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Comparison of Artificial Neural Network and Regression Models to Diagnose of Knee Disorder in Different Postures Using Surface Electromyography

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Abstract

The surface electromyography (sEMG) is useful tool to diagnose of knee disorder in clinical environments. It assists in designing the clinical decision support systems based classification. These systems exhibit complex structure because of sEMG data obtained at different postures at this study. In this context, we have researched the classification performance of each posture using artificial neural network (ANN) and logistic regression (LR) models and have showed that the classification success of the model used sitting posture data is higher than other postures (gait and standing). We have promoted this finding by using machine learning and statistical methods. The results show that the proposed models can classify with over 95% of success, and also the ANN model has higher performance than the LR model. Our ANN model outperforms reported studies in literature. The accuracy results indicate that the models used the only sitting posture data can exhibit successful classification for the knee disorder. Therefore, the usage of complex dataset is prevented for diagnosing knee disorder.

1. INTRODUCTION

The knee deformations are very common health problem that causes movement limitations. Treatment period of this deformations increases requirements of the physiotherapy and rehabilitation. The aim of the treatment period is improving the life quality with pain reduction, and also is assignment of truth treatment technics. There are many known clinical process to diagnose knee deformations. Some of them are Varus stress test, the Lachman test, posterior drawer test, slump test, radiographic examination and electromyography (EMG). In clinical process, EMG is the most referenced method since it gives significant findings related with myopathy [1,2].

EMG is a diagnostic procedure that assess the health of muscles and also the nerve cells which control muscles activities. These nerve cells, known as motor neurons, make the muscles' contraction and relaxation, by transmitting electrical signals. These signals are converted into graphs or numbers in EMG recordings to make accurate diagnosis. EMG recordings can be obtained by two different methods (invasive or not) based on the type of electrodes used in recording and excitation. One is surface EMG (sEMG), which is recorded with use of non-invasive electrodes, and the other is intramuscular EMG recorded by invasive electrodes. Nowadays, it is more preferable to use sEMG recording to obtain information about the time or intensity of superficial muscle activation [2]. Both specialists and engineers make use of these EMG recordings to comprehend the human body's behaviors under normal and pathological situations. But EMG recordings are affected by different types of noises such as movement artifacts, inherent noise of electrodes, electromagnetic noise. Therefore, the comprehension of EMG recordings are carried out by three significant stages that comprise of data pre-processing, feature extraction, and classification [3-5].

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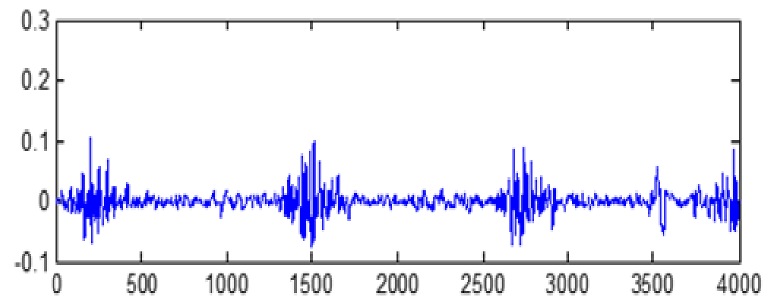
In literature, one can find many studies about analysis of EMG recordings. Abou-Chadi et al. (2001) combined the parametric modeling of sEMG algorithms which use automatic sEMG feature extraction and artificial neural networks (ANN) to both analysis and classify the myopathic disorders [6]. They have investigated the performance of three different algorithms of ANN by comparing with the old fisher linear discriminant (FLD) classifier and have shown that ANN models exhibit higher performance. Tepe et al. (2012) have developed a system that can estimate the hand’s opening and closing speed using support vector machine (SVM) algorithms for three different speeds [7]. The accuracy performance of the system is evaluated by K-fold cross-validation analysis with 96% success. Herrera-González et al. (2015) proposed a medical decision support system to examine and classify knee injuries with artificial neural network using sEMG and goniometric signals [2]. They have shown that sEMG recordings are quite successful to give information about the muscle performance and also the best classification performance is observed, when the model of ANN used sEMG and goniometry signals. Cai et al. (1999) have studied the classification of EMG signals obtained from the forearm motion (hand grasp, hand extension, forearm supination and forearm pronation) using ANN with wavelet transform method [8]. They obtain the classification accuracy of 90% with the proposed model. Jiang et al. (2005) have used wavelet transform method to classify six finger movements [9]. They have indicated that proposed method is an alternative approach for controlling prosthetic hand finger movements with performance over 80%.

The literature surveys leave us with the impression that there are no any studies that classify of sEMG recordings obtained from the different postures. Therefore, in this study, we exhibit ANN and LR models used wavelet feature extracting method for the classification of the muscle disorders. And also we compare ANN model with LR model examining the statistical performance of both models with the confusion matrix.

2. EXPERIMENTAL

2.1. sEMG Dataset

The dataset which consists of knee sEMG recordings of twenty-two subjects measured from three different postures were taken from UCI database [10]. The obtained dataset for each posture (gait, standing and sitting) includes 22 samples and two classes (normal: 11, abnormal: 11). Each sample has 33 features calculated with wavelet transform. Figure 1 and 2 show example of the normal and abnormal sEMG recordings in each posture, respectively.



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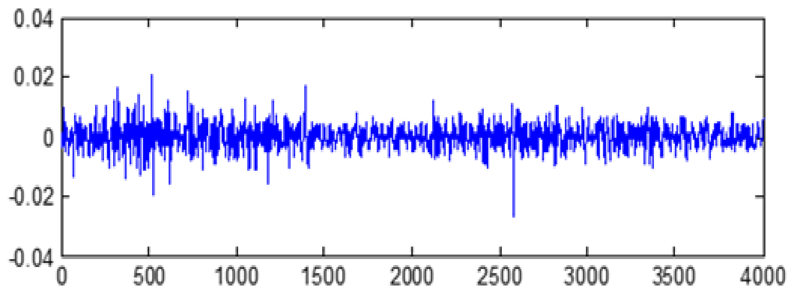

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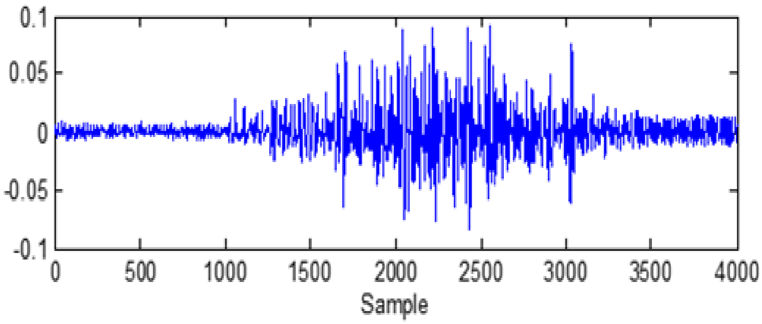

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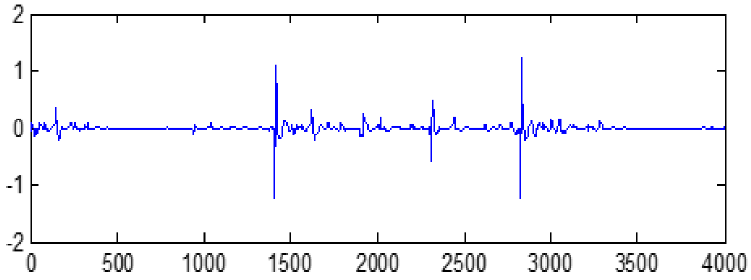
Figure 1. *sEMG signals taken from normal subject for each postures; a) Gait, b) Standing, c) Sitting*



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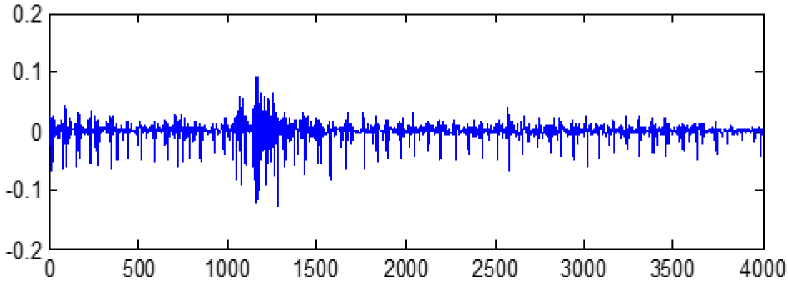

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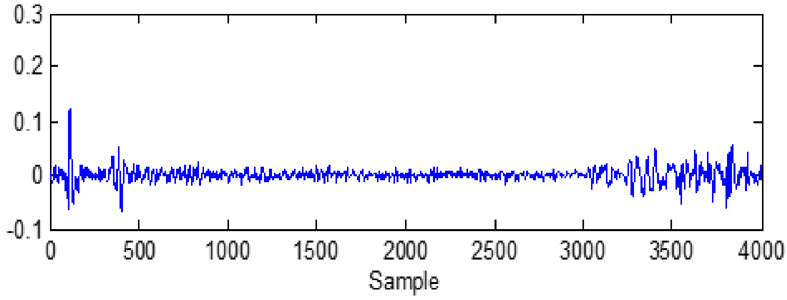

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Figure 2. *sEMG signals taken from abnormal subject for each postures; a) Gait, b) Standing, c) Sitting*

2.2. Discrete Wavelet Transform (DWT)

Wavelet transform is derived as an alternative method for the conventional Fourier transform. The most significant advantage of wavelet transform is the usage of different windows size in high and low frequencies. This gives an optimum time-frequency resolution in whole frequency-domain. Wavelet transform is further classified as discrete and continuous forms. In biomedical signal processing, discrete form is more preferred than continuous due to structures of biological signals. The computing of wavelet coefficients is both difficult and time consuming, therefore, the original signal is divided a certain scale, named as “Multiresolution Decomposition”, by wavelet transform (Figure 3) [11].

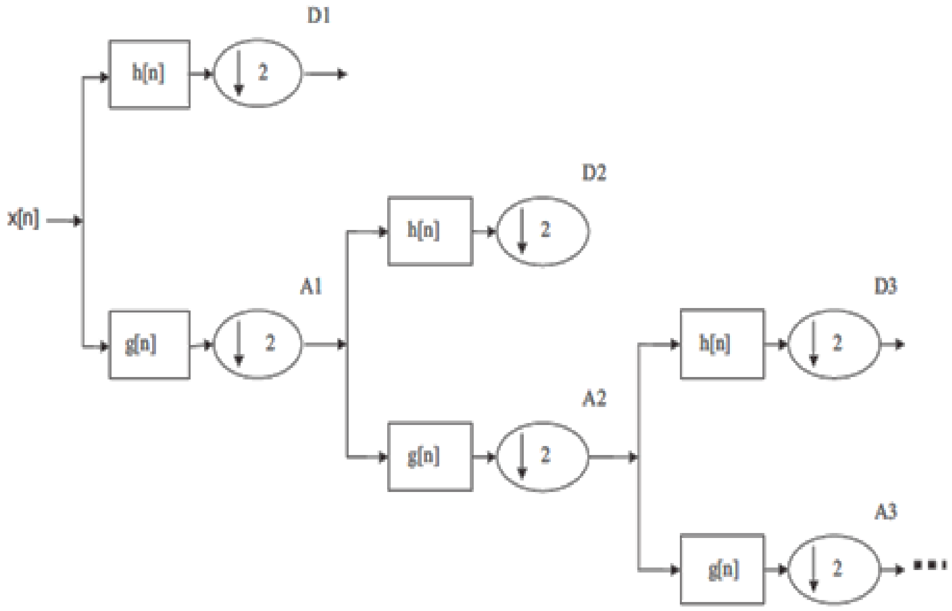

Figure 3. *Decomposition with sub-bands by DWT method [12]*

As seen in Figure. 3, the original signal (x[n]) is first passed over a high pass filter (g[n]) and a low pass filter (h[n]) to obtain the detail (D1) and approximation (A1) coefficients, respectively. Then, the same process is continued up to defined decomposition level only for approximation coefficients. Determination of the decomposition level selected by the signal's dominant frequency and also wavelet type are the most important steps in analyzing of a signal [13]. Although various types of wavelet have been characterized, Daubechies wavelet (DB5) is used for calculating wavelet coefficients of sEMG recordings in this study. The calculated coefficients are taken as feature vectors. Because of high-dimensional of feature vectors, the statistical properties are carried out to reduce the vectors' dimension as follows:

(1) Standard deviation of the coefficients in each sub-band.
(2) Maximum of the coefficients in each sub-band.
(3) Mean of the absolute values of the coefficients in each sub-band.
(4) Variance of the coefficients in each sub-band.
(5) Minimum of the coefficients in each sub-band.

The statistical properties of the extracted feature vectors are shown in Table 1.

Table 1. *The statistical properties of the extracted feature vectors*

Features	GAIT					STANDING					**SITTING**				
	Mean	Deviation	Variance	Min	Max	Mean	Deviation	Variance	**Min**	**Max**	**Mean**	**Deviation**	**Variance**	**Min**	**Max**
F1	0.066191	0.017072	0,000291	0.047059	0.118731	0,049526	0,024421	0,000596	0,020381	0,105777	0,042544	0,022471	0,000505	0,01444	0,079071
F2	0.694668	0.411969	0,169718	0.212132	1.767767	0,342529	0,147878	0,021868	0,141421	0,636396	0,346174	0,195253	0,038124	0,070711	0,862317
F3	3.98E-05	0.000555	3,08E-07	-0.00128	0.000877	-9E-05	0,000359	1,29E-07	-0,00057	0,001119	7,59E-05	0,000289	8,37E-08	-0,00043	0,000654
F4	0.00466	0.002658	7,07E-06	0.002215	0.014097	0,003022	0,002977	8,86E-06	0,000415	0,011189	0,002292	0,002009	4,04E-06	0,000209	0,006252
F5	-1.79602	5.231549	27,3691	-25.1023	-0.21213	-1,902	5,03529	25,35414	-19,1626	-0,14142	-0,34711	0,174026	0,030285	-0,6364	-0,08803
F6	0.13369	0.024317	0,000591	0.084804	0.200138	0,072956	0,019803	0,000392	0,043505	0,107664	0,091853	0,14422	0,020799	0,030039	0,708617
F7	1.272348	1.010341	1,02079	0.5	4.95	0,53783	0,143648	0,020635	0,3	0,8029	2,468339	9,258038	85,71127	0,2	43,9
F8	0.000168	0.001254	1,57E-06	-0.00268	0.003038	-0,00037	0,000606	3,67E-07	-0,00118	0,001664	-0,00014	0,000916	8,38E-07	-0,00285	0,001787
F9	0.018437	0.007033	4,95E-05	0.007192	0.040055	0,005697	0,003159	9,98E-06	0,001893	0,011592	0,028291	0,106447	0,011331	0,000902	0,502138
F10	-2.1125	3.761457	14,14856	-17.65	-0.55	-1,58949	3,456302	11,94602	-13,4	-0,336	-5,82641	25,10005	630,0126	-118,2	-0,2
F11	0.387009	0.085806	0,007363	0.204823	0.556484	0,246744	0,238621	0,05694	0,102029	1,219051	0,409152	0,433744	0,188134	0,076532	1,525013
F12	3.609941	3.55245	12,6199	1.378858	13.82394	4,783283	12,50302	156,3254	0,540406	56,88674	13,04249	28,40859	807,0481	0,467751	96,72422
F13	4.41E-05	0.004034	1,63E-05	-0.00649	0.010118	-0,00072	0,001746	3,05E-06	-0,0054	0,001495	-0,00108	0,003602	1,3E-05	-0,01206	0,004181
F14	0.156804	0.068824	0,004737	0.041952	0.309675	0,115235	0,311856	0,097254	0,01041	1,486086	0,346988	0,59422	0,353098	0,005857	2,325664
F15	-10.5782	18.10726	327,873	-66.4457	-1.44957	-9,80706	28,58648	817,1869	-133,506	-0,6364	-31,3799	46,90853	2200,41	-123,107	-0,42426
F16	1.061067	0.371771	0,138214	0.545213	2.500325	0,609963	0,546795	0,298985	0,209941	2,794655	0,750443	0,565604	0,319908	0,20938	2,159851
F17	8.566874	8.166423	66,69046	3.2	39.15	4,94	8,053754	64,86295	1,225	38,6	11,20749	20,15892	406,382	1,15	68,21935
F18	-0.00064	0.014426	0,000208	-0.04617	0.028912	-0,00345	0,008794	7,73E-05	-0,04088	0,002563	-0,00278	0,009469	8,97E-05	-0,02016	0,019895
F19	1.257795	1.180307	1,393125	0.297257	6.251627	0,65745	1,636816	2,679168	0,044075	7,810097	0,86853	1,216092	1,478879	0,04384	4,664956
F20	-17.1637	23.06152	531,8338	-92.6292	-3.7	-17,293	41,01577	1682,293	-175,951	-1,425	-45,2342	61,49194	3781,259	-176,875	-1,05
F21	3.170353	1.209621	1,463182	1.506971	6.141257	1,467883	0,796717	0,634758	0,542331	3,871103	2,499239	1,303729	1,699708	0,602784	4,539525
F22	24.84205	26.29546	691,4512	8.997934	129.542	11,18213	11,44075	130,8907	3,394113	53,18984	44,43352	70,75939	5006,892	3,181981	227,9584
F23	-0.00948	0.046919	0,002201	-0.13866	0.068461	-0,00777	0,014583	0,000213	-0,05386	0,018376	-0,01309	0,043373	0,001881	-0,0828	0,081003
F24	11.44781	9.723735	94,55103	2.27096	37.71504	2,760586	3,401573	11,5707	0,294123	14,98544	7,868645	6,571145	43,17995	0,363348	20,60729
F25	-49.781	57.97003	3360,525	-204.584	-9.77575	-25,3582	46,9606	2205,298	-200,223	-4,06586	-97,854	79,95298	6392,479	-223,925	-3,55321
F26	62.20742	11.05267	122,1615	48.73355	85.26667	151,0428	21,41367	458,5451	108,6187	191,4352	119,708	23,52774	553,5545	74,89023	197,868
F27	259.6745	142.7077	20365,48	0.105677	415.1954	412,1189	266,9797	71278,18	0,144762	685,6814	315,6316	208,6636	43540,49	0,06889	637,3153
F28	12.34616	20.25017	410,0694	-32.8084	50.4285	27,17994	53,48314	2860,446	-68,9688	79,17608	21,41821	46,91535	2201,05	-61,9099	82,45266
F29	3986.371	1467.342	2153093	2374.958	7270.406	23251,63	6479,101	41978751	11798,03	36647,43	14858,4	6466,348	41813654	5608,546	39151,74
F30	-105.974	154.6909	23929,29	-391.649	-0.16529	-198,897	293,7162	86269,23	-734,878	-0,08966	-146,555	219,664	48252,29	-538,815	-0,04428

