ALSNET: A DILATED 1-D CNN FOR IDENTIFYING ALS FROM RAW EMG SIGNAL

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ABSTRACT

Amyotrophic Lateral Sclerosis (ALS) is one of the most common neuromuscular diseases which affects both lower and upper motor neurons. In this paper, a dilated one dimensional convolutional neural network, named ALSNet, is proposed for identifying ALS from raw EMG signal. No hand-crafted feature extraction is required, rather, ALSNet is able to take raw EMG signal as input and detect EMG signals of ALS subjects. This makes the method more feasible for practical implementation by reducing the computational cost required for extracting features. To our best knowledge, no research work for identification of ALS from raw EMG signal has been conducted yet. The performance of the ALSNet was evaluated using popular metrics such as overall accuracy, sensitivity, specificity and balanced accuracy and compared with other existing methods. The proposed method showed a better performance than the other existing methods with an overall accuracy of 97.74%.

***Index Terms*—** Neuromuscular, Amyotrophic Lateral Sclerosis (ALS), Electromyography (EMG), Convolutional Neural Network (CNN), Dilation

1. INTRODUCTION

Neuromuscular diseases affect the muscles and their nervous control systems which results in either spasticity or motor neuron disorder. Parkinson's disease, Huntington's disease, Creutzfeldt–Jakob disease, spinal muscular atrophies, amyotrophic lateral sclerosis are some of the examples of neuromuscular diseases. Amyotrophic lateral sclerosis (ALS), also known as Lou Gehrig's disease or Motor Neuron Disease (MND), is the most common type of neuromuscular disease [1]. ALS is a fatal disease that causes progressive loss of both upper and lower motor neurons that controls different voluntary muscles [2]. The term "Amyotrophic" refers to the muscle weakness signifying the disorder of lower motor neurons. "Lateral sclerosis" refers to the disorder in the motor neurons of spinar cord [3]. Numerous direct and indirect symptoms of ALS [4] continue to develop over a long period until the affected person loses his ability to move, talk or eat. Eventually it results in an early death, usually from respiratory failure. There is no cure for ALS and 90-95% cases of ALS have unknown cause [5]. But early diagnosis can be helpful to prevent the relentlessly progressive disorder and improve quality of life for ALS patients [6]. Since there is no specific diagnosis test, it is sometimes difficult to distinguish between ALS and other neuromuscular diseases [3].

There are different signal domain techniques for analyzing the EMG signal. In case of time domain, zero-crossing rate, turns–amplitude ratio, root-mean-square (RMS) value and autoregressive (AR) coefficients are considered as useful features to analyze EMG signal [7]. Different frequency domain and spectral features [8], the wavelet transform [9], and various morphological features [10] have been investigated for EMG signal analysis. EMG signals are consisted of several Motor Unit Action Potentials (MUAPs) and various features and information can also be extracted from MUAPs. All the types of features mentioned above plays a useful role of classification of EMG signals. Based on the features many classification methods for identifying ALS from EMG signal have been developed.

The authors in [11] proposed a mel-frequency cepstral coefficient (MFCC) based feature extraction scheme with a K-nearest neighbourhood (KNN) classifier for the classification of ALS. The authors in [12] proposed a discrete cosine transform (DCT) of EMG signal based feature extraction method. KNN algorithm was used as the classifier. The authors in [13] extracted six features from intrinsic mode functions (IMFs) of the EMG signal using empirical mode decomposition (EMD). Finally, these features were used in the least square support vector machine (LS-SVM) classifier for classification. In [14] a spectral features extraction method from the dominant motor unit action potential (MUAP) of EMG signals was proposed with a KNN classifier. CNN classifiers have been proposed in [15] and [16] based on the time-frequency (T-F) representation of EMG signal. Short Time Fourier Transform (STFT), Spectrogram, continuous wavelet transform (CWT), and smoothed pseudo Wigner–Ville distribution (SPWVD) have been employed for T-F representation. All of these methods are based on hand-crafted feature extraction or T-F representation of EMG Signal. Classification of ALS directly

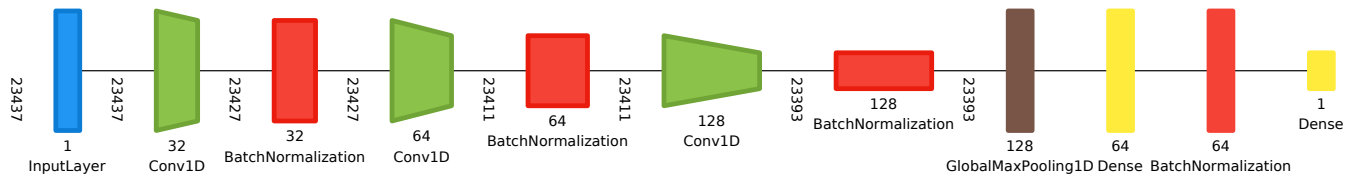

Fig. 1. Network Architecture of ALSNet.

without any T-F domain feature extraction or transformation is not considered in these research works. A classifier that classifies the raw EMG signal and does not depend on any hand-crafted signal features will reduce the computational cost required for extracting features. Thus it will be more suitable for a practical implementation. Hence, an ALS classification method from EMG signal without any time-domain feature extraction or transformation was the motivation of the proposed research work.

In this paper, a dilated one dimensional (1D) Convolutional Neural Network (CNN) named as ALSNet is proposed to identify ALS from raw EMG signal. The performance of ALSNet is compared with different existing methods in terms of four evaluation metrics- overall accuracy, sensitivity, specificity and balanced accuracy.

2. PROBLEM DESCRIPTION

EMG signal is a time-series biomedical signal that measures current or voltage generated in the muscles which represents the neuromuscular activities. The problem encountered in this study is to classify the normal and ALS affected subjects from the corresponding EMG signals. The EMG signals of normal and ALS subjects are named as *Normal EMG* and *ALS EMG* respectively throughout this paper. Following the conventional rule of binary classification, Normal and ALS EMG are considered as class 0 and class 1 respectively in this study.

3. PROPOSED SYSTEM

A 1D CNN, named ALSNet is proposed in this study for detecting ALS from EMG signals. The details of the proposed system is described in this section.

3.1. Network Architecture of ALSNet

The network architecture of ALSNet is shown in Fig. 1. The EMG signals are used as the input of ALSNet without any pre-processing or time-frequency domain feature extraction. The network architecture of ALSNet is developed following the state-of-the-art CNN systems. There are total of three 1D convolution layers and each of the convolution layers is followed by the ReLU (Rectified Linear Unit) activation function and a batch normalization layer. Each of the layers has a higher dilation rate than the previous one. Increasing the dilation rate increases the gap between two kernels and helps to integrate more information from a wider context. The idea of dilated convolution is successfully used in biomedical image segmentation [17]. It is also used in speech synthesis [18] and sound source localization [19] from raw audio data. In this study, the dilation rate is increased by one. So, the dilation rate of the three convolution layers are 1,2,3 respectively. After the final convolution layer, there is a global max pooling layer. The output from the pooling layer then passes through two fully connected layers. The first fully connected or dense layer has 64 nodes followed by a ReLU activation function and a batch normalization. The final dense layer is the output layer having a single node with a Sigmoid activation function.

3.2. Class Prediction from ALSNet

Since the activation function of the output layer of ALSNet is Sigmoid, the output is mapped between 0 to 1. This value between 0 to 1 found from ALSNet as output represents the probability of a test segment being class 1 (ALS EMG). If the probability value is equal to or above than a certain threshold, the segment is predicted as class 1, otherwise, it is predicted as class 0 (Normal EMG). The threshold is set 0.5 in this study.

4. EXPERIMENT

In this section, the dataset and the experiment is discussed in detail.

4.1. Dataset

The clinical EMG signals of N2001 EMGLAB open access Dataset was used in our experiment [20]. The Dataset was consisted of three groups- Normal, Myopathy and ALS. The EMG signals of Normal and ALS groups were used in this experiment. The Normal group consisted of 10 normal subjects (4 females and 6 males) aged 21-37 years and the ALS group consisted of 8 patients (4 females and 4 males) aged 35-67 years. All the EMG signals were recorded under usual conditions for MUAP analysis:

- The recordings were made at low (just above threshold) voluntary and constant level of contraction.

- Visual and audio feedback were used to monitor the signal quality.
- A standard concentric needle electrode were used.
- The EMG signals were recorded from five places in the muscle at three levels of insertion (deep, medium, low).
- The high and low pass filters of the EMG amplifier were set at 2 Hz and 10 kHz.

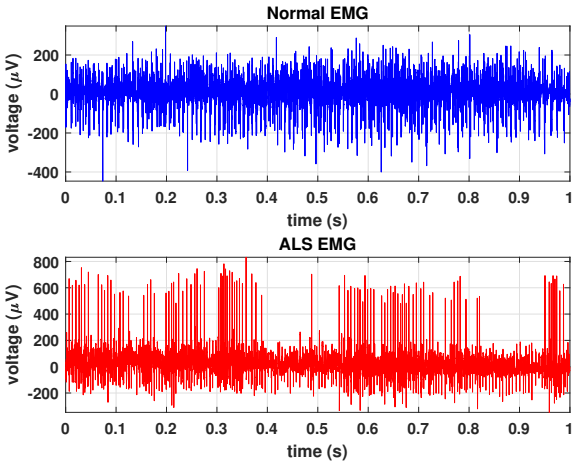

Fig. 2. Arbitrary segments of Normal and ALS EMG signals

Each of the EMG signals was sampled at 24 kHz frequency and recorded for almost 11 seconds. A total number of 302 EMG signals recorded from the brachial biceps and medial vastus muscles were used in this experiment. Out of the 302 EMG signals, 151 signals were from the Normal group and the rest of the 151 signals were from the ALS group. Each of these 302 signals was then segmented into 11 segments where each of the segments had a time duration of 1s. So, the size of the dataset used in this experiment is- $302 \times 11 = 3322$. An arbitrary segment from each of the Normal and ALS EMG signals is shown in Fig. 2.

The dataset was splitted into train, validation and test set by a ratio of 80:20:25. The training, validation and test sets were made up of data from different subjects so that the proposed model can be trained and evaluated properly. Summary of the datset is shown in Table 1.

Table 1. Summary of the dataset used in the experiment

	Train	**Validation**	**Test**
No. of segments	2125	532	665

4.2. ALSNet Model Training

The proposed model, ALSNet was developed using the Keras and Tensorflow frameworks. Kaggle's GPU was used as the hardware accelarator for training the model. The loss function for the training algorithm was *Binary Cross-entropy*. *Adam* was used as the optimizer algorithm with an initial learning rate of 0.001. The learning rate was decreased by a factor of 10 whenever the validation loss did not decrease or started increasing for consecutive epochs. The minimum learning rate set 10^{-10}. The training was stopped early if there was no significant improvement of the validation loss for consecutive epochs.

The summary of the model training is provided in Table 2 and the loss curves (both training and validation) are shown in Fig. 3.

Table 2. Summary of the training configurations of ALSNet

Accelerator	GPU
Loss function	Binary Cross-entropy
Optimizer	Adam
Initial learning rate	0.001
No. of epochs	67
Batch size	48
Execution time	721.7s

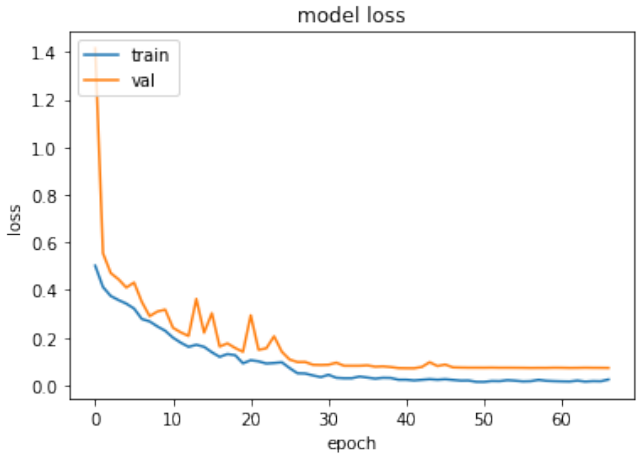

Fig. 3. Training and validation loss curves

5. PERFORMANCE EVALUATION

The achieved results of the proposed approach along with the evaluation metrics are discussed in this section.

5.1. Evaluation Metrics

The metrics used for evaluating our proposed methods are- Overall Accuracy, Sensitivity, Specificity and Balanced Accuracy,

- *Overall Accuracy*: $\frac{TP+TN}{TP+FP+TN+FN}$

- *Sensitivity (True Positive Rate)*: $\frac{TP}{TP+FN}$
- *Specificity (True Negative Rate)*: $\frac{TN}{TN+FP}$
- *Balanced Accuracy*: $\frac{Sensitivity + Specificity}{2}$

TP, FP, TN, FN are True Positive, False Positive, True Negative and False Negative respectively.

5.2. Results

Let, the test set be denoted by $\mathcal{S}$. As mentioned in Section 3.2, for a segment $s \in \mathcal{S}$, the output of ALSNet is a probability value which indicates the probability of that segment being an ALS EMG. Let that probability value is denoted by $P(s = 1)$ $(\forall s \in \mathcal{S})$. If $P(s = 1) > threshold$, then the predicted class is class 1 (ALS EMG), otherwise, it will be class 0 (Normal EMG). Since the problem encountered in this experiment is a binary classification, the threshold was set to 0.5. Finally, the predicted classes were matched with the ground truth. The probability values for the test segments are shown in Fig.4.

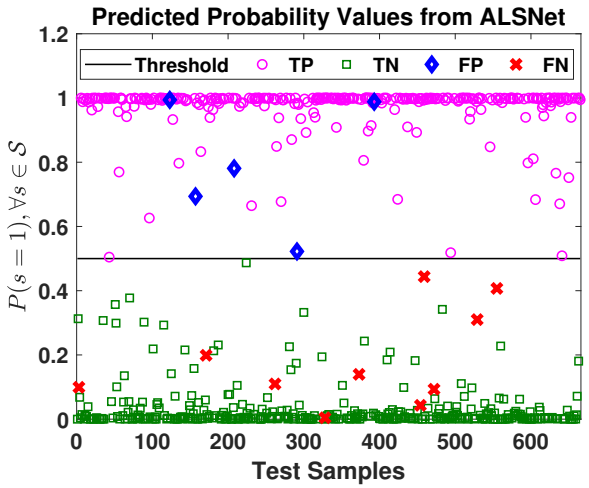

Fig. 4. Probability values of class 1 predicted from ALSNet on test segments

ALSNet was able to predict 650 EMG signal segments accurately out of 665 segments in the test set. The confusion matrix is shown in Fig. 5.

The result of the proposed method is compared with the results shown in different existing research works in terms of the evaluation metrics mentioned in Section 5.1. The comparison is shown in Table. 3. From Table. 3, it is clear that ALSNet performs better than the mentioned methods in case of overall accuracy and sensitivity. In case of specificity, the methods in [14] and [16] perform slightly better. But if the balanced accuracy is considered, ALSNet outperforms the other methods.

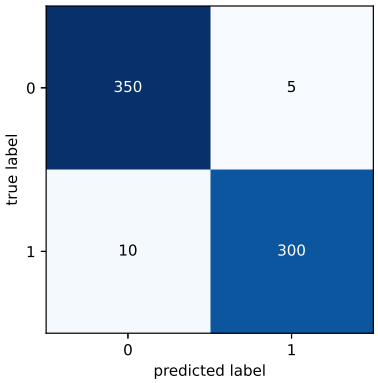

Fig. 5. Confusion matrix

Table 3. Result comparison of ALSNet with existing methods

Method	Overall Accuracy (%)	Sensitivity (%)	Specificity (%)	Balanced Accuracy (%)
Doulah A.B.M.S.U. and Fattah S.A. [11]	92.50	76.00	98.00	87.00
Doulah A.B.M.S.U. et al. [12]	95.00	86.00	98.00	92.00
Misra V.K. et al. [13]	95	93.00	92.54	92.75
Krishna A. and Thomas P. [14]	96.5	88	99.33	93.67
Sengur A. et al. [15]	96.69	94.24	97.59	95.92
Sengur A. et al. [16]	96.80	94.8	98.8	96.8
ALSNet	**97.74**	**96.77**	**98.59**	**97.68**

6. CONCLUSION

A 1D dilated convolutional neural network based approach is proposed in this paper for identifying ALS from raw EMG signal. The performance of the method in terms of overall accuracy, sensitivity, specificity and balanced accuracy showed good promise. This method can be useful in early diagnosis of ALS which will help improving the quality of life and prolong survival of an ALS patient. Since any hand-crafted feature extraction is not required for ALSNet, the computational cost of extracting those features will also be reduced. So, the proposed method is more applicable for practical implementation.

Acknowledgment

The authors would like to thank the organizers of EMGLAB [20] for their public dataset which was used to develop this research work.

7. REFERENCES

[1] E. Zucchi, V. Bonetto, G. Sorarù, I. Martinelli, P. Parchi, R. Liguori, and J. Mandrioli, "Neurofilaments in motor neuron disorders: towards promising diagnostic and prognostic biomarkers," *Molecular neurodegeneration*, vol. 15, no. 1, pp. 1–20, 2020.

[2] P. K. Kasi, L. S. Krivickas, M. Meister, E. Chew, M. Schmid, G. Kamen, E. A. Clancy, and P. Bonato, "Motor unit firing characteristics in patients with amyotrophic lateral sclerosis," in *2009 IEEE 35th Annual Northeast Bioengineering Conference*. IEEE, 2009, pp. 1–2.

[3] L. P. Rowland and N. A. Shneider, "Amyotrophic lateral sclerosis," *New England Journal of Medicine*, vol. 344, no. 22, pp. 1688–1700, 2001.

[4] J. D. Mitchell and G. D. Borasio, "Amyotrophic lateral sclerosis," *The lancet*, vol. 369, no. 9578, pp. 2031–2041, 2007.

[5] NHS, "Motor neurone disease," online, January 2018. [Online]. Available: www.nhs.uk

[6] M. Swash, "Early diagnosis of als/mnd," *Journal of the Neurological Sciences*, vol. 160, pp. S33 – S36, 1998. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0022510X98002159

[7] A. Fuglsang-Frederiksen, "The utility of interference pattern analysis," *Muscle & Nerve: Official Journal of the American Association of Electrodiagnostic Medicine*, vol. 23, no. 1, pp. 18–36, 2000.

[8] S. A. Fattah, M. A. Iqbal, M. A. Jumana, and A. S. U. Doulah, "Identifying the motor neuron disease in emg signal using time and frequency domain features with comparison," *Signal & Image Processing*, vol. 3, no. 2, p. 99, 2012.

[9] E. W. Abel, H. Meng, A. Forster, and D. Holder, "Singularity characteristics of needle emg ip signals," *IEEE transactions on biomedical engineering*, vol. 53, no. 2, pp. 219–225, 2006.

[10] C. D. Katsis, T. P. Exarchos, C. Papaloukas, Y. Goletsis, D. I. Fotiadis, and I. Sarmas, "A two-stage method for muap classification based on emg decomposition," *Computers in Biology and Medicine*, vol. 37, no. 9, pp. 1232–1240, 2007.

[11] A. B. M. S. U. Doulah and S. A. Fattah, "Neuromuscular disease classification based on mel frequency cepstrum of motor unit action potential," in *2014 International Conference on Electrical Engineering and Information Communication Technology*, 2014, pp. 1–4.

[12] A. B. M. S. U. Doulah, S. A. Fattah, W. Zhu, and M. O. Ahmad, "Dct domain feature extraction scheme based on motor unit action potential of emg signal for neuromuscular disease classification," *Healthcare Technology Letters*, vol. 1, no. 1, pp. 26–31, 2014.

[13] V. K. Mishra, V. Bajaj, A. Kumar, and G. K. Singh, "Analysis of als and normal emg signals based on empirical mode decomposition," *IET Science, Measurement Technology*, vol. 10, no. 8, pp. 963–971, 2016.

[14] V. A. Krishna and P. Thomas, "Classification of emg signals using spectral features extracted from dominant motor unit action potential," *International Journal of Engineering and Advanced Technology*, vol. 4, no. 5, pp. 196–200, 2015.

[15] A. Sengur, M. Gedikpinar, Y. Akbulut, E. Deniz, V. Bajaj, and Y. Guo, "Deepemgnet: An application for efficient discrimination of als and normal emg signals," in *Mechatronics 2017*, T. Březina and R. Jabłoński, Eds. Cham: Springer International Publishing, 2018, pp. 619–625.

[16] A. Sengur, Y. Akbulut, Y. Guo, and V. Bajaj, "Classification of amyotrophic lateral sclerosis disease based on convolutional neural network and reinforcement sample learning algorithm," *Health information science and systems*, vol. 5, no. 1, p. 9, 2017.

[17] S. Hossain, S. Najeeb, A. Shahriyar, Z. Abdullah, and M. Haque, "A pipeline for lung tumor detection and segmentation from ct scans using dilated convolutional neural networks," in *2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*. Brighton, United Kingdom: Institute of Electrical and Electronics Engineers(IEEE), 2019, pp. 1348–1352.

[18] A. v. d. Oord, S. Dieleman, H. Zen, K. Simonyan, O. Vinyals, A. Graves, N. Kalchbrenner, A. Senior, and K. Kavukcuoglu, "Wavenet: A generative model for raw audio," *arXiv preprint arXiv:1609.03499*, Sep 19 2016.

[19] A. B. A. Qayyum, K. N. Hassan, A. Anika, M. F. Shadiq, M. M. Rahman, M. T. Islam, S. A. Imran, S. Hossain, and M. A. Haque, "Doanet: a deep dilated convolutional neural network approach for search and rescue with drone-embedded sound source localization," *EURASIP Journal on Audio, Speech, and Music Processing*, vol. 2020, no. 1, pp. 1–18, 2020.

[20] M. Nikolic, "Detailed analysis of clinical electromyography signals: Emg decomposition, findings and firing pattern analysis in controls and patients with myopathy and amytrophic lateral sclerosis," Ph.D. dissertation, Faculty of Health Science, University of Copenhagen, Copenhagen, Denmark, 2001. [Online]. Available: http://www.emglab.net