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Deep neural network assisted diagnosis of time-frequency transformed electromyograms

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Abstract
Electromyograms (EMG) are recorded electrical signals generated from the muscles and these signals are closely interrelated with the muscle activity and hence are useful for the investigation of neuro-muscular disorders. The feature mining, feature collection and development of classification systems are greatly significant steps in the differentiation of normal and abnormal EMG signals to evaluate the abnormality. In this work, time-frequency domain based features of regular, myopathy and Amyotrophic Lateral Sclerosis (ALS) EMG signals were extracted from four different techniques namely Stockwell-Transform (ST), Wigner-Ville Transform (WVT), Synchro-Extracting Transform (SET) and Short-Time Fourier Transform (STFT). The Particle Swarm Optimization (PSO) with fractional velocity update technique was implemented for feature reduction. Further, the classifier based on the Deep Neural Networks (DNN) was developed by employing the features selected using fractional PSO. Finally, the performance of the DNN was compared with that of the Shallow Neural Network (SNN) classifier. Results of this work demonstrate that, the performance measure of the DNN classifiers is higher than that of the SNN classifier. This work appears to be of good clinical significance since efficient classification techniques are required for the development of robust neuro-muscular diagnosis systems.

Keywords Electromyograms · Transformation techniques · Time-frequency features · Feature selection · Deep neural networks · Shallow neural networks

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1 Introduction

The Neuro-Muscular (NM) disorders comprise of several disorders which influence the human muscular system and nervous system and the early diagnosis leads to efficient treatment strategies [13]. There are two most frequent muscular disorders namely the Amyotrophic Lateral Sclerosis (ALS) and Myopathy [10]. ALS is a fast-developing NM disease which is fatal and affects the neurons in peripheral and central nervous systems [4]. Myopathies are manifested by muscle weakness, muscle dysfunction, muscle cramps, stiffness, spasm, etc. [14].

Normally, NM malfunction is normally evaluated based on the EMG recorded in a controlled environment. During this recording procedure, the electric signals from the human muscular system are acquired using surface electrodes or needle electrodes from the voluntary or non-voluntary muscles. Further, the EMG signals are utilized in several medical applications, such as machine interfacing, robotic control, medical diagnostics, prosthesis, and rehabilitation [47]. The investigation of EMG signals is preferred only in quantitative analysis techniques instead of qualitative inspection, due to the non-stationary nature of EMG signals [49]. Hence, the feature extraction, feature optimization and development of classification techniques need to be employed for the efficient discrimination of normal and abnormal EMGs.

The feature extraction involves the process of extracting useful information which describes the characteristics of original EMG signals [33]. Recently, several researchers have utilized various time domain features, frequency and time frequency domain features, such as auto-correlation, contrast, spectral peak power, mean frequency, entropy, mean etc., to implement efficient classification of normal and abnormal EMG signals [1–3, 15, 38, 45]. Ambikapathy et al. (2018) [5] have analyzed the quality of information content of EMG signals recorded with the help of three types of electrodes such as mono polar needle, concentric needle, and surface electrodes. The authors have concluded that the information quality of EMG signals recorded using needle electrodes is superior compared to that of the surface electrodes. Wang et al. (2014) [48] have utilized the time and time-frequency features of EMG signals recorded with surface electrodes for the classification of different forearm movements. These authors concluded that the time-frequency features of surface EMG signals are more prominent for the classification of different forearm movements when compared to the time domain features. Karthick et al. (2018) [27] have considered the time-frequency features of surface EMG signals for the classification of fatigue and non-fatigue conditions. They concluded that the time-frequency features of surface EMG signals have higher classifier accuracy for the discrimination of non-fatigue and fatigue conditions.

Generally, for the extraction of different time-frequency features, transformation techniques are required to convert one dimensional time series into two dimensional time-frequency images [11]. Recently, several researchers have utilized various transformation techniques such as Discrete Cosine transform (DCT), Stockwell-Transform (ST), Wigner-Ville Transform (WVT), Synchro-Extracting Transform (SET), Continuous Wavelet Transform (CWT), etc., for the examination of EMG signals [16, 21].

The performance of the developed classifiers may be influenced by several issues, such as redundant features and the large dimensionality of the feature set [39]. Hence, the feature selection or feature reduction is a necessary step for the selection of optimal feature sub-set and also useful for the improvement of the classifier performance [40]. In recent years, several algorithms have been implemented to determine the appropriate feature set for the classification of bio-signals [17, 18, 24, 25, 36, 39–41, 44].

In recent years, several machine learning algorithms with supervised and unsupervised learning schemes, such as K-means, K-nearest neighbor, support vector machines, decision tress, artificial neural networks, and deep learning techniques have been adopted for the discrimination of EMG signals [8, 9, 22, 23, 26, 30]. The Deep Neural Network (DNN) is a novel machine learning technique that has more learning ability and can solve complex problems which require higher generalization capabilities. DNN models are highly useful in biomedical applications such as the development of diagnosis systems, signal and image analysis [7].

In this work, the EMG signal features extracted using four different time-frequency transformation techniques namely ST, WVT, SET, and STFT have been utilized for the development of DNN classifier for the automated diagnosis of myopathy and ALS conditions.

2 Methodology

2.1 Acquisition of EMG signals

In this work, EMG signals were acquired from brachial biceps muscles of normal and abnormal (myopathy and ALS) subjects, using concentric needle electrodes. The one hundred and fifty EMG signals from normal, myopathy and ALS cases were recorded. The sampling rate of acquired EMG signals is 23,437.5 Hz. The EMG signals were taken from the benchmark EMG signals database [www.emglab.net] [31].

