

Subject-Independent Automated Detection of Amyotrophic Lateral Sclerosis from Electromyography Signals Using ALSNet

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الكشف الآلي عن التصلب الجانبي الضموري بصورة مستقلة عن المريض باستخدام إشارات تخطيط كهربية العضلات وشبكة ALSNet

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Abstract:

Amyotrophic Lateral Sclerosis (ALS) is a progressive disorder of the nervous system that affects motor neurons and causes progressive weakness and loss of function of motor neurons. Clinically relevant information on neuromuscular activity is provided by Electromyography (EMG) and can be used to assist the diagnosis of ALS. The use of EMG interpretation can be difficult due to their complex temporal and morphological characteristics, however. In this study, the novel approach of a deep learning method (ALSNet) to automatically classify ALS and Normal EMG signals is explored. The experiments were performed with processed EMG data extracted from publicly available N2001 EMGLAB database. All 302 EMGs (151 Normal, 151 ALS) were divided into 3,322 one-second EMG segments. A subject-independent partitioning strategy for the dataset was used. ALSNet is a deep network developed based on Keras and TensorFlow frameworks, and trained with Adam optimizer by using binary cross-entropy loss. The accuracy, sensitivity, specificity, precision, F1-score, and balanced accuracy were used for evaluation of the model. ALSNet obtained 97.74% accuracy, 96.77% sensitivity, 98.59% specificity, 98.36% precision, 97.56% F1-score and 97.68% balanced accuracy on the independent test set. The findings show the promise of deep learning analysis of EMG signals for automated ALS detection and offer a foundation for future analysis with more and varied clinical datasets.

Keywords: Amyotrophic Lateral Sclerosis; Electromyography; EMG Signal; ALS Detection; ALSNet; Deep Learning; One-Dimensional Convolutional Neural Network; Biological Signals; Automated Diagnosis; EMGLAB Dataset.

المخلص

يُعد التصلب الجانبي الضموري (Amyotrophic Lateral Sclerosis – ALS) اضطرابًا عصبيًا تقدميًا يؤثر في الخلايا العصبية الحركية، مما يؤدي إلى ضعف تدريجي وفقدان الوظيفة الحركية. ويوفر تخطيط كهربية العضلات (Electromyography – EMG) معلومات سريرية مهمة حول النشاط العصبي العضلي، ويمكن الاستفادة منه في دعم تشخيص التصلب الجانبي الضموري. ومع ذلك، قد يكون تفسير إشارات تخطيط كهربية العضلات أمرًا صعبًا بسبب خصائصها الزمنية والمورفولوجية المعقدة. في هذه الدراسة، يتم استكشاف نهج جديد قائم على التعلم العميق (ALSNet) لتصنيف إشارات تخطيط كهربية العضلات تلقائيًا إلى إشارات مرتبطة بالتصلب الجانبي الضموري وإشارات طبيعية. أُجريت التجارب باستخدام بيانات تخطيط كهربية العضلات المعالجة والمستخرجة من قاعدة بيانات N2001 EMGLAB المتاحة للعامة. شملت البيانات جميع الإشارات البالغ عددها 302 إشارة EMG، منها 151 إشارة طبيعية و151 إشارة لمرضى التصلب الجانبي الضموري، وقُسمت إلى 3,322 مقطعًا من إشارات EMG، مدة كل منها ثانية واحدة. واعتمدت الدراسة استراتيجية تقسيم للبيانات مستقلة عن المريض (Subject-Independent) لضمان تقييم أكثر موثوقية لقدرة

النموذج على التعميم. تم تطوير شبكة ALSNet باستخدام إطار Keras وTensorFlow، وتدريبها باستخدام خوارزمية التحسين Adam ودالة خسارة الانتروبيا المتقاطعة الثنائية (Binary Cross-Entropy). وتم تقييم أداء النموذج باستخدام الدقة، والحساسية، والنوعية، والدقة الإيجابية (Precision)، ودرجة F1، والدقة المتوازنة. حققت شبكة ALSNet على مجموعة الاختبار المستقلة دقة بلغت 97.74%، وحساسية 96.77%، ونوعية 98.59%، ودقة إيجابية 98.36%، ودرجة F1 بلغت 97.56%، ودقة متوازنة بلغت 97.68%. وتشير هذه النتائج إلى الإمكانيات الواعدة لتقنيات التعلم العميق في تحليل إشارات تخطيط كهربية العضلات للكشف الآلي عن التصلب الجانبي الضموري، كما توفر أساساً لتطوير دراسات مستقبلية باستخدام مجموعات بيانات سريرية أكبر وأكثر تنوعاً.