2.3 Artificial Neural Network (ANN)

ANN, which is a topology constructed with adaptive processing nodes (neurons), is a mathematical approach inspired from the human brain activities. This topology is created adding different weighted feed forward connections between neurons. Multi-Layer perceptron network (MLP), which is generally composed with three layers: input, output and hidden layer, is the most common ANN topology. The interconnected neurons in MLP performs parallel computation between layers to process knowledge. This data processing period named as training is iterated up to obtain desired output with minimum error [14,15]. The training phase can be used different learning algorithms such as back-propagation [16,17], Quasi-Newton [18] and Levenberg-Marquardt [19]. The general form of output and error functions of MLP are defined as follows:

$$y_i = f\left(\sum_{i=1}^{N}(w_{ij}x_i + b_i)\right) \tag{1}$$

$$Er = \frac{1}{N}\sum_{i=1}^{N}(d_i - y_i)^2 \tag{2}$$

Where xi is the input data, wij is weights, f( ) is activation function, yi is the network output, bi is bias value of neuron, and di is the desired output. The MLP topology used in this study is shown in Figure 4.

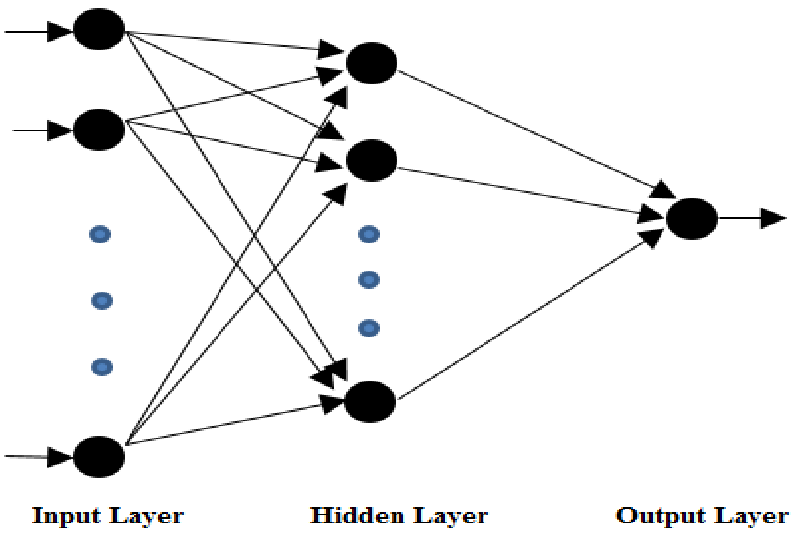

Figure 4. *Neural network structure*

2.4 Logistic Regression (LR)

Logistic regression emerged with the generalization of the linear regression is a predictive mathematical analysis method. It describes the relationship between independent variables and dependent variable [20]. The largest difference of logistic regression from the linear regression model is the discrete or discontinuous dependent variables to predict desired responses. The advantage of logistic regression is that the independent variables can be defined as Boolean, numerical and proportional scale [21]. The logistic regression model equation is given below:

$$\log\frac{p(x)}{1-p(x)} = \beta_0 + \sum_{i=1}^{n}x_i\beta_i \tag{3}$$

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The equation for which the solution is obtained for the p parameter:

$$p(x;b,w) = \exp(\beta_0 + \sum_{i=1}^{n} x_i \beta_i) \tag{4}$$

where β is the coefficient of predictor values.

3. RESULTS and DISCUSSION

We consider a clinical decision support system based on ANN to detect the muscle disorders originating from knee injuries. As a first step, we have extracted features with wavelet transform used Daubechies wavelet (DB5). In feature extracting process, for each sEMG signals, the wavelet coefficients are obtained by dividing into sub-band frequencies: approximate coefficient (A5) and detail wavelet coefficients (D1-D5). Then fifth statistical features expressed in the material and method section are calculated each the wavelet coefficients. Hence the dataset is derived with 30 features and 66 samples. As a second step, we have constructed an ANN topology with 30 inputs, one output and one hidden layer. We analysis performance of the topology by selecting the neuron number of hidden layer between 8 and 25 and the result is given in Figure 5.

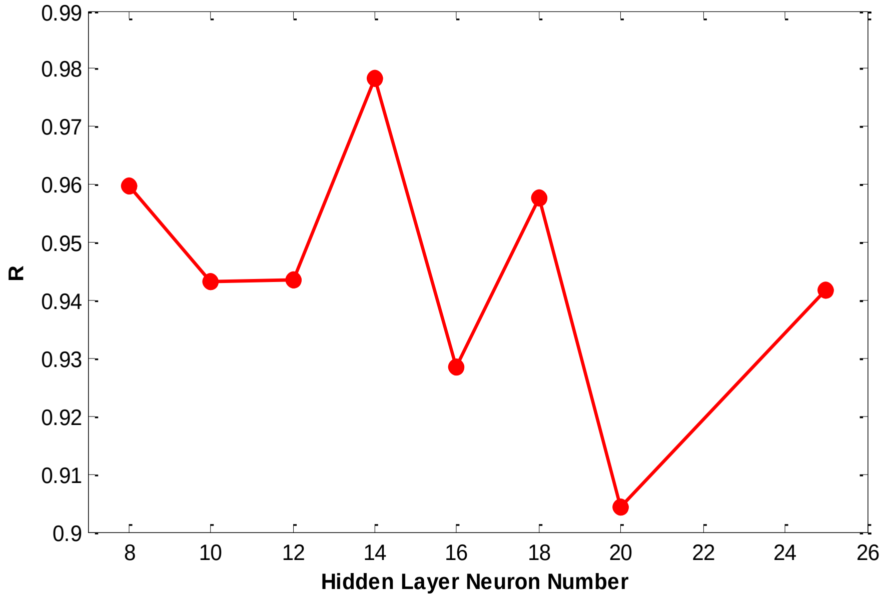


Figure 5. *The performance of ANN topologies*

As seen Figure 5, the best performance is obtained with the topology having 14 neurons in hidden layers. Therefore, this topology is focused in the rest of the work. As a third step, training and test processes using 10-fold cross-validation method are applied for dataset percentages (training: 70%- test: 30%). In this process, the dataset with 66 samples is normalized by min-max method in the range [0-1]. After training phase, the ANN model is tested with test dataset. To obtain the statistical performance of the model, the accuracy analysis (the confusion matrix) is realized for each posture (gait, standing and sitting) and the test results are given in Table 2. It is seen that the ANN model shows the more robust character for sitting posture (100%) than gait and standing posture (95%).

Table 2. *Statistical performance results of the ANN model*

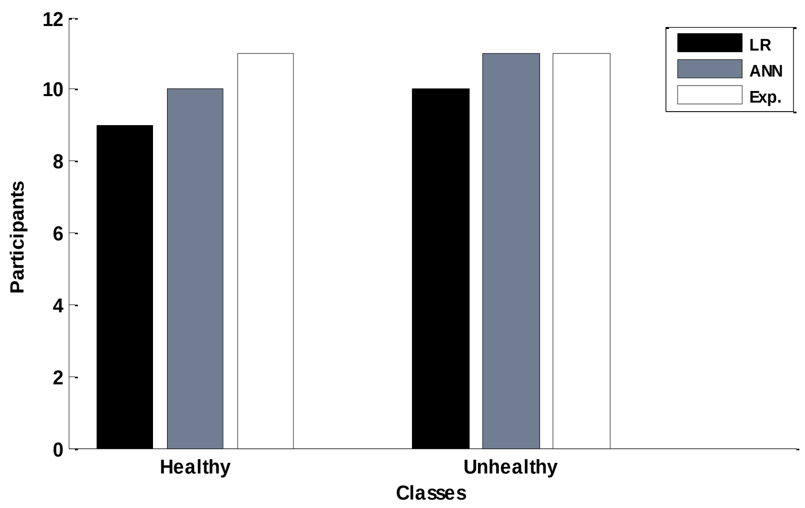
	Statistical Parameters (ANN)		
Position	**Sensitivity (%)**	**Specificity (%)**	**Accuracy (%)**
Gait	100	90	95
Standing	90	100	95
Sitting	100	100	100

In addition, the logistic regression (LR) is a powerful statistical method for modeling binomial results and is used commonly for prediction problems. Therefore, we have used LR method to compare with the ANN model. The LR model is trained and tested with the dataset. The performance of the model is given Table 3.

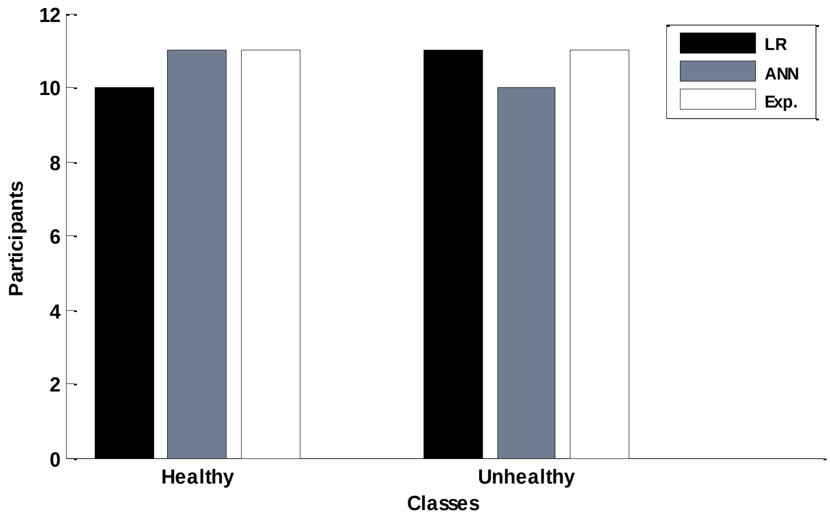
Table 3. *Statistical performance results of the LR model*

	Statistical Parameters (LR)		
Position	**Sensitivity (%)**	**Specificity (%)**	**Accuracy (%)**
Gait	86.4	13.6	86.36
Standing	90.9	9.1	90.91
Sitting	95.5	4.5	95.45

As seen in Table 3, the LR exhibits the more performance for sitting posture (95.45%) than gait (86.36) and standing posture (90.91%). The ANN model operate more successfully performance of classification for difference postures (accuracy= 95%, 95% and 100%, respectively) than the LR model (accuracy = 86.36%, 90.91% and 95.45% respectively), and also average sensitivity and specificity of the ANN are 98.3%. Average sensitivity and specificity of the LR model are 90.93%, 9.06%, respectively. Finally, the graphical presentation of the accuracy analysis for each the models are shown in Figure 6.



(a)



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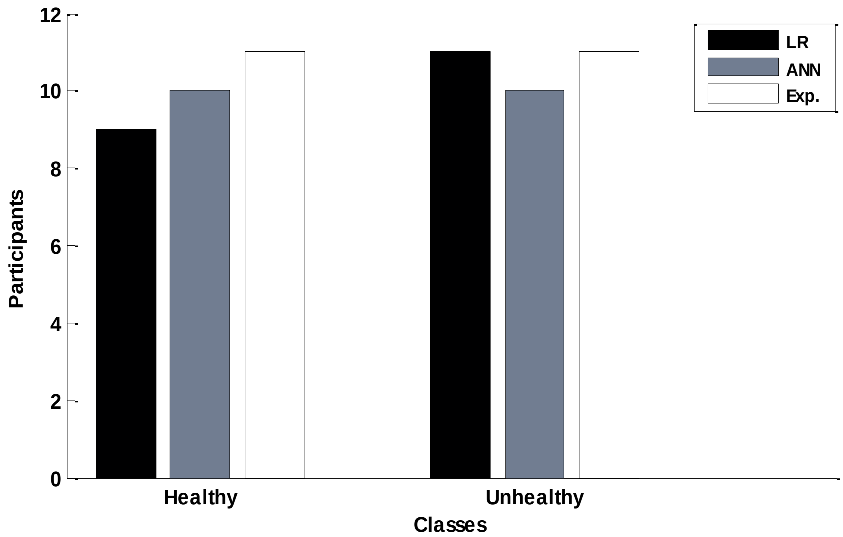

(c)

Figure 6. *The graphical presentation of models performance for each postures; a) Gait, b) Standing, c) Sitting*

It seems that sEMG recordings are comprised of important findings about giving a decision of the knee disorder. In this study, sEMG recordings measured from different postures (gait, standing and sitting) are used to determine which posture is more satisfactory to diagnose knee disorder by physicians. To do this, first, the features of sEMG are extracted by using the discrete wavelet analysis for each posture. An ANN and statistical LR model are proposed used these features to classify of disease.

In the light of all the findings, the average classification performance of the ANN model is obtained higher than the LR models for each posture measurements. When the classification performance of posture is analyzed, it seems that the best performance of models is obtained for the sitting posture. The ANN model exhibits 100% success rate and the LR model exhibits 95.45% success rate. In sum, we showed that sEMG which is measured from sitting posture without using the other postures, can be used to diagnose the knee disorder properly. In this way, the usage of excessive data has been prevented in designing of decision support systems. On the other hand, the proposed analysis may also give new perspectives for diagnosis of the knee disorder.

CONFLICTS OF INTEREST

No conflict of interest was declared by the authors.

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