2.2 Feature extraction and selection

Initially, the time-frequency transformation techniques, such as SWT, WVT, STFT and SET were implemented to extract useful features from normal and abnormal EMG signals. Finally, eighty valuable features were extracted from the time-frequency images obtained using four different transformation techniques to analyze and classify these EMG signals. The overview of this research work is presented in Fig. 1. Initially, various class of EMG signals such as normal, myopathy and ALS were extracted from a chosen muscle group using various electrodes. The essential signal features are then extracted using time-frequency transformation techniques and a PSO with fractional velocity update algorithm is then implemented to select the key feature sub-set among the extracted initial time-frequency features. Finally, a classifier system based on the DNN and SNN were developed and its classification performance were evaluated and recorded.

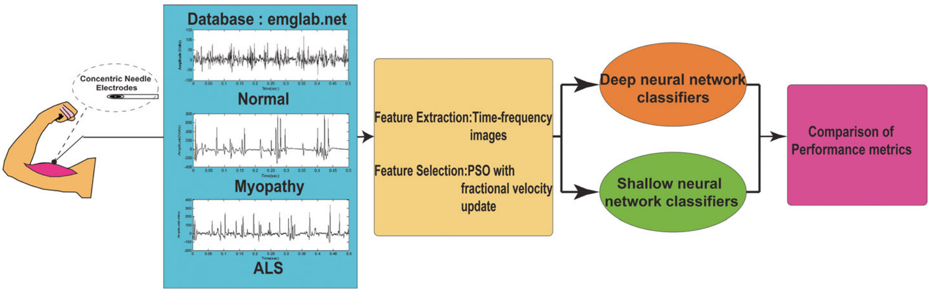


Fig. 1 Overview of proposed EMG evaluation approach

2.2.1 Stock-well transform (ST)

Hence, it is also referred as phase corrected continuous wavelet transform or frequency dependent short time Fourier transform [35, 46]. Considering the continuous time sequence $h(t)$, the spectrum time at $t-\tau$ can be found by the product of $h(t)$ with the Gaussian window $g(t-\tau, \sigma)$ placed atτ. Hence, the S transform $S(f, \tau, \sigma)$ can be expressed as [35],

$$S(f,\tau,\sigma)=\int_{-\infty}^{\infty} h(t)g(t-\tau,\sigma)e^{-i2\pi ft}dt \tag{1}$$

The Gaussian window $g(t-\tau, \sigma)$ is given by,

$$g(t-\tau,\sigma)=\frac{1}{\sqrt{2\pi\sigma}}e^{-\frac{t^2}{2\sigma^2}} \tag{2}$$

$$\sigma=\frac{1}{f} \tag{3}$$

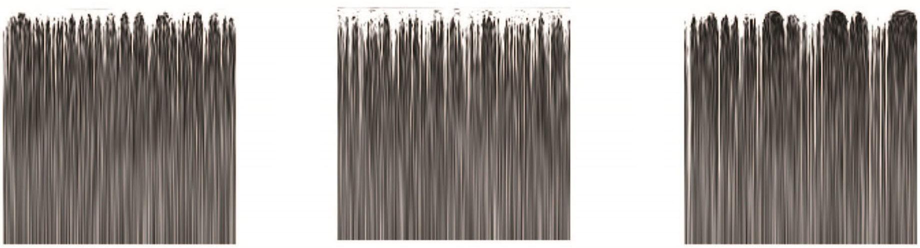
where, σ is the dilation parameter of frequency and $e^{-i2\pi ft}$ is the exponential kernel function. Figure 2(a) to (c) show the typical time-frequency images of normal, myopathy and ALS EMG signals, respectively, obtained using SWT.

2.2.2 Wigner-Ville transform (WVT)

Essentially the WVT is the double Fourier transform of the symmetrical ambiguity function [6]. The expression for the WVT is given by [16, 43],

$$P_w(t,f)=\int_{-\infty}^{\infty} e^{-j2\pi f\tau}S^*\left(t-\frac{1}{2}\tau\right)S\left(t+\frac{1}{2}\tau\right)d\tau \tag{4}$$

where, $S^*(t)$ and $S(t)$ are the real and imaginary signals [16, 43]. Figure 3(a) to (c) show the typical time-frequency images of normal, myopathy and ALS EMG signals, respectively, obtained using WVT.



(a) (b) (c)

Fig. 2 Typical SWT based time-frequency images of EMG signals (**a**) Normal, (**b**) Myopathy and (**c**) ALS

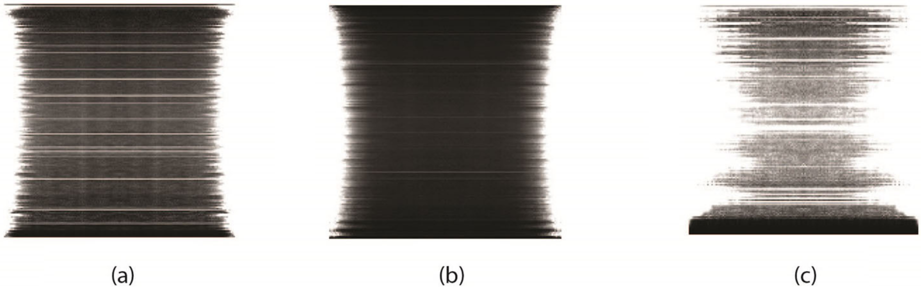


Fig. 3 Typical Wigner-Ville transform based time frequency images of (**a**) Normal, (**b**) Myopathy and (**c**) ALS EMG signals

2.2.3 Synchro-extracting transform (SET)

SET is a novel time-frequency method to evaluate the instantaneous amplitude and frequency of the signals. In time-frequency analysis, SET giveshigh energy concentration than the other conventional techniques. Considering, the multi signal component $S(t)$ can be given as [50],

$$S(t) = \sum_{k=1}^{n} A_k(t).e^{i\varphi_k(t)} \tag{5}$$

The different signals are separated by the distance and compared to the window function, i.e.

$$\varphi'_{k+1}(t) - \varphi'_k(t) > 2\Delta \tag{6}$$

where, A_k is the instantaneous amplitude of the k^{th} signal,φ_k is the instantaneous phase of the k^{th} signal and Δ is the frequency of the window function [50]. Figure 4(a) to (c) show the time-frequency images of normal, myopathy and ALS EMG signals, respectively, obtained using SET.