الكلمات المفتاحية: التصلب الجانبي الضموري؛ تخطيط كهربية العضلات؛ إشارات EMG؛ الكشف عن التصلب الجانبي الضموري؛ ALSNet؛ التعلم العميق؛ الشبكة العصبية الالتفافية أحادية الأبعاد؛ الإشارات الحيوية؛ التشخيص الآلي؛ قاعدة بيانات EMGLAB

1. Introduction

Biological signals are useful for understanding the physiological and functional condition of the human body and have gained significance in recent times for use in diagnosis of diseases. Electrocardiography (ECG), Electroencephalography (EEG), Electromyography (EMG), Electrooculography (EOG), and Photoplethysmography (PPG) are all signals that reflect the various aspects of human biological activity and can reveal abnormalities that may not be easily detected through traditional clinical examination [1]. The application of biological signals for disease assessment was further boosted by the development of non-invasive biosensors, digital signal acquisition systems and computational analysis techniques that allow for an objective, quick and automatic evaluation. The integration of signal processing, machine learning and deep learning opens up the potential to identify subtle patterns in the physiological signals and help clinicians identify complex neurological and muscular diseases [2].

Biological signals of particular relevance to the assessment of neuromuscular diseases include electromyography (EMG) which measures the voltage or electrical activity generated by a muscle. EMG signals provide information about motor-unit recruitment, muscle activation, firing characteristics and neuromuscular function. When these characteristics are abnormal, they can be important clues to neurological and muscular abnormalities. As a result, EMG has become a commonly employed tool for diagnosis and evaluation in peripheral nervous system and/or motor unit disorders, as an adjunct to other tests. For this reason, EMG has been extensively used as an adjunct to other tests in evaluating peripheral nervous system and/or motor unit disorders. Typically, however, EMG interpretation relies heavily on clinical experience and the visual and quantitative evaluation of EMG recordings is subject to the effects of signal variability, noise, recording conditions and the experience of the examiner [3].

Amyotrophic lateral sclerosis (ALS) is one such important neurological disorder that can be studied with EMG. ALS is a progressive neurodegenerative disease with the main feature being the progressive degeneration of the upper and lower motor neurons, leading to progressive muscle weakness, impaired motor function, and severe disability in the later stages. Although the clinical features of ALS are not unique, early and accurate diagnosis is still difficult. Therefore, EMG may be useful in showing evidence of denervation and reinnervation seen with motor-neuron degeneration and can be a valuable part of the diagnostic work-up of suspected ALS patients. However, the task of interpreting the complex temporal and morphological feature of EMG recordings is a challenging one [4].

The recent developments in artificial intelligence have opened new opportunities for analyzing the EMG signal for automated disease detection. New opportunities have been opened by the recent developments in the field of artificial intelligence for analyzing the EMG signal for the purpose of automated disease detection. Machine-learning algorithms can detect features from the time domain, frequency domain and the time-frequency domain and deep-learning models can capture complex patterns directly from signal data without relying heavily on the features designed by humans. These methods can help standardize the diagnosis, minimize the burden of manual interpretation of signals, and supply decision-support capabilities for clinicians. The usefulness of such systems, however, is heavily dependent on the quality, uniformity and proper preprocessing of the underlying EMG data. Therefore, noise removal, segmentation, normalization, artifact reduction, and appropriate representation of the signals are essential steps to develop reliable computational diagnostic models [5].

