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Original Article

Elbow Joints for Upper-Limb Prosthesis: Analysis of Biomedical EEG Signals using Discrete Wavelet Transform

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Abstract - *Signal classification is an essential feature in cognitive science, which separates large datasets into classes based on frequency. This research was conducted to analyze the brain signals by signal classification using a convolutional neural network (CNN) to obtain the required frequency spectrum. The signals can be used for upper-limb prostheses, especially elbow joint applications. The feature extraction process is an important step in brain signal classification. During the current study, electroencephalography (EEG) signals are extracted using a 10-20 electrode system from the flexion and extension movement of the elbow joints. Using MATLAB tools, it is done through a user interface. The expected performance is obtained as an exact parameter analysis, e.g., the classifier's precision, simplicity, and sensitivity using a convolution neural network should be connected as a benchmark for applications for the upper-limb prosthesis.*

Keywords - *Convolutional Neural Network, Elbow joint, Electroencephalography, Prosthesis, Signals.*

1. Introduction

Electroencephalography (EEG) is a technique of brain signal acquisition that enables the understanding of the brain's complicated internal machinery and abnormal brain waves associated with different brain malfunctions[1,2]. EEG examination is essential for treating significantly different symptoms and signs in the brain[3,4]. MATLAB offers a graphical user interface allowing users to channel their high-density EEG dataset [5] interactively. The EEG element technology has been slowly enabled for its great theoretical value and practical application. Its classification accuracy is used as an evaluation criterion to demonstrate the current system's effectiveness [6]. Brain signal classification is derived using certain previous information such as strength and other features[7]. There are currently no generally accepted methods; therefore, automated and accurate detection methods are greatly needed and important.

Convolutional Neural Network's use in classifying data for the elbow joint EEG signals issues is not yet fully exploited. The data collection of EEG signals is performed in this project using a 10 – 20 electrode device in which all the electrodes are positioned on the scalp at different points. Such scalp electrodes record the EEG using a computer known as an electroencephalograph[8-10]. An experiment was conducted to acquire EEG data from subjects while conducting normal and motion signals with the open eye of the elbow joint, including flexion and extension, to obtain the frequency domain. The extraction function of both signals is produced via the Discrete Wavelet Transform (DWT) method[11,12]. The parameter analysis obtained from the signals is further processed by classification, using the neural network convolution in deep learning[13]. Using Alexnet, which offered better classification accuracy and sensitivity, the feature's information from the data was extracted using CNN [14-16].

Browsed as the sample, this input signal is pre-processed to filter the noise signals[17]. The DWT analogous to discrete filter banks should filter sub-bands before extracting the function. DWT plays an important role in signalling and image processing applications. Most researchers use various wavelet toolboxes for their application and analysis[18-20].

The next phase of EEG signal analysis is the extraction of features, where different signal processing techniques such as DWT are used to obtain features of the signal. The time-frequency domain allows for the simultaneous extraction of information in both domains; EEG analysis is based on the processing technique of time-frequency images which maps the signal into a two-dimensional frequency and time function[21,22]. This section presents a review of the literature using the Gray Level Co-occurrence matrix (GLCM) to extract features of EEG signals[23,24].

This research study aims to classify the elbow joint EEG brain signals to distinguish between normal and movement EEG signals from normal people to acquire better classification accuracy. Using a CNN in the classification process, the values are trained after extracting the feature to classify the signals together to get the parameter analysis. The validation values for future applications of upper limb prosthesis and rehabilitation are taken as reference values. In this study, the system uses the convolutional neural network for signal classification using Alex net, which follows the supervised training and non-knowledge-based classification. For Neural network training, the principal statistical features will be extracted with the help of database samples[25]. The database sample will be classified using network parameters and feature extraction values. The system gives better performance accuracy for both normal and movement signals together.

2. Experimental Methods

2.1. Preprocessing

Occasionally called post-processing, referring to being after purchase. Removal of unnecessary signals here is being taken[26,27]. The median filtering is mainly used to minimize the noise in an input signal, like the filtering process[28,29]. The key goal of the task is to discover the parameter analysis of available EEG data sets of the signals and other data acquisition techniques, pre-processing procedures, feature extraction methods, and the analysis of the results was implemented via the classification using Alexnet.

2.2. Discrete Wavelet Transform (DWT)

For numerous common signals, the DWT provides an inadequate representation. In other words, the important features of many natural signals are represented by a subset of DWT coefficients typically much smaller than the original one. This will 'compress' the signal. In the case of the DWT, usually, a few big DWT coefficients catch the suspense signal, while the noise generates several small DWT coefficients, which can be thrown away [30-32].

2.3. Feature Extraction technique

EEG analysis is based on the processing technique of the time-frequency image or spectrogram, a method widely used in the short-term transformation of the Fourier, which maps the signal into a two-dimensional frequency and time function. This section summarizes the literature using GLCM to extract features of EEG signals[33-35]. Using Gray co matrix feature to build a GLCM. Since the signal processing needed for calculating a GLCM is restrictive for the maximum dynamic values of the signals, the gray matrix scales the input image.

2.4. CNN Classification

Convolutional neural networks reflect a generalization of methods used to process 1-D or 2-D signals (filtering, classification, etc.). Deep learning training normally needs a large number of data sets to be successful[9,22]. However, few EEG signal data are unlabelled, and the Classification process can be very difficult or even impossible manually. Convolutional neural network (CNN) architecture for EEG signal classification is proposed to address these challenges.

2.5. MATLAB

MATLAB is a technical-computing language of high performance. In a setting where questions and plans are expressed in common scientific notation, it integrates calculation, visualization, and programming, which is simple to use and assists the entire process of data analysis from acquiring databases employing Graphical User Interface, Pre-processing, Discrete Wavelet Transform sub-bands to render values the extraction of the function. It includes numerical, mathematical, and capability architecture to assist basic building and science activities since the processor libraries are designed for the various platforms supported by MATLAB[36-38].

3. Results and Discussion

The proposed system approach was tested around sixty elbow joint EEG signals taken from the subjects' electroencephalogram. This study finds the percentage of classification of each parameter, such as accuracy, sensitivity, and simplicity, by the validation process using CNN classification. The results from the whole set of databases conducted in the experiments show that feature-extraction values of each signal and classification part show whether the signal is normal or movement brain signals using the classifier Alexnet. The proposed method has tested for around sixty brain signals that combine both the normal and movement of elbow joint brain signals to evaluate the performance analysis from the signal classification using CNN by the process of feature extraction parameter. We achieved the results that show better classification accuracy and a few more in our experiment. Then the collected signals are processed in the excel format for every channel, including parental, frontal, etc., and the results are shown in Table 1.

Preprocessing is usually done for experimental design, occasionally called pre-analysis, after the signals' acquisition process to filter the unwanted noise in the input signal under this method. Preprocessing a signal means preparing the signals to introduce it to an algorithm for further processes such as recognition, DWT, Feature extraction, etc. It mainly filters the dataset as an input of each signal to remove the noises. The result of the input signal and preprocessing signal is shown in Fig. 1.

The discrete transformation of the wavelet equals discrete filter banks. They are discrete filter banks that are tree-structured, where the signal is filtered. The filter outputs at each successive stage are sampled in the DWT. The DWT sub-bands (Low Low, Low High, High Low, and High High Pass filter) are shown in Fig. 2. During the experiment, features are extracted from both normal and movement signals, namely flexion, and extension of the elbow joint, the feature extracted includes Entropy, Skewness, Kurtosis, Mean, Standard deviation, and Variance. These are the features extracted from around sixty signals of the subject. This result will be applied to the classification process.

Table 1. Elbow joint EEG input signal in excel format

P2 - F4	F4 - C4	C4 - P4	P4 - O2	FP1 - F3	F3 - C3	C3 - P3	P3 - O1	FP2 - F8	F8 - T4	T4 - T6	T6 - O2	FP1 - F7	F7 - T3	T3 - T5	T5 - O1
-5	-200	200	-1	-3	3	-3	-183	-4	0	0	-2	-65	61	3	-184
-4	-678	678	-1	-3	3	-3	-673	-4	0	0	-1	-217	213	3	-675
-146	-744	743	-1	-159	193	-128	-890	-146	0	22	-24	-178	19	132	-955
-486	-104	104	-1	-531	648	-427	-483	-485	0	76	-78	148	-680	440	-702
-484	369	-588	116	-646	838	-698	231	-572	-119	52	52	477	-1099	473	-126
113	228	-971	395	-347	479	-774	1087	-187	-404	-89	446	634	-898	76	634
834	-193	-1024	649	8	-115	-609	1766	341	-662	-229	815	546	-401	-355	1260
1332	-595	-817	751	264	-617	-338	2112	734	-719	-336	992	330	105	-633	1620
1468	-921	-348	671	323	-864	-50	2035	865	-526	-399	930	35	470	-663	1602
1264	-1094	157	471	138	-808	213	1561	715	-226	-341	650	-295	637	-450	1213
833	-860	310	216	-239	-453	432	1102	346	91	-146	209	-407	421	-91	921
428	-369	207	-32	-556	-97	687	802	26	372	77	-242	-309	41	198	906
250	1	36	-140	-606	20	860	713	-40	412	233	-459	-176	-147	237	1074
295	-27	119	-121	-424	-178	1025	613	181	219	316	-450	-214	15	73	1163
389	-270	451	-121	-186	-505	1215	356	470	45	332	-398	-412	327	-72	1037
306	-267	750	-261	-71	-685	1418	72	607	87	329	-494	-533	378	-22	910
218	-95	989	-466	47	-840	1726	-193	735	266	328	-684	-544	331	25	927
256	-1	1081	-603	129	-884	1920	-306	769	491	300	-827	-493	312	12	1027
547	-295	1300	-656	233	-967	2137	-444	819	741	242	-906	-503	515	-134	1082
968	-783	1617	-622	449	-1201	2390	-633	1002	890	173	-885	-585	943	-427	1074
1220	-1061	1849	-576	675	-1412	2446	-676	1190	962	70	-790	-587	1268	-724	1076

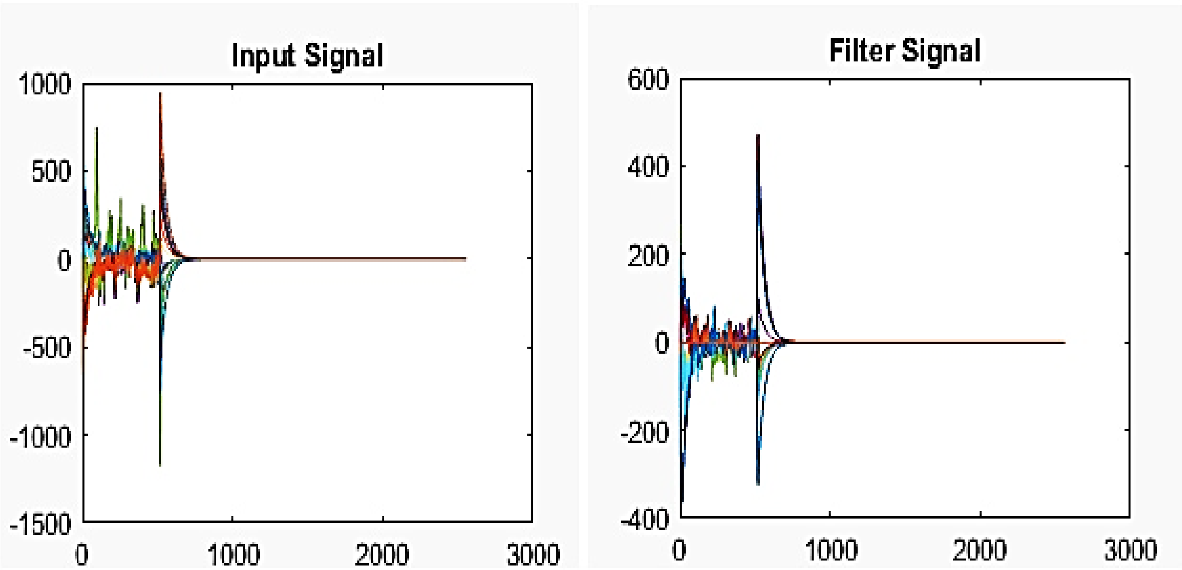

Fig. 1 Input signal and Pre-processing signal

It is rather easy to classify with these feature values. This process aims to identify the features that contain the signal information to strengthen the classifier efficiency. It is used to accomplish the classification process. Table 2 shows the result of the Feature Extraction output of the normal EEG signals in the eyes-closed condition.

The feature extraction of the EEG signals with the movement (i.e., flexion and extension of elbow joint) was shown in Table 3. Table 4 shows the average values of feature extraction of both normal and elbow joint movement.

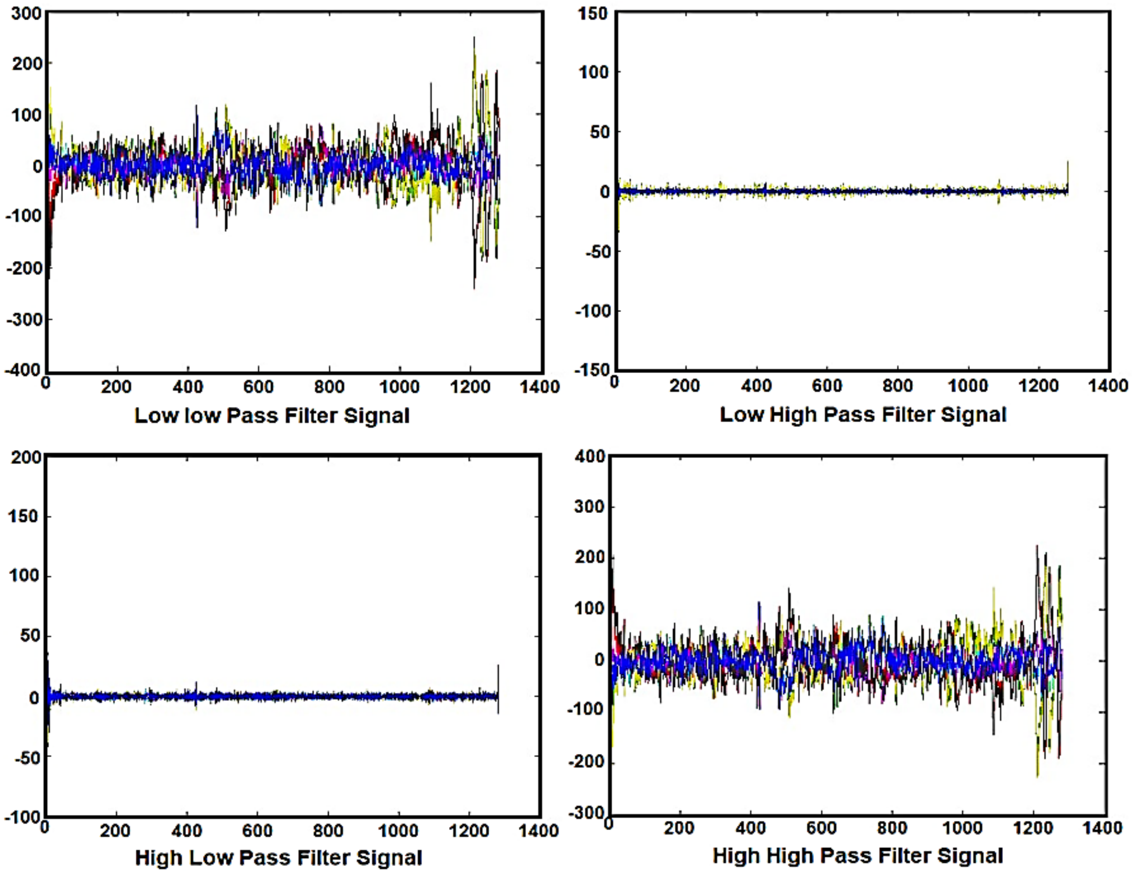

Fig. 2 DWT sub-bands (Low Low, Low High, High Low, and High High Pass filter)

Table 2. Feature extraction of normal EEG signals in eyes closed condition

Signal	P-P	Mean	Median	Entropy	Skewness	Kurtosis	Variance	SD
Normal ec1	65.057	26.988	27.295	1.1380	0.5744	3.858	11.0703	3.326
Normal ec2	65.201	26.907	27.219	1.1378	0.5747	3.902	11.0757	3.329
Normal ec3	65.107	26.886	27.050	1.1386	0.5747	3.916	11.0659	3.327
Normal ec4	65.048	27.113	27.181	1.1386	0.5747	3.898	11.0707	3.326
Normal ec5	65.082	26.932	27.110	1.1379	0.5748	4.026	11.0774	3.329
Normal ec6	65.455	27.143	26.912	1.1395	0.5748	4.129	11.0843	3.329
Normal ec7	65.330	26.949	26.965	1.1395	0.5746	3.811	11.0664	3.330
Normal ec8	65.080	27.158	27.214	1.1388	0.5745	3.861	11.0796	3.328
Normal ec9	65.008	26.916	27.105	1.1382	0.5747	4.129	11.0639	3.328
Normal ec10	65.326	27.097	27.088	1.1399	0.5746	4.104	11.0768	3.326
Normal ec11	65.394	27.096	27.038	1.1387	0.5747	4.097	11.0810	3.329
Normal ec12	65.459	27.192	26.989	1.1395	0.5745	4.183	11.0821	3.326
Normal ec13	65.352	26.960	27.072	1.1379	0.5746	4.080	11.0759	3.328
Normal ec14	65.043	27.019	27.226	1.1386	0.5746	3.942	11.0624	3.330
Normal ec15	65.442	27.104	26.978	1.1390	0.5747	4.069	11.0798	3.327
Normal ec16	65.225	27.039	26.953	1.1372	0.5748	3.983	11.0717	3.327
Normal ec17	65.199	27.148	27.086	1.1387	0.5747	3.804	11.0866	3.328
Normal ec18	65.384	27.171	27.230	1.1377	0.5746	3.961	11.0645	3.329
Normal ec19	65.397	26.964	27.107	1.1396	0.5746	3.804	11.0710	3.329
Normal ec20	65.266	26.850	27.274	1.1392	0.5747	3.868	11.0766	3.329

Table 3. Feature extraction of movement EEG signals in eyes closed condition

Signal	P-P	Mean	Median	Entropy	Skewness	Kurtosis	Variance	SD
Movement E1	61.13	31.643	32.098	1.0386	-0.6201	4.448	41.4350	6.437
Movement E2	57.994	28.871	28.855	1.0307	0.1242	4.694	54.2432	7.365
Movement E3	66.992	28.283	28.218	1.0446	-0.0881	4.093	56.1001	7.49
Movement E4	64.622	28.819	28.655	1.4361	1.037	4.744	54.6269	7.391
Movement E5	62.642	28.491	28.525	1.0334	1.0115	3.995	57.2292	7.565
Movement E6	72.962	25.686	25.346	1.4148	0.0043	4.418	42.5887	6.526
Movement E7	58.794	26.781	31.138	1.0633	0.0096	4.343	52.9256	7.275
Movement E8	67.992	27.184	27.875	1.0357	0.0605	4.394	54.0225	7.35
Movement E9	65.722	27.356	28.324	1.0075	0.0941	4.626	55.9654	7.481
Movement E10	61.442	29.381	27.845	1.0445	0.0048	4.296	58.7522	7.665
Movement F1	72.962	31.426	32.079	1.234	-0.1032	4.441	39.4384	6.28
Movement F2	71.363	28.268	28.524	1.1097	0.2864	4.335	47.0596	6.86
Movement F3	72.761	27.167	27.207	1.0094	0.3496	4.329	54.5973	7.389
Movement F4	67.663	29.164	29.438	1.0286	-0.0657	4.287	50.3816	7.098
Movement F5	71.66	27.375	27.508	1.0042	0.0325	4.817	51.2226	7.157
Movement F6	62.137	29.359	29.203	1.0104	0.0786	4.418	38.9376	6.24
Movement F7	52.961	30.316	27.424	1.0036	0.0179	4.675	45.6976	6.76
Movement F8	73.365	27.168	28.307	1.0281	-0.0868	4.158	52.9838	7.279
Movement F9	71.763	28.267	28.238	1.0067	0.0206	4.551	51.8112	7.198
Movement F10	68.662	29.765	28.708	1.0308	0.0245	4.263	51.6530	7.187

Table 4. Average of feature extraction output

S.No	Features	Normal Signals	Movement Signals
1	Peak-to-peak	65.2428	66.2795
2	Mean	27.0316	28.5385
3	Median	27.1046	28.6758
4	Entropy	1.1386	1.0807
5	Skewness	0.5747	0.1096
6	Kurtosis	3.9713	4.4163
7	Variance	11.0741	50.5836
8	SD	3.328	7.0997

Fig. 3 shows the variance feature comparison of normal and movement signals of all the samples. It shows that the variance of the elbow joint movement is increasing concerning the normal condition. From Fig. 4, the current study shows the variance of an average elbow movement signal is as high as the normal signal. Other features are showing almost slight changes concerning the normal signal.

After the process of database training, the signals have to be classified using CNN (Convolutional neural network) with the classifier Alexnet. It shows whether the given signal is normal or movement in the classification process. This process helps to determine the classification accuracy by the validation process. The classification output shows whether the given input is normal or movement, and the result is shown in Fig. 5.

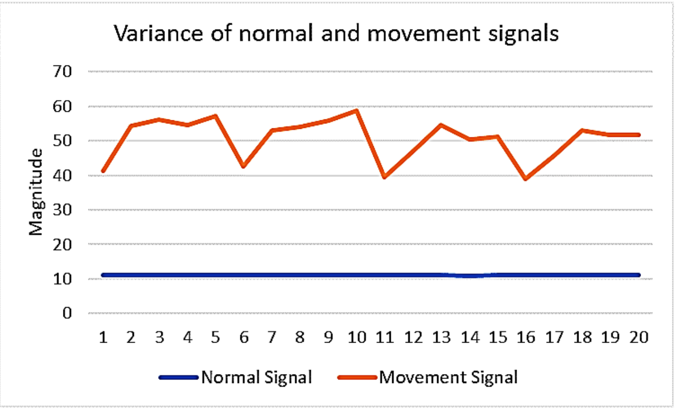

Fig. 3 Variance output of normal and movement signal

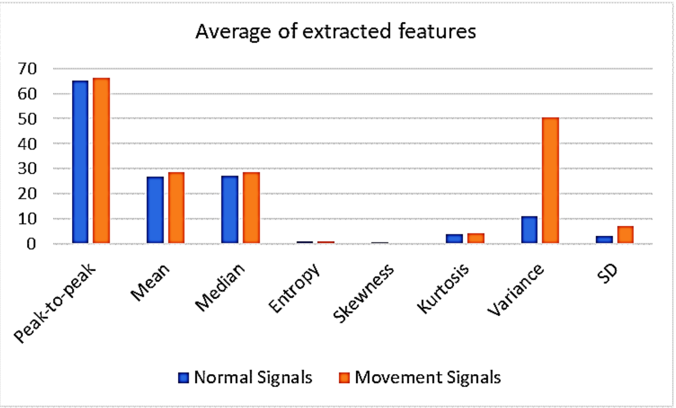

Fig. 4 Average features output

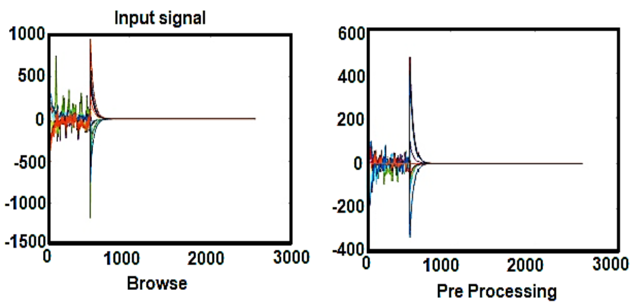

Fig. 5 Classification output

Fig. 6 shows the validation values by the classification process that shows the performance analysis from the whole data set. The system performance was evaluated using a Convolutional neural network using the accuracy, sensitivity, and specificity measures under the validation process.

Many researchers make use of the feature extraction and neural networks of brain signals for research purposes to identify brain disorders to evaluate certain information in upper limb prosthesis applications or need to develop the prosthetic device for the subject[39]. It is done with the help of the MATLAB function. This project's main purpose is to acquire brain signals by flexion and extension of elbow joints to obtain the frequency domain based on DWT and the feature extraction process.

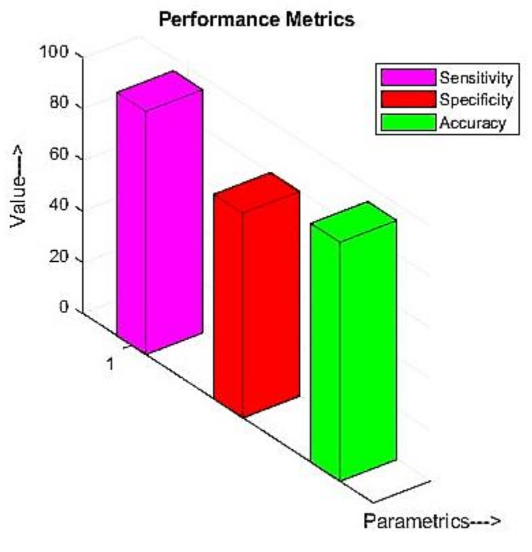

Fig. 6 Validation process

The obtained frequency domain from the whole signals is further processed by classification using a convolutional neural network in deep learning. The classified signals collect the required parameter analysis from the whole dataset. The acquired parameter analysis is used as the reference for applying upper limb prosthesis and rehabilitation, etc. Moreover, in the existing system, signal processing is done with a Brain-computer interface. The proposed technique processed the elbow joint brain signal based on discrete wavelet transformation and is done for both normal and elbow joint EEG signals. Backpropagation and custom neural networks are not available for upper limb action or movement, especially for elbow joint EEG signals. Several methods for EEG monitoring of upper limb strength assist artificial limbs in perceiving joint elbow speeds using these EEG signals.

Using different classification methods, the discrete wavelet transform method can be used for epileptic detection from brain signals. The other existing method is done with wavelet analysis to obtain the automated artifact rejection from the multichannel EEG Scalp, which is slightly similar to the acquisition process of EEG signals. Still, the proposed technique consists of a Discrete wavelet transform for EEG signal processing to compress the signals into sub-bands such as low and high pass bands as discrete filter banks before the Preprocessing of brain signals to filter the noise over the signals for the next process such as Feature extraction. In the proposed system, Electroencephalogram (EEG) signals given as input are composed of narrowband signal series with the help of DWT.

Extraction of the function reduces the input signal dimensions by maintaining the informative features. The current research presents successful feature extraction techniques for classifying the elbow joined EEG signal. This proposed method includes this process to create a dataset with a reduced number of features that contain the signals information, including the Peak-to-peak value, Mean, Median, Entropy, Skewness, Kurtosis, Variance, and Standard deviation of the given input. This extracted feature helps the classifier classify the signals to compare the normal movement of the elbow joint for the classification process.

For the diagnosis of brain disorders, the development of prosthetic devices is mainly useful for the upper-limb prosthesis and rehabilitation of the subject. These obtained performance analyses help the researchers identify and evaluate or understand the problem related to the upper limb prosthesis or elbow joint region for better understanding and diagnosis. Many researchers have found the process of feature extraction and deep learning method for upper-limb prosthesis or controlling the movement of the upper limb. No other field of research has effectively contributed to the diagnostic purposes. In the existing approach of classification method containing continuous small convolutional neural network, this method’s classification accuracy and kappa value are used as evaluation criteria to verify the effectiveness of the method of study and the performance of Continuous small convolutional neural networks is better with an average value of 0.663. This method is similar to the proposed method of classification.

The current investigation uses a convolutional neural network for the classification process to obtain the performance analysis of the brain signals of the elbow joint to compare the normal and movement, which is done by a classifier, namely Alexnet. The result of one of the existing methods for classifying speed across seven subjects was an average of 83.71 percent accuracy using a Fisher Linear

Discriminant classifier. Other methods are done with CNN for achieving the Single-trial EEG classification of motor imagery. The proposed approach is to compare the different signals such as normal and movement signals, for better classification accuracy, which is used as a reference for upper-limb prosthesis application. The obtained classification method extracts the validation process's accuracy, specificity, and sensitivity as a final output. This automated classification process is helpful for the researchers as well as the doctors. It supports diagnosis and research purposes related to upper limb prosthesis because it provides feature extraction values and better classification accuracy when CNN Classification achieves this. Until now, others have not evaluated the performance analysis that the CNN classification has done. It would be helpful to the researchers to have research for treatment or diagnosis of upper limb prosthesis and rehabilitation using the elbow joint brain signals as a reference from the classification output. It can be useful for future work to develop the prosthetic device related to the upper limb prosthesis.

4. Conclusion

In the proposed research, the feature extraction and classification of elbow joint EEG signal output is mainly used as a reference value for upper limb prosthesis application and rehabilitation purposes. With the help of experimental results, (i.e.) validation values of the whole data set as the graphical representation to show the better classification. These proposed techniques are also used for diagnosis and medical purposes related to upper limb movement. The scope of this proposed method can be useful to the researcher regarding the brain disorders correlated with the upper limb. In the existing method, no records are related to the elbow joint EEG signals to achieve the upper limb prosthesis application. But the proposed method has a better classification accuracy of brain signals. The proposed method included an enhancement stage that compresses the signals without any loss to obtain the information on elbow joint EEG signals. Overall, the proposed approach achieved a better classification that shows the validation part, such as accuracy of 93.33%, sensitivity of 90%, and simplicity of 80% from the whole process, which can be taken as a reference for upper-limb prosthesis applications.

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References

[1] Iqbal, M.U., Shahab, M.A., Choudhary, M., Srinivasan, B., Srinivasan, R, “Electroencephalography (EEG) Based Cognitive Measures for Evaluating the Effectiveness of Operator Training,” *Process Saf Environ*, vol.150, Pp.51-67, 2021.

[2] Su, Y., Chen, P., Liu, X., Li, W., Lv, Z, “A Spatial Filtering Approach To Environmental Emotion Perception Based on Electroencephalography,” *Med Eng Phys*, vol.60, Pp.77-85, 2018.

[3] T. Sudhakar, G. Hari Krishnan, N. R. Krishnamoorthy, B. Janney J, M. Pradeepa and J. P. Raghavi, “Sleep Disorder Diagnosis Using EEG Based Deep Learning Techniques,” *in Proc. ICBSII* 2021, Pp.1-4, 2021.

[4] Hari Krishnan, G., Hemalatha, R.J., Umashankar, G., Ahmed, N., Nayak, S.R, “Development of Magnetic Control System for Electric Wheel Chair Using Tongue,” *Series Adv Intellsystcomput*, vol.308, Pp.635–41, 2014.

[5] Krishnan, G.H., Natarajan, R.A., Nanda, A, “Microcontroller Based non Invasive Diagnosis of Knee Joint Diseases,” *in Proc. ICICES* vol. 2014, no. 7034178, 2015.

[6] Rong, Y., Wu, X., Zhang, Y, “ Classification of Motor Imagery Electroencephalography Signals Using Continuous Small Convolutional Neural Network,” *Int J Imagsyst Tech*, vol.30, no.3, Pp.653-659, 2020.

[7] Saha, M., Das, S, “Electrochemical Detection of L-Serine and L-Phenylalanine At Bamboo Charcoal–Carbon Nanosphere Electrode,” *Jnanostructure Chem*, vol.4, Pp.102, 2014.

[8] Khosla, A., Khandnor, P., Chand, T, “A Comparative Analysis of Signal Processing and Classification Methods for Different Applications Based on EEG Signals,” *Biocybern Biomed Eng*, vol.40, no.2, Pp.649-690, 2020.

[9] Liang, W., Pei, H., Cai, Q., Wang, Y, “Scalp EEG Epileptogenic Zone Recognition and Localization Based on Long-Term Recurrent Convolutional Network,” *Neurocomputin*g, vol.396, Pp.569-576, 2020.

[10] Usman, S.M., Khalid, S., Akhtar, R., Bortolotto, Z., Bashir, Z., Qiu, H, “Using Scalp EEG and Intracranial EEG Signals for Predicting Epileptic Seizures: Review of Available Methodologies,” *Seizure*, vol.71, Pp.258-269, 2019.

[11] Chakraborty, J., Nandy, A, “Discrete Wavelet Transform Based Data Representation in Deep Neural Network for Gait Abnormality Detection,” *Biomed Signal Process Control*, vol.62, Pp.102076, 2020.

[12] Santhosh, S., Juliet, A.V. & Krishnan, G.H, “Predictive Analysis of Identification and Disease Condition Monitoring Using Bioimpedance Data,” *J Ambient Intell Human Comput*, vol.12, Pp.2955–2963, 2021.

[13] Zarei, A., Asl, B.M, “Automatic Seizure Detection Using Orthogonal Matching Pursuit, Discrete Wavelet Transform, and Entropy Based Features of EEG Signals,” *Computbiol Med*, vol.131, Pp.104250, 2021.

[14] Bajpai, R., Yuvaraj, R., Prince, A, “Automated EEG Pathology Detection Based on Different Convolutional Neural Network Models: Deep Learning Approach, “ *Computbiol Med*, vol.133, Pp.104434, 2021.

[15] Raghu, S., Sriraam, N., Temel, Y., Rao, S.V., Kubben, P.L, “ EEG Based Multi-Class Seizure Type Classification Using Convolutional Neural Network and Transfer Learning, “ *Neural Netw*, vol.124, Pp.202-212, 2020.

[16] Yildiz, A., Zan, H., Said, S, “Classification and Analysis of Epileptic EEG Recordings Using Convolutional Neural Network and Class Activation Mapping, Biomed Signal Process, Control,” vol.68, Pp.102720, 2021.

[17] Guru Anand, V., Hari Krishna, G., Mohandass, G., Hemalatha, R.J., Sundaram, S, " Predicting Grade of Prostate Cancer Using Image Analysis Software," *in Proc. TISC-2010,* no.5714621, Pp.122–124, 2010.

[18] Diwakar, M., Tripathi, A., Joshi, K., Sharma, A., Singh, P., Memoria, M., Kumar, N, "A Comparative Review: Medical Image Fusion Using SWT and DWT," *Mater. Today: Proc,* vol.37. no.2, Pp. 3411-3416, 2021.

[19] Vijayarajan, R., Muttan, S, " Discrete Wavelet Transform Based Principal Component Averaging Fusion for Medical Images," *AEU-Int. Jelectron Commun,* vol.69, no.6, Pp. 896-902, 2015.

[20] Q!*Electreng Technol,* vol.9, no.6, Pp.2114–2117, 2014.

[21] Guerrero, M.C., Parada, J.S., Espitia, H.E, "EEG Signal Analysis Using Classification Techniques: Logistic Regression, Artificial Neural Networks, Support Vector Machines, and Convolutional Neural Networks," *Heliyon,* vol.7, no.6, Pp.E07258, 2021.

[22] Mammone, N., Leracitano, C., Morabito, F.C, "A Deep CNN Approach To Decode Motor Preparation of Upper Limbs From Time–Frequency Maps of EEG Signals At Source Level," *Neural Netw,* vol.124, Pp.357-372, 2020.

[23] Asadzadeh, S, Rezaii, T.Y., Beheshti, S., Delpak, A., Meshgini, S, "A Systematic Review of EEG Source Localization Techniques and Their Applications on Diagnosis of Brain Abnormalities," *J Neurosci Methods,* vol.339, Pp.108740, 2020.

[24] Miragila, F., Tomino, C., Vecchio, F., Alu, F., Orticoni, A., Judica, E., Cotelli, M., Rossini, P.M, "Assessing the Dependence of the Number of EEG Channels in the Brain Networks' Modulations," *Brain Res Bull,* vol.167, Pp.33-36, 2021.

[25] Vijayaraghavan, V., Garg, A., Wong, C.H., Tai, K., Bhalerao, Y,"Predicting the Mechanical Characteristics of Hydrogen Functionalized Graphene Sheets Using Artificial Neural Network Approach, " *J Nanostructure Chem,* vol.3, Pp.83, 2013.

[26] Santhosh S, Juliet V, Krishnan G. H, "Impact of Electrodes Separation Distance on Bio-Impedance Diagnosis, " *Biomed Pharmacol J*. vol.14, no.1, 2021.

[27] Yogendra Narayan. "Motor-Imagery based EEG Signals Classification using MLP and KNN Classifiers" International Journal of Engineering Trends and Technology 69.1(2021):121-125.

[28] Yao, Y., Plested, J., Gedeon, T, "Information-Preserving Feature Filter for Short-Term EEG Signals," *Neurocomputing,* vol.408, Pp.91-99, 2020.

[29] Krishnan, G.H, Nanda, A., Natarajan, A, "Synovial Fluid Density Measurement for Diagnosis of Arthritis," *Biomed Pharmacol J,* vol.7, no.1, Pp.221–224, 2014.

[30] Guido, R.C, "A note on A Practical Relationship Between Filter Coefficients and Scaling and Wavelet Functions of Discrete Wavelet Transforms, " *Appl Math Lett,* vol.24, no.7, Pp.1257-1259, 2021.

[31] Tabassum, F., Islam, M.I., Amin, M.R, "Comparison of Filter Banks of DWT in Recovery of Image Using One Dimensional Signal Vector," *J. King Saud. Univ – Comput. Inf. Sci,* vol.33, no.5, Pp.542-551, 2021.

[32] Mohandass, G., Ananda Natarajan, R., Hari Krishnan, G, "Comparative Analysis of Optical Coherence Tomography Retinal Image Using Multidimensional and Cluster Methods," *Biomed Res* (India), vol.26, no.2, Pp.273-285, 2015.

[33] Alcin, O.F, Siuly, S, Bajaj, V, Guo, Y, Sengu, A., Zhang, Y, "Multi-Category EEG Signal Classification Developing Time-Frequency Texture Features Based Fisher Vector Encoding Method," *Neuro Computing,* vol.218, Pp.251-258, 2016.

[34] Li, Y., Cui, W., Luo, M., Li, K., Wang, L, "Epileptic Seizure Detection Based on Time-Frequency Images of EEG Signals Using Gaussian Mixture Model and Gray Level Co-Occurrence Matrix Features," *Int J Neural Syst,* vol.28, no.2, Pp.1850003, 2018.

[35] Sengur, A., Guo, Y., Akbulut, Y, "Time–Frequency Texture Descriptors of EEG Signals for Efficient Detection of Epileptic Seizure," *Brain Inf,* vol.3, Pp.101-108, 2016.

[36] Gupta, R., Bera, J.N., Mitra, M, "Development of an Embedded System and MATLAB-Based GUI for Online Acquisition and Analysis of ECG Signal, Measurement," vol.43, no.9, Pp.1119-1126, 2010.

[37] Krishnan, G.H, Natarajan, R.A., Nanda, A, "Comparative Study of Rheumatoid Arthritis Diagnosis Using Two Different Methods," *Biomed Pharmacol J,* vol.**7**, no.4, Pp.379–382, 2014.

[38] John, A.A., Subramanian, A.P., Jaganathan, S.K., Sethuraman, B, "Evaluation of Cardiac Signals Using Discrete Wavelet Transform With MATLAB Graphical User Interface," *Indian Heart J,*vol.67, no.6, Pp.549-551, 2015.

[39] Priyadarsini, S., Mohanty, S., Mukherjee, S., Basu, S., Mishra, M, " Graphene and Graphene Oxide As Nanomaterials for Medicine and Biology Application," *J Nanostructure Chem,* vol.8, Pp.123-137, 2018.

[40] T. Sudhakar, G. Hari Krishnan, G Umashankar, Sindudivakaran, U. Bhurnima and B. Shanchita, "Drug Retrieving System in Hospitals Using Robotics," *Biomed Pharmacol J,* vol.3, no.3, 2020. 1239-1244.