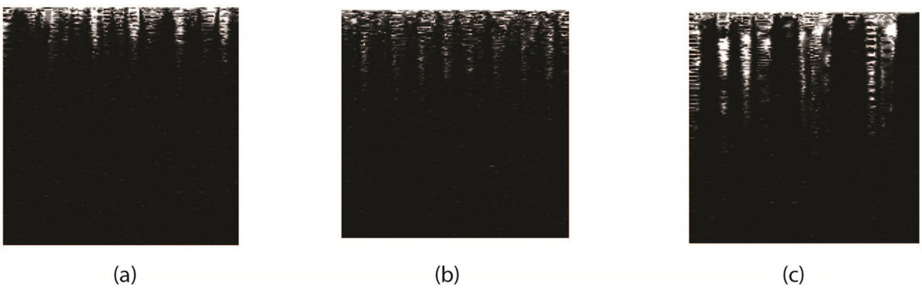


Fig. 4 Typical Synchro-Extracting based time-frequency images (**a**) Normal, (**b**) Myopathy and (**c**) ALS EMG signals

2.2.4 Short-time Fourier transform (STFT)

The STFT is the techniques, which is used to examine the bio-medical signals,which consists of time fragment multiplied by window function of the signal [28]. Such equation can be expressed as [28],

$$X(k)=\frac{1}{N}\sum_{n=0}^{N-1}w(n).x(n).e^{-i\frac{2\pi}{N}kn} \tag{7}$$

where, $X(k)$ is the frequency spectrum of k^{th} signal, $w(n)$ is the window function, $x(n)$ is the signal sample up to n^{th} times and N is the sample number in the window [32]. The peak frequency is determined by using frequency spectrum of the signal, which is expressed using the formula [32],

$$f_{\max}=\arg\left(\frac{f_p}{N}\max\sum_{k=0}^{N-1}X(k)\right) \tag{8}$$

where, f_p is the sampling frequency. Figure 5(a) to (c) show the typical time-frequency images obtained using STFT, from normal, myopathy and ALS EMG signals, respectively.

In this work, nineteen GLCM features [19, 37, 42] were extracted along with the fractal dimension for the analysis of EMG signals. Finally, eighty useful features were extracted from the time-frequency images obtained using four different transformation techniques. Further, the particle swarm optimization algorithm with fractional velocity update has been used to select the feature subset consisting of fifteen optimal features from the original feature set. The fifteenselected featuresare mentioned in Table 1.

2.3 Shallow and deep neural network classifiers

In recent years, researchers have used various architectures and algorithms in deep learning such as the DNN, Deep Belief Network (DBN), Convolutional Neural Network (CNN), auto encoder etc., for solving the complex problems in biomedical applications [29]. Also, the deep learning algorithms can perform efficiently when compared to the conventional shallow network architecture since the deep networks have higher learning and generalization capability. In other words, the shallow neural networks have higher memorization capability while the deep architectures have more generalization capabilities. The Deep Neural network (DNN) architecture is an extension of the Neural Network (NN) architecture and has more than two

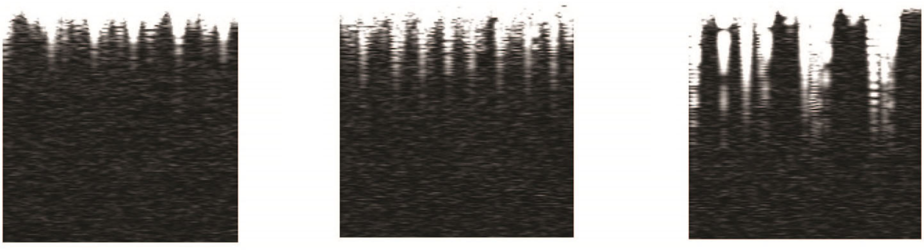


Fig. 5 Typical Short-time Fourier transform based time-frequency images (**a**) Normal, (**b**) Myopathy and (**c**) ALS EMG signals

Table 1 The Fifteen selected features for development of DNN classifiers

Transformation Techniques	Features selected using PSO with fractional velocity update
SWT	Cluster Shade (CS)
	SumEntropy (SE)
WVT	Auto Correlation (AC)
	Contrast (CON)
	DifferenceVariance (DV)
	Fractal Dimension (FD)
SET	Auto Correlation (AC)
	InformationMeasure of Correlation1(IMC1)
	SumAverage (SA)
STFT	ClusterProminence (CP)
	DifferenceVariance (DV)
	Homogeneity (H)
	Information Measure of correlation2 (IMC2)
	SumEntropy (SE)
	Fractal Dimension (FD)

hidden layers in the architecture across the input and the output layers [12, 20]. Due to this architectural complexity, the DNN can efficiently explore the complex and nonlinear problems in science and technology. Figure 6 shows the architecture of shallow and deep neural networks where IL is the input layer, OL is the output layer, L is the number of hidden layers and N is the number of hidden neurons. In the case of SNN, only one hidden layer (L = 1) is presented in the architecture. In this work, both SNN and DNN were developed with different number of neurons (N = 5, 10, 15, 20) and with different number of layers (L = 1, 2, 3, 4, 5) for the classification of the EMG signals using the adopted feature subset. In the case of the developed SNN, four different number of neurons (N = 5, 10, 15, 20) were adopted. Further, the DNN classifiers were developed with various numbers of hidden layers (L = 2, 3, 4, 5) and with different number of neurons (N = 5, 10, 15, 20). Further, a tan-sigmoid activation function was utilized. The selected features from 70% of the total number of signals was used for training the classifiers and the remaining 30% was used for testing the classifiers.

Finally, the comparative analysis of the developed DNN and SNN classifiers was performed using the performance measures such as the Accuracy, Sensitivity, Specificity, Positive Predictive Values (PPV) and Negative Predictive Values (NPV).

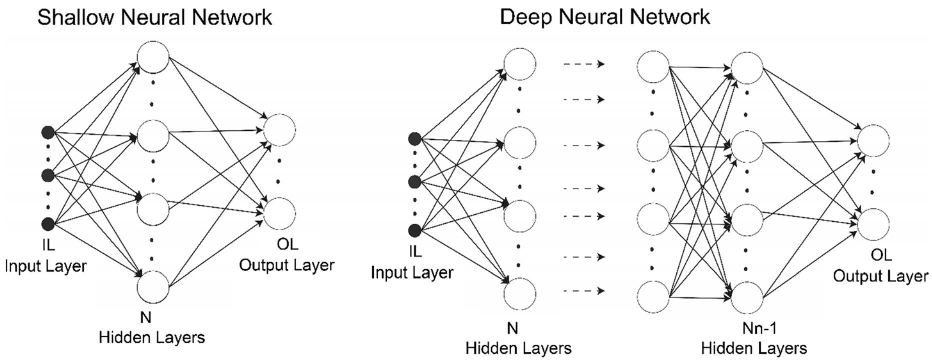


Fig. 6 Architecture of Shallow and Deep neural networks

3 Results and discussion

In this section summaries the results obtained with the experimental work. The proposed work is implemented using a workstation of Intel® core i3-3217 U CPU@1.80GHz 8 GB RAM equipped with Matlab software.

Figure 7 shows the accuracy of developed shallow and deep neural networks for the classification of normal, ALS and myopathy EMG signals. It is observed that the accuracy of developed SNN with 15 neurons ($N = 15$) is higher when compared to the accuracy of SNN with other adopted number of neurons ($N = 5, 10, 20$). Further, the accuracy of the developed DNN with four hidden layers and with neurons ($N = 5$) is higher when compared to the accuracy of the developed deep neural networks with different number of layers (Layers = 2, 3, 5) with different combination of neurons. Also, it is seen that the accuracy of developed deep neural network classifiers with five hidden layers and with different combination of neurons is lesser when compared to the accuracy of the developed deep neural network classifiers for other adopted number layers with different number of neurons. Results demonstrate that the accuracy of the developed classifiers is high when the number of layers is selected between 2 and 4. Further increase in the number of hidden layers is found to decrease the diagnostic accuracy.

The sensitivity for the developed SNN and DNN classifiers for the discrimination of normal, ALS and myopathy EMG signals with different number of layers and for different number of neurons is presented in Fig. 8. In the case of shallow neural network, the sensitivity of the developed classifier with 15 neurons (N = 15) is higher when compared to the sensitivity of developed classifiers with other adopted number of neurons (N = 5, 10, 20). Further, the sensitivity of the DNN with four hidden layers and with neuron (N = 5) is higher when compared to the sensitivity of the DNN with different number of layers (Layers = 2, 3, 5) with different combination of neurons. Also, it is found that the sensitivity of developed deep neural network classifiers with five hidden layers and with different combination of neurons is lesser when compared to the sensitivity of the developed deep neural network classifiers for other adopted number layers with different number of neurons. Results demonstrate that the sensitivity of the developed classifiers is

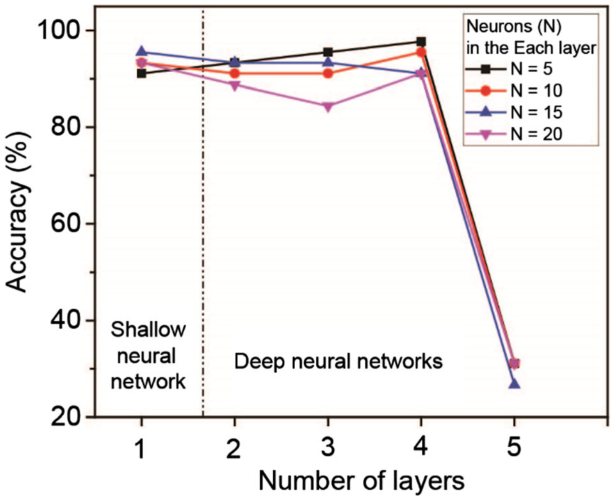


Fig. 7 The variation of accuracy for the developed SNN and DNN classifiers with different the number of neurons, shown as a function of the number of hidden layers

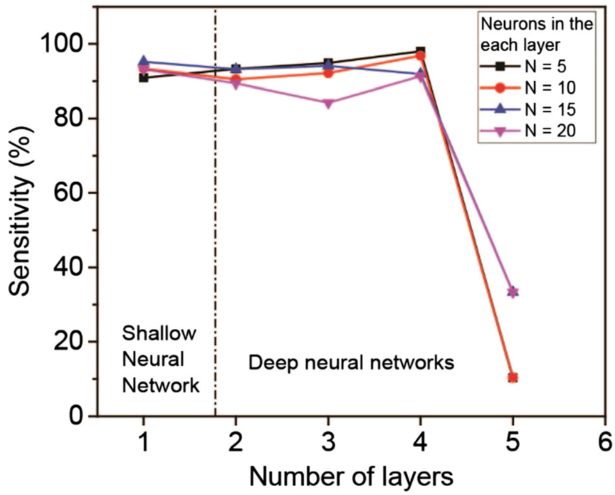


Fig. 8 The variation of Sensitivity for the developed SNN and DNN classifiers with different the number of neurons as a function of the number of hidden layers

high when the number of layers is selected between 2 and 4. Further increase in the number of hidden layers is found to decrease the classification sensitivity.