The EMGLab dataset is useful as a source of biological signal data for the investigation of automated ALS detection in this context. Pre-processing is especially crucial when the biomedical signals being recorded are not

in their raw state, as raw biomedical recordings could have noise, artifacts, variation in the amplitude of the signals to be classified and other factors that have negative impact on the classification performance. By processing an EMGLab data set carefully, meaningful characteristics of the signal can be extracted from it, and a solid machine learning or deep learning model can be created for identifying ALS. This kind of processing also aids in repeatable experimentation and systematic assessment of computational methods [6].

Thus, in this study, the focus is on the processed EMG data from the EMGLab dataset used for the diagnosis of ALS using biological signals. The goal of the study is to develop a successful signal processing and computational framework for differentiating EMG patterns from ALS patients and non-ALS recordings. The proposed method combines biomedical signal processing and intelligent classification methods, aiming to showcase the feasibility of EMG-based analysis in providing an automated mechanism for diagnosis support. The final framework can be used in larger, more varied clinical EMG datasets for future study and in neurological disease assessment, without the need for tissue biopsy.

2. Related Works

Zhang et al. [7] introduce the surface electromyography technique to aid in the diagnosis of ALS through extracting quantitative features from muscle electric activity. The techniques were based on the three diagnostic biomarkers – the clustering index, kurtosis of EMG amplitude histogram and kurtosis of EMG crossing-rate expansion, and the further application of the linear discriminant analysis for classification. Surface electromyography signals of 10 ALS patients and 11 neurologically healthy individuals were utilized for the study. The results are very encouraging – the application of the three biomarkers together reaches 90% sensitivity and 100% specificity. The drawbacks of the study are the extremely small size of the sample, the application of only one local sample and the absence of external validation. Hence, while the results prove the diagnostic capabilities of surface electromyography, bigger and more diverse datasets are required.

In their work, Gokgoz and Subasi [8] presented a new automatic EMG classification system for classification of normal, ALS, and myopathic signals. The techniques are based on multiscale principal component analysis (MSPCA) for noise removal, followed by extraction of features using multiple signal classification (MUSIC) and classification of EMGs through k-nearest neighbor (k-NN), artificial neural networks (ANN), and support vector machines (SVM). The findings demonstrated the effectiveness of denoising in EMG classification with the highest accuracy obtained using SVM at 92.55%. In the case of ALS, the same algorithm delivered high sensitivity and AUC measures. The drawbacks include the limited size of the subject sample with 10 healthy, 8 ALS and 7 myopathic subjects used in the study and reliance on hand-crafted features. Moreover, the method was tested under experimental laboratory conditions.

The framework suggested by Mishra et al. [9] aims at discriminating ALS patients from normal EMG recordings through an approach that relies on empirical mode decomposition. It involves using empirical mode decomposition (EMD) to decompose EMG recordings into narrow-band intrinsic mode functions (IMFs). Then, six features are extracted based on the analysis of these IMFs, which include the area of complex plot, modulation bandwidth, frequency modulation bandwidth, normalized instantaneous frequency, momentum of power spectral density, and mean first derivative of instantaneous frequency. Finally, these features are fed into a least squares support vector machine classifier. This method shows better classification accuracy than previous methods tested on the same database. However, its limitations are reliance on handcrafted features from EMD and the small size of the database. Also, the task under consideration is binary classification of ALS patients and normal people.

Sengur et al. [10] present a deep learning framework for automatic classification of ALS and normal EMG data. The methods are designed using conversion of the one-dimensional EMG data into their time-frequency domain representations using spectrogram, continuous wavelet transform (CWT), and smoothed pseudo-Wigner-Ville distribution (SPWVD). These time-frequency representations are then fed into a CNN model that comprises convolutional layers, pooling layers, and fully connected layers. Additionally, reinforcement sample learning method is utilized in the training process. The results indicate 96.80% accuracy rate obtained using the publicly available EMG dataset comprising 89 ALS and 133 normal EMG signals. The paper illustrates the capability of CNN models to learn discriminative features from time-frequency representations. The weaknesses include small dataset, binary classification problem, reliance on preprocessing, and no external validation.

