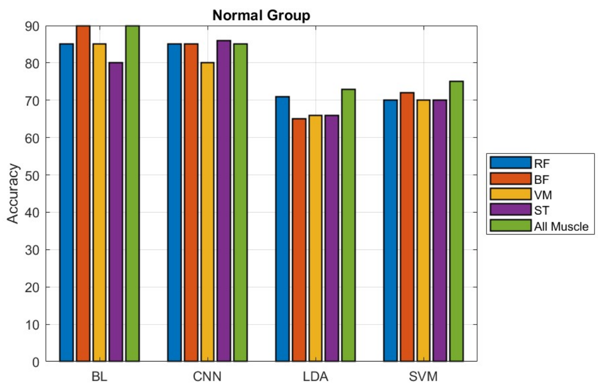


Figure. 7: Accuracy Results for each Muscle in Normal Group

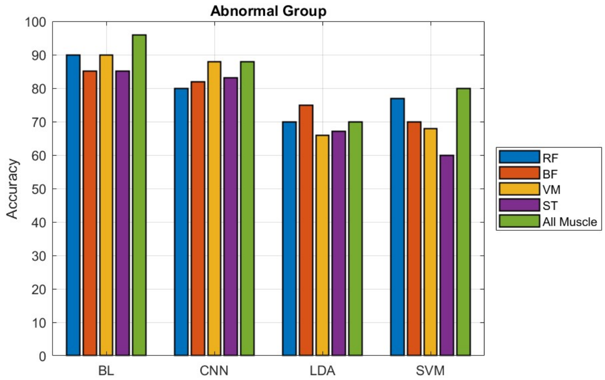


Figure. 8: Accuracy Results for each Muscle in Abnormal Group

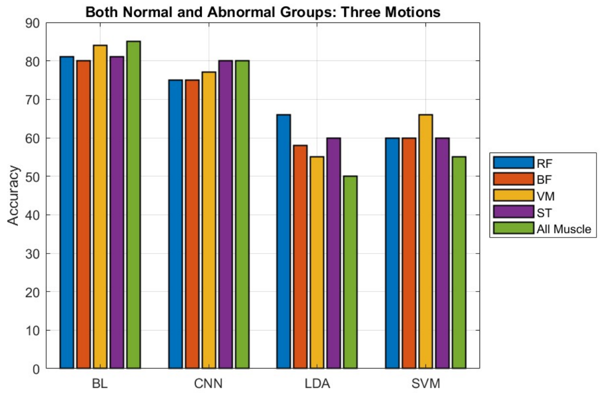


Figure. 9: Accuracy Results for each Muscle in Both Groups: Three Motions

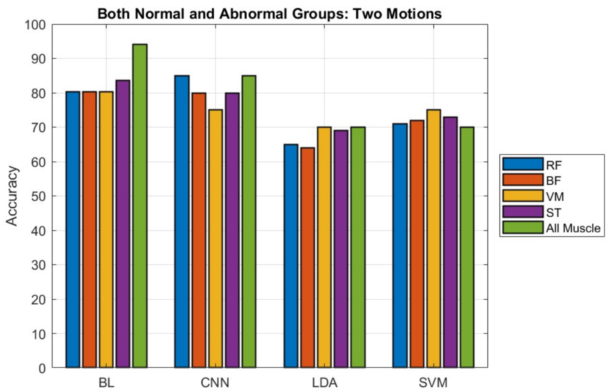


Figure. 10: Accuracy Results for each Muscle in Both Groups: Two Motions

Due on the experimental results, the proposed power spectrum feature shows better results for lower limb motion prediction among abnormal group in case of two motions, followed by normal, and both groups together. Where, the achieved accuracy results are 96%, 94%, and 90%, respectively.
On the other hand, it is clear that the best results are for broad learning, followed by deep learning and ordinary machine learning, respectively. Although deep learning model is considered as a powerful classifier and provide reliable high re-

sults [28, 34, 35], its construction requires a deep dimension layers and complex consuming calculations. Hence, huge calculation space and much time are needed during classifier training [28, 29].
In contrast, the flat and simple structure of BL classifier achieved better accuracy results in all experiments according to its efficient feature learning, as well as, in the proposed system experiment, BL classifier training time is ten times faster than CNN classifier.
Figure 11 below shows the difference in training time consumption between the trained classifiers.

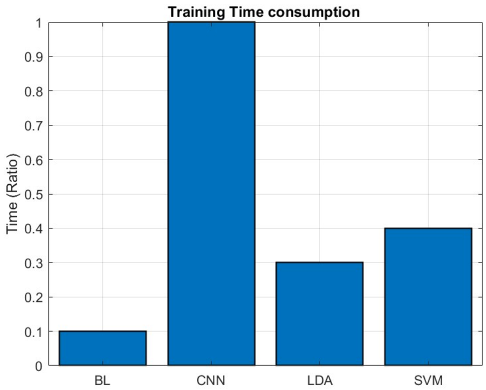


Figure. 11: Training Time Consumption Among Classifiers

Moreover, BL classifier training is flexible, which means that any addition to the database could be treated automatically without re-training all the system again from the beginning as in deep learning [28, 29]. This improved feature suggest to extend our proposed system using variant database during time without slow down the system processing as a future work plan.
Table 6 provides a comparison between the proposed methodology and other recent literature in general, and including the researches which based on our used public database (UCI Database). Compared with other recent studies, the proposed work provides an enhanced extracted feature with less spatial dimension, and higher prediction results without using any complex feature selection methods, and/or support signals [13, 15, 16, 17, 18, 19, 20, 21, 22, 23].

V. Conclusion

The proposed article produces a new extracted feature depending on the texture of EMG power spectrum. In experiments, the constructed Broad Learning (BL) classifier achieved a reliable and good results for both normal, knee-abnormal, and both groups together, respectively. Furthermore, Broad Learning (BL) exceeds the powerful deep Convolutiona Neural Network (CNN) in terms of much lower training time consumption. In future work, the proposed method will be expanded to be applied in real time applications, as well, further experiments are needed to enhance the system reliability.

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Table 6: Comparison between the Proposed Methodology and other Recent Approaches

Study	Method	DB	Results
[19] 2018	Several Time Domain Features	UCI	LDA, 3 Motions 96.1% Normal 86.2% Abnormal
[13] 2017	Wavelet Coefficients	Other	LDA,SVM, 5 Motions 95% Normal
[21] 2021	Time Domain Features + Frequency Domain Features	Other	KNN 80.1% Normal
[22] 2017	Wavelet + SVD	Other	KNN, 4 Motions 91.85% Normal
[23] 2019	Several Time Domain Features	Other	ANN, 2 Motions 87.4% Normal
[20] 2021	Time-frequency + Texture Filter	UCI	CCN 92% Normal 3-Motions 95% Abnormal 2-Motions
[15] 2021	Time Domain	UCI	LDA 3 Motions 90.69% Normal 97.45% Abnormal
[16] 2020	End-End Transfer Learning	UCI	LRCN 3 Motions 92.4% Abnormal
[17] 2017	NA-EMD	UCI	LRCN 3 Motions 81.66% Normal
[18] 2015	Time-Frequency Domain	UCI	MP-ANN 3 Motions 91.3% Normal
Proposed	Power Spectrum + Texture Filter	UCI	BL 3 Motions 90% Normal 96% Abnormal 2-Motions 94% Both Groups

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