Figure 9 presents the variation in specificity for the developed shallow and deep neural networks for the classification of EMG signals with different number of layers and with different number of neurons. The results demonstrate that the specificity of the developed deep neural networks with four hidden layers and with five neurons in each layer is higher when compared to the specificity of the developed deep neural networks with different layers and with different number of neurons. Also, it is found that the number of layers is selected between 2 and 4, the classification specificity of the developed classifiers is high. Additionally, decreases in the classification specificity are found to be increase in the number of hidden layers.

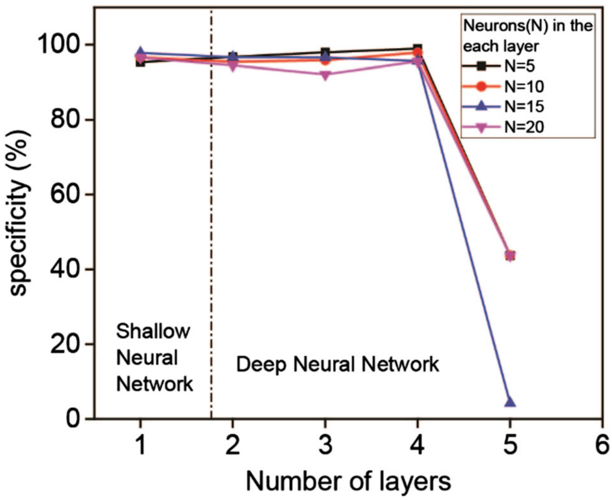


Fig. 9 The variation of specificity for the developed Shallow and deep neural network classifiers with different the number of neurons, shown as a function of the number of hidden layers

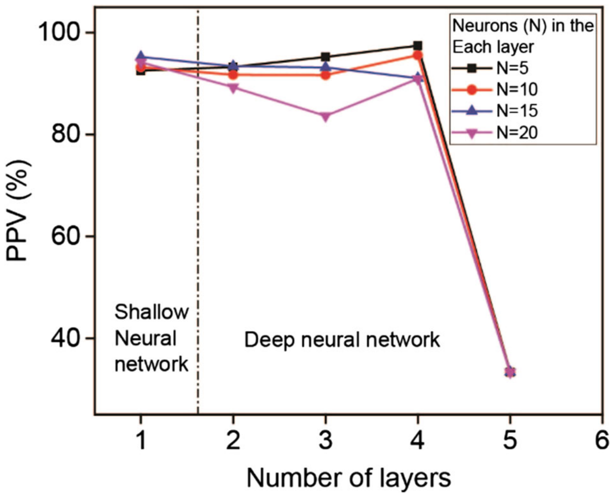


Fig. 10 The variation of PPV for the developed Shallow and deep neural network classifiers with different the number of neurons as a function of the number of hidden layers

The Positive Predictive Value (PPV) of developed SNN and DNN classifiers with different number of neurons and with different number of layers is presented in Fig. 10. It is seen that the PPV of the developed deep neural networks with four hidden layers and with neuron (N = 5) is higher than the PPV of the developed deep neural networks with different number of layers (Layers = 2, 3, 5) with different number of neurons. Results demonstrate that the PPV of the developed classifiers is high when the number of layers is selected between 2 and 4. Further increase in the number of hidden layers is found to decrease the classification PPV.

Figure 11 shows the Negative Predictive Value (NPV) of DNN and SNN for the classification of normal, myopathy and ALS EMG signals with different number of layers and with different number of neurons. It is observed that the NPV of SNN classifiers with 15 neurons (N = 15) is

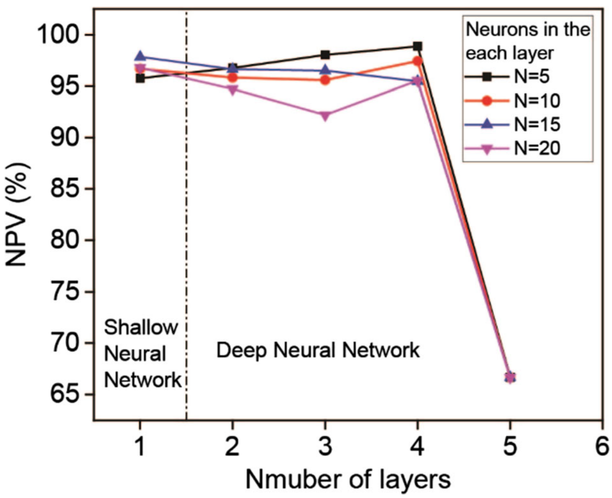


Fig. 11 The variation of NPV for the developed Shallow and deep neural network classifiers with different the number of neurons, shown as a function of the number of hidden layers

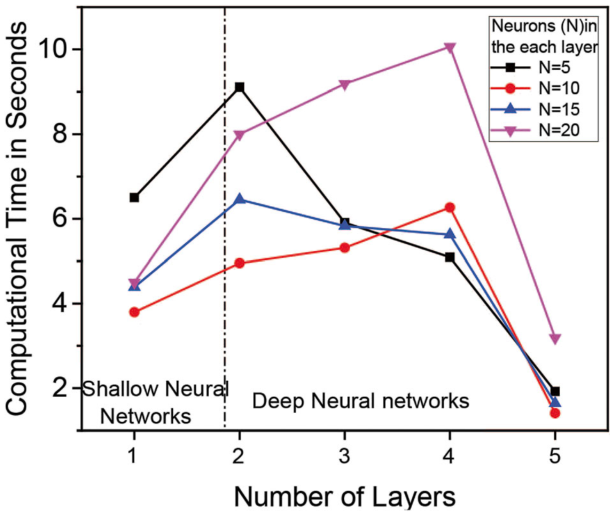


Fig. 12 The variation of computational time for the developed shallow and deep neural network classifiers with different the number of neurons, shown as a function of the number of hidden layers

higher when compared to the NPV of developed shallow neural network classifiers with other adopted number of neurons (N = 5, 10, 20). Further, the NPV of the developed deep neural networks with four hidden layers and with neuron (N = 5) is higher than the NPV of the DNN with different number of layers (Layers = 2, 3, 5) with different combination of neurons. Results demonstrate that the NPV of the developed classifiers is high when the number of layers is selected between 2 and 4. Further increase in the number of hidden layers is found to decrease the classification NPV.

Figure 12 shows the computational time (in seconds) for DNN and SNN with different number of layers and with different combination of neurons. It is seen that the computational time is increases with increases of number of layers between 1 and 4. Further, the computational time is decreases with increases of number layers more than 4.

Table 2 presents the computational time for the training the DNN and SNN classifiers with different number of layers and with different combination of neurons. It is found that the computational time is increases with increases of number of layers and with the number of neurons.

Table 3 presents the numerical values of the performance metrics of the DNN and SNN classifiers, for various numbers of hidden layers and hidden neurons. It is seen that the deep neural network with L = 4 (Fourth hidden layer) and $N = 5$ (neurons), is more efficient than the other developed classifiers, with an Accuracy of 97.7%, Sensitivity of 98.03%, Specificity of 98.98%, NPV of 97.43% and PPV of 98.85%.

Table 2 Computational time (seconds) for the developed shallow and deep neural network classifiers

Neurons	Layers			
	1 Computational Time (seconds)	2	3	4
5	6.5	9.1093	5.906	5.093
10	3.796	4.953	5.312	6.265
15	4.39	6.453	5.828	5.625
20	4.5	8	9.187	10.062

Table 3 The performance measures of the developed shallow and deep neural network classifiers

Quality Measures	Shallow Neural Network				Deep Neural Network															
					Number of Layers (L) in Deep Neural Network															
					L = 2				L = 3				L = 4				L = 5			
	Neurons (N) in each layer																			
	5	10	15	20	5	10	15	20	5	10	15	20	5	10	15	20	5	10	15	20
Accuracy	91.10	93.30	95.5	93.30	93.30	91.10	93.30	88.80	95.50	91.10	93.30	84.40	97.70	95.50	91.10	91.10	31.10	31.10	26.66	31.10
Sensitivity	90.89	93.37	95.21	93.15	93.27	90.47	93.19	89.44	94.87	92.15	94.11	84.25	98.03	96.82	91.91	91.31	10.30	10.36	33.33	33.33
Specificity	95.33	96.64	97.84	96.58	96.77	95.46	96.68	94.51	97.97	95.86	96.63	92.14	98.98	97.91	95.67	95.57	43.66	43.7	4.21	43.70
PPV	92.50	93.19	95.21	94.16	93.26	91.72	93.38	89.32	95.23	91.66	93.17	83.70	97.43	95.55	91.06	90.93	33.33	33.33	33.33	33.33
NPV	95.75	96.68	97.84	96.78	96.76	95.82	96.64	94.72	98.03	95.58	96.50	92.20	98.85	97.43	95.47	95.54	66.66	66.66	66.66	66.66

4 Conclusion

The electrical signals from the human muscles were utilized to analyze the neuromuscular disorders and these signals are referred as Electromyograms. In this work, the time-frequency domain images were obtained from four different transformation techniques. Further, the time-frequency features sub set were extracted from the time-frequency images. A feature selection approach based on PSO with fractional velocity update was implemented for the selection of 15 significant features for the efficient classification of EMG signals [34]. Also, the two classifiers networks were developed using shallow and deep neural network classifiers and the comparative analysis of developed shallow and deep neural network classifiers were performed using the performance metrics of the developed classifiers networks. Results demonstrate that the accuracy of the developed DNN classifier with fourth layer (L = 4) and with 5 neurons in each layer,is higher when compared to the accuracy of the other developed neural networks with different number of layers and with different number of neurons in each layer. Also, the other performance metrics such as sensitivity, specificity, PPV and NPV values of the developed deep neural network classifier with four layer and with neurons (N = 5) is higher when compared to the developed other neural network classifiers with different number of layers and with different combination of adopted neurons. This work seems to be of high clinical relevance since that the developed deep neural network classifiers is more efficient for the classification of EMG signals and also it is necessary for proper diagnosis of neuromuscular disorders.

References

1. Alagumariappan P, Krishnamurthy K (2018) An Approach Based on Information Theory for Selection of Systems for Efficient Recording of Electrogastrograms. In Proceedings of the International Conference on Computing and Communication Systems (pp. 463–471). Springer, Singapore
2. Alagumariappan P, Rajagopal A, Krishnamurthy K (2016) Complexity Analysis on Normal and Abnormal Electrogastrograms Using Tsallis Entropy. In 3rd International Electronic and Flipped Conference on Entropy and Its Applications. Multidisciplinary Digital Publishing Institute
3. Alagumariappan P, Krishnamurthy K, Kandiah S, Ponnuswamy MJ (2017) Effect of electrode contact area on the information content of the recorded electrogastrograms: an analysis based on Rényi entropy and Teager-Kaiser energy. *Polish Journal of Medical Physics and*. Engineering 23(2):37–42
4. Al-Barazanchi KK, Al-Neami AQ, Al-Timemy AH (2017). Ensemble of bagged tree classifier for the diagnosis of neuromuscular disorders. In Advances in Biomedical Engineering (ICABME), 2017 Fourth International Conference on (pp. 1–4). IEEE
5. Ambikapathy B, Krishnamurthy K (2018) Analysis of electromyograms recorded using invasive and noninvasive electrodes: a study based on entropy and Lyapunov exponents estimated using artificial neural networks. J Ambient Intel Humanized Comput 1–9
6. Amin M, Cohen L, Williams WJ (1993). Methods and applications for time frequency analysis. In Conference Notes, University of Michigan
7. Amin J, Sharif M, Yasmin M, Fernandes SL (2018) Big data analysis for brain tumor detection: deep convolutional neural networks. Futur Gener Comput Syst. https://doi.org/10.1016/j.future.2018.04.065
8. Ansari GJ, Shah JH, Yasmin M, Sharif M, Fernandes SL (2018) A novel machine learning approach for scene text extraction. Future Gen Comput Syst
9. Arunkumar N, Ramkumar K, Venkatraman V, Abdulhay E, Fernandes SL, Kadry S, Segal S (2017) Classification of focal and non focal EEG using entropies. Pattern Recogn Lett 94:112–117

10. Belkhou A, Jbari A, Belarbi L (2017) A continuous wavelet based technique for the analysis of electromyography signals. In Electrical and Information Technologies (ICEIT), 2017 International Conference on (pp. 1–5). IEEE
11. Boashash B (1991) Time-frequency signal analysis. Prentice Hall
12. Chandra B, Sharma RK (2016) Fast learning in deep neural networks. Neurocomputing 171:1205–1215
13. Christodoulou CI, Pattichis CS (1999) Unsupervised pattern recognition for the classification of EMG signals. IEEE Trans Biomed Eng 46(2):169–178
14. Duque CJG, Muñoz LD, Mejía JG, Trejos ED (2014). Discrete wavelet transform and k-nn classification in EMG signals for diagnosis of neuromuscular disorders. In Image, Signal Processing and Artificial Vision (STSIVA), 2014 XIX Symposium on (pp. 1–5). IEEE
15. Daud WMBW, Yahya AB, Horng CS, Sulaima MF, Sudirman R (2013) Features extraction of electromyography signals in time domain on biceps Brachii muscle. Int J Model Opt 3(6):515
16. Davies MR, Reisman SS (1994) Time frequency analysis of the electromyogram during fatigue. In Bioengineering Conference, 1994., Proceedings of the 1994 20th Annual Northeast (pp. 93–95). IEEE
17. Fernandes SL, Chakraborty B, Gurupur VP, Prabhu G (2016) Early skin cancer detection using computer aided diagnosis techniques. J Integr Des Process Sci 20(1):33–43
18. Fernandes SL, Gurupur VP, Lin H, Martis RJ (2017) A novel fusion approach for early lung Cancer detection using computer aided diagnosis techniques. J Med Imaging Health Inform 7(8):1841–1850
19. Haralick RM, Shanmugam K, Dinstein I (1973) Textural features for image classification. IEEE Trans Syst Man, Cybernet 3(6):610–621
20. Havaei M, Davy A, Warde-Farley D, Biard A, Courville A, Bengio Y, Larochelle H (2017) Brain tumor segmentation with deep neural networks. Med Image Anal 35:18–31
21. Jang GC, Cheng CK, Lai JS, Kuo TS (1994) Using time-frequency analysis technique in the classification of surface EMG signals. In Engineering in Medicine and Biology Society, 1994. Engineering Advances: New Opportunities for Biomedical Engineers. Proceedings of the 16th Annual International Conference of the IEEE (Vol. 2, pp. 1242–1243). IEEE
22. Kamalanand K, Jawahar PM (2012) Coupled jumping frogs/particle swarm optimization for estimating the parameters of three dimensional HIV model. BMC Infect Dis 12(1):P82
23. Kamalanand K, Jawahar PM (2013a) Particle swarm optimization based estimation of HIV-1 viral load in resource limited settings. Afr J Microbiol Res 7(20):2297–2304
24. Kamalanand K, Jawahar PM (2014b) Hybrid BFPSO algorithm based estimation of optimal drug dosage for antiretroviral therapy in HIV-1 infected patients. BMC Infect Dis 14(S3):E14
25. Kamalanand K, Mannar Jawahar P (2015) Comparison of swarm intelligence techniques for estimation of HIV-1 viral load. IETE Tech Rev 32(3):188–195
26. Kamalanand K, Mannar Jawahar P (2016) Comparison of particle swarm and bacterial foraging optimization algorithms for therapy planning in HIV/AIDS patients. Int J Biomath 9(02):1650024
27. Karthick PA, Ghosh DM, Ramakrishnan S (2018) Surface electromyography based muscle fatigue detection using high-resolution time-frequency methods and machine learning algorithms. Comput Methods Prog Biomed 154:45–56
28. Kuniszyk-Józkowiak W, Jaszczuk J, Sacewicz T, Codello I (2012). Time-frequency Analysis of the EMG Digital Signals. In *Annales UniversitatisMariae Curie-Sklodowska* (Vol. 12, No. 2, p. 19). De Gruyter Open Sp. z oo
29. Liu W, Wang Z, Liu X, Zeng N, Liu Y, Alsaadi FE (2017) A survey of deep neural network architectures and their applications. Neurocomputing 234:11–26
30. Manickavasagam K, Sutha S, Kamalanand K (2014) Development of systems for classification of different plasmodium species in thin blood smear microscopic images. J Adv Microsc Res 9(2):86–92
31. Nikolic M (2001) Detailed Analysis of Clinical Electromyography Signals EMG Decomposition, Findings and Firing Pattern Analysis in Controls and Patients with Myopathy and Amytrophic Lateral Sclerosis. PhD Thesis, Faculty of Health Science, University of Copenhagen. [The data are available as dataset N2001 at http://www.emglab.net]
32. Nuwer MR, Comi G, Emerson R, Fuglsang-Frederiksen A, Guerit JM, Hinrichs H et al (1999) IFCN standards for digital recording of clinical EEG. The International Federation of Clinical Neurophysiology. Electroencephalogr Clin Neurophysiol Suppl 52:11
33. Phinyomark A, Phukpattaranont P, Limsakul C (2012) Feature reduction and selection for EMG signal classification. Expert Syst Appl 39(8):7420–7431
34. Pires ES, Machado JT, de Moura Oliveira PB, Cunha JB, Mendes L (2010) Particle swarm optimization with fractional-order velocity. Nonlinear Dynamics 61(1–2):295–301
35. Quynh TL, Ardi HA, Gilat M, Rifai C, Ehgoetz MK, Georgiades M, … Nguyen HT (2017). Detection of turning freeze in Parkinson's disease based on S-transform decomposition of EEG signals. In Conference

proceedings:... Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE Engineering in Medicine and Biology Society. Annual Conference (Vol. 2017, p. 3044)
36. Raja NSM, Rajinikanth V, Fernandes SL, Satapathy SC (2017) Segmentation of breast thermal images using Kapur's entropy and hidden Markov random field. J Med Imaging Health Inform 7(8):1825–1829
37. Raja NSM, Fernandes SL, Dey N, Satapathy SC, Rajinikanth V (2018) Contrast enhanced medical MRI evaluation using Tsallis entropy and region growing segmentation. Journal of Ambient Intelligence and Humanized Computing, 1–12
38. Rajagopal A, Alagumariappan P, Krishnamurthy K (2018) Development of an Automated Decision Support System for Diagnosis of Digestive Disorders Using Electrogastrograms: An Approach Based on Empirical Mode Decomposition and K-Means Algorithm. In *Expert System Techniques in Biomedical Science Practice* (pp. 97–119). IGI Global
39. Rajinikanth V, Satapathy SC, Fernandes SL, Nachiappan S (2017) Entropy based segmentation of tumor from brain MR images–a study with teaching learning based optimization. Pattern Recogn Lett 94:87–94
40. Rajinikanth V, Raja NSM, Satapathy SC, Fernandes SL (2017) Otsu's multi-thresholding and active contour snake model to segment dermoscopy images. J Med Imaging Health Inform 7(8):1837–1840
41. Rajinikanth V, Raja NSM, Kamalanand K (2017) Firefly algorithm assisted segmentation of tumor from brain MRI using Tsallis function and Markov random field. J Control Eng Appl Inform 19(2):97–106
42. Rajinikanth V, Dey N, Satapathy SC, Ashour AS (2018) An approach to examine magnetic resonance angiography based on Tsallis entropy and deformable snake model. Futur Gener Comput Syst 85:160–172
43. Ricamato AL, Absher RG, Moffroid MT, Tranowski JP (1992). A time-frequency approach to evaluate electromyographic recordings. In Computer-Based Medical Systems, 1992. Proceedings., Fifth Annual IEEE Symposium on (pp. 520–527). IEEE
44. Sharif M, Khan MA, Faisal M, Yasmin M, Fernandes SL (2018) A framework for offline signature verification system: best features selection approach. Pattern Recogn Lett
45. Sharma S, Farooq H, Chahal N. Feature Extraction and Classification of Surface EMG Signals for Robotic Hand Simulation
46. Stockwell RG, Mansinha L, Lowe RP (1996) Localization of the complex spectrum: the S transform. IEEE Trans Signal Process 44(4):998–1001
47. Subasi A (2012) Classification of EMG signals using combined features and soft computing techniques. Appl Soft Comput 12(8):2188–2198
48. Wang G, Zhang Y, Wang J (2014) The analysis of surface emg signals with the wavelet-based correlation dimension method. Comput Math Methods Med
49. Yousefi J, Hamilton-Wright A (2014) Characterizing EMG data using machine-learning tools. Comput Biol Med 51:1–13
50. Yu G, Yu M, Xu C (2017) Synchroextracting Transform. IEEE Transactions on Industrial Electronics

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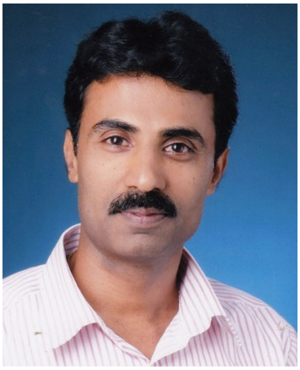

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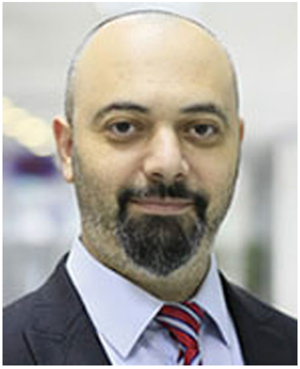

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