In their work, Nagineni et al. [11] suggest using VMD for detection of neuromuscular diseases based on EMG signals. Variational mode decomposition is used for decomposition of the signal into several band-limited modes. Spectral features such as spectral flatness, spectral spread, and spectral decrease are combined with

kurtosis, mean absolute deviation, and interquartile range as statistical measures of EMG signal. Classification is performed using an extreme learning machine. Results show that VMD is capable of producing useful representation for separation between normal, ALS, and myopathic EMG signals. The drawbacks include small data set, feature engineering, and lack of results regarding robustness to acquisition conditions. Additionally, selection of VMD parameters needs to be done correctly.

Time frequency analysis technique by Chatterjee et al. [12] is designed to automatically differentiate between ALS and myopathy diseases using EMG data. The techniques are based on window Stockwell transform, which provides time-frequency representation with adjustment of analysis window. Different features are extracted from the representation, and the statistical significance of the features is determined using the Student's t-test. The chosen features are classified using benchmark machine learning algorithms: SVM, k-NN, decision tree, and Naïve Bayes. According to the results, the proposed technique gives strong classification performance, the highest reported mean accuracy equals 98.58%. The work confirms the utility of local time-frequency representation for neuromuscular disease detection. The limitations of the work include the low number of the subjects, specific dataset properties, use of handcrafted features and lack of external validation.

The work by Khan et al. [13] offers an approach to automate the diagnosis of the distinction between healthy and ALS EMG signals considering differences due to the use of different muscles and the depth of the needle insertion. The methods rely on empirical mode decomposition for denoising and time-domain and frequency-domain feature extraction. The classification is performed using LR and SVM classifiers and tested using sensitivity, specificity, F-measure, accuracy and area under the ROC curve criteria. The findings of the work show that the best results were achieved using logistic regression classifier, reaching accuracy of 95.1%. The advantages of the research are that the framework is able to function despite the difference in muscle from which EMG is acquired. The limitations of the research include limited data set size, manual feature selection and limited clinical validation. Additionally, the problem of classification was focused only on binary one.

Dubey et al. [14] present a diagnostic system which is able to classify ALS, myopathy, and normal EMG patterns by applying automation. The methodology applied by Dubey et al. is empirical mode decomposition, selection of suitable intrinsic mode functions statistically and generation of complex plane representation. Geometrical measures like quadrilateral area and circumference were computed from these representations and fed to the feed-forward neural networks, SVM and decision trees. It was observed that the feed-forward neural network performed best, obtaining 99.53%, 99.25% and 99.60% accuracy, sensitivity and specificity respectively. This research shows the feasibility of using nonlinear decomposition and geometric features of the signal. The weaknesses include small population size, controlled recordings and hand-crafted geometric features. In addition, this high performance requires independent validation in a clinical setup.

Overall research gap

Taken together, these studies show that, as an automated diagnostic system for ALS, EMG is among the most promising biological signals, and machine-learning and deep-learning techniques are often able to achieve high accuracy. The methodological question however, frequently makes its way into many papers. We found 51 studies in 2024 scoping review with 61% focused on the open source EMGLab dataset (only 25 subjects across healthy, ALS and myopathy groups). The review also highlighted issues of bias and overtraining, and concluded that the current state of AI models was not ready for clinical use. Likewise, a systematic review and meta-analysis published in 2024 detected good pooled diagnostic performance of AI-based ALS detection technique, with pooled sensitivity of 92.3% and pooled specificity of 96.5% for EMG-based classification, but noted concerns about evidence quality. This provides a strong rationale for the proposed study – instead of applying another classifier to the raw EMGLab signals, the study can focus on systematic processing of the EMGLab dataset, on improving the quality of the signals and extending the reliability of the results, on the representation of the features, on the solid evaluation of the classification. This comparison can then be used to determine if the biological signals can be processed appropriately to improve the reliability of ALS detection when compared to the older handcrafted approaches and modern machine/deep-learning methods.

3. Methodology

This section highlights the methodology used for the diagnosis of Amyotrophic Lateral Sclerosis (ALS) using EMG signals. In the methodology, a processed EMG dataset and a pre-trained deep learning model called ALSNet will be used to classify EMG samples into two classes. This chapter explains the stages that the methodology involves, such as loading the test dataset, preprocessing test samples, loading the trained model ALSNet, generating probability of predictions, converting the probabilities into predictions of two classes, and evaluation of predictions through a number of metrics. These metrics include accuracy, sensitivity, specificity, precision, F1-score, confusion matrix, receiver operating characteristic (ROC), area under the ROC curve (AUC), and precision-recall analysis. The predicted probabilities and labels of the data are also exported for further analysis. For the presentation of the whole methodology to be achieved, Figure (1) provides a flowchart representing the process that was taken to perform the ALS diagnosis using the ALSNet model, pre-trained on the dataset. First, the test features and their labels were loaded, after which the test features were reshaped into the format necessary for input into ALSNet model. Afterward, the model was used to compute prediction probabilities from which class predictions were produced using a given threshold. Then, the confusion matrix was created, along with the calculation of classification metrics, such as accuracy, sensitivity, specificity, precision, and F1-score. The generation of ROC and precision-recall curves and saving of the predictions followed the process.

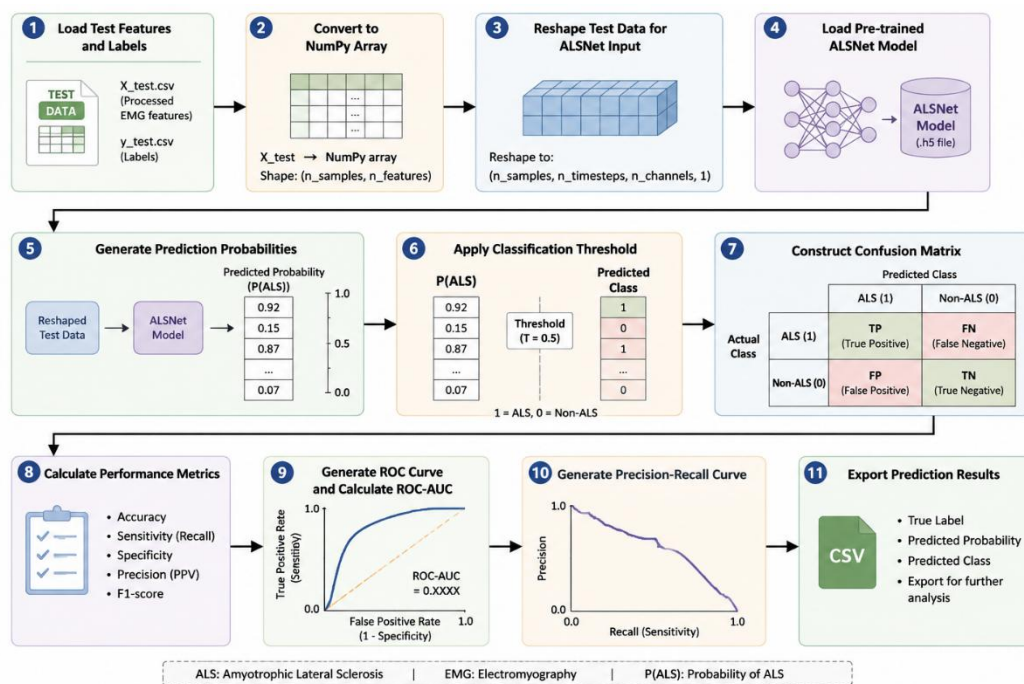


Figure 1: Methodology Workflow

3.1 Dataset Description

The dataset we use in this study is the processed electromyography (EMG) signals of two classes: normal subjects and subjects suffering from Amyotrophic Lateral Sclerosis (ALS). The data were originally collected from the publicly available dataset N2001 EMGLAB, a collection of EMG data for use in the study of neuromuscular signal analysis. The data includes clinically relevant EMG signals which can be analysed for differences between healthy and pathological neuromuscular activity. The processed EMG signals in this research are used to check the performance of the deep learning architecture specifically designed for identification of ALS from raw EMG signals, referred to as **ALSNet**. The pre-processing applied to the original recordings results in normalized signal representations which can be fed into the proposed detection framework. There is a class label with each sample, which is either "ALS" or "normal". Thus, the dataset can be used for a supervised binary classification problem, where the goal is automatic classification of ALS related EMG patterns from normal EMG patterns.

The data set is appropriate for this study because EMG signals have temporal and morphological properties that relate to neuromuscular abnormalities. Characteristic changes in motor-unit activity can be produced by ALS

and can be seen in the recorded EMG signals. Therefore, deep learning methods can be used to gain discriminative information directly from the signal data, and lessen reliance on manually designed features. The data and ALSNet methodology were reported by Hassan et al. in the paper titled “ALSNet: A Dilated 1-D CNN for Identifying ALS from Raw EMG Signal” at the IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP) 2022. The proposed ALSNet architecture is implemented by one dimensional dilated CNN to learn relevant temporal patterns from EMG signals for automated ALS identification. The processed dataset is then subjected to ALSNet to evaluate the classification characteristics of the unseen test samples, and to calculate comprehensive classification indicators such as accuracy, sensitivity, specificity, precision, F1 score, precision-recall performance and ROC-AUC.

The original data set is openly accessible in EMGLAB repository, while the methodological approach in ALSNet underlies the data processing in this study. When the dataset has been used for research or further development there is thus a need for appropriate citation of the original dataset and of the ALSNet publication.

Dataset Link: <https://www.kaggle.com/datasets/naimulhassan/processed-emglab-dataset-for-als-detection/data>

3.2 Processed EMG Dataset

The methodology used is applied to a processed EMG dataset intended for the diagnosis of ALS. The test data features are saved in $X_test.pkl$, whereas the test labels are saved in $y_test.pkl$. The test features matrix can be described as:

$$X_{test} = [x_1, x_2, \dots, x_N]^T, \quad (1)$$

where N represents the number of test samples and x_i represents the feature vector or processed EMG representation of the i -th sample. The corresponding ground-truth labels are represented as:

$$y_{test} = [y_1, y_2, \dots, y_N], \quad (2)$$

Where $y_i \in \{0,1\}$. The meaning of labels 0 and 1 follows the class definition of the processed EMGLab dataset.

3.3 Test Data Preparation

These test data are read as Pandas objects and then converted to NumPy arrays. This will create a numeric format which will be usable by the TensorFlow/Keras inference process. This is done through:

$$X_{test} = \text{NumPy}(X_{test}). \quad (3)$$

Assuming that the original feature matrix has dimensions $N \times L$, the data are reshaped into a three-dimensional tensor:

$$X_{test} \in \mathbb{R}^{N \times L \times 1}. \quad (4)$$

The reshaping operation is given by:

$$X_{test}^* = \text{reshape}(X_{test}, (N, L, 1)). \quad (5)$$

The final dimension corresponds to the single input channel of the EMG representation.

3.4 Pre-Trained ALSNet Model

The deep learning algorithm that has been used to detect ALS is called ALSNet. This model is loaded from the pre-trained model file called ALSNet3.hdf5. Mathematically, the model can be described as:

$$f_{\theta}: \mathbb{R}^{L \times 1} \rightarrow [0,1], \quad (6)$$

where θ denotes the learned model parameters. For an input EMG sample x_i , ALSNet produces a prediction probability:

$$\hat{p}_i = f_{\theta}(x_i). \quad (7)$$

The output $\hat{p}_i$ represents the estimated probability of the positive class. What must be noted is the fact that inference code for the network uses the previously saved model from the HDF5 file and does not provide any

information about the inner structure of the network. This means that details about the number of convolutional layers, kernel sizes, filters, pooling operations, and dense layers used in the network must be found separately.

3.5 Probability-Based Classification

After loading the trained model, prediction probabilities are generated for all test samples:

$$\hat{\mathbf{p}} = [\hat{p}_1, \hat{p}_2, \dots, \hat{p}_N]. \quad (8)$$

The probability output is retained because it is required for threshold analysis, ROC analysis, and precision-recall analysis. For the final binary classification, a threshold of 0.5 is employed:

$$\hat{y}_i = \begin{cases} 1, & \hat{p}_i \geq 0.5, \\ 0, & \hat{p}_i < 0.5. \end{cases} \quad (9)$$

Therefore, samples with a predicted probability greater than or equal to 0.5 are assigned to the positive class.

3.6 Confusion Matrix

The predicted labels are compared with the ground-truth labels to construct the confusion matrix:

$$\mathbf{CM} = \begin{bmatrix} TN & FP \\ FN & TP \end{bmatrix}. \quad (10)$$

The four elements have the following meanings:

- *TN*: correctly classified negative samples;
- *FP*: negative samples incorrectly classified as positive;
- *FN*: positive samples incorrectly classified as negative;
- *TP*: correctly classified positive samples.

These four quantities form the basis for calculating the principal classification metrics.

3.7 Performance Evaluation Metrics

Several metrics are used to evaluate the performance of ALSNet.

Accuracy: Accuracy represents the proportion of correctly classified samples:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN}. \quad (11)$$

Sensitivity: Sensitivity, also called recall or true positive rate, measures the ability to correctly identify positive samples:

$$Sensitivity = \frac{TP}{TP+FN}. \quad (12)$$

Sensitivity is particularly important in disease detection because a false negative corresponds to an affected sample incorrectly classified as negative.

Specificity: Specificity measures the ability to correctly identify negative samples:

$$Specificity = \frac{TN}{TN+FP}. \quad (13)$$

Precision: Precision measures the proportion of predicted positive samples that are actually positive:

$$Precision = \frac{TP}{TP+FP}. \quad (14)$$

F1-Score: The F1-score is the harmonic mean of precision and recall:

$$F1 = \frac{2 \times Precision \times Recall}{Precision + Recall}. \quad (15)$$

Precision-Recall Analysis: Precision-recall analysis is performed using the continuous prediction probabilities rather than only the binary predictions obtained using the 0.5 threshold. For a threshold t , precision and recall are expressed as

$$Precision(t) = \frac{TP(t)}{TP(t)+FP(t)}, \quad (16)$$

and

$$Recall(t) = \frac{TP(t)}{TP(t)+FN(t)}. \quad (17)$$

The precision-recall curve is obtained by plotting precision against recall over a range of classification thresholds.

Receiver Operating Characteristic Analysis: ROC analysis evaluates the discriminative ability of ALSNet over a range of classification thresholds. For each threshold t , the true positive rate is

$$TPR(t) = \frac{TP(t)}{TP(t)+FN(t)}, \quad (18)$$

while the false positive rate is

$$FPR(t) = \frac{FP(t)}{FP(t)+TN(t)}. \quad (19)$$

The ROC curve is generated by plotting $TPR(t)$ against $FPR(t)$. The area under the ROC curve is calculated as:

$$AUC = \int_0^1 TPR(FPR) d(FPR). \quad (20)$$

A larger ROC-AUC value indicates stronger discrimination between the two diagnostic classes.

4. Results and Discussions

This section presents the experimental outcomes garnered from the proposed ALSNet-based automatic detection framework for Amyotrophic lateral sclerosis (ALS) signals obtained from electromyography (EMG) signals. The EMG data was obtained from the N2001 EMGLAB database, where EMG signals from healthy subjects and ALS patients were used for binary classification. The experimental analysis is conducted on the characteristics and preparation of the data set, the training configuration of the proposed ALSNet model and the quantitative evaluation of the classification performance of the model. In the first step, the characteristics of the dataset are described such as the number of subjects, EMG recordings, conditions of the EMG acquisition, the sampling frequency, the segmentation procedure, and the division of the obtained samples to training, validation, and test set. The first step is the description of the characteristics of the dataset, including the number of subjects, the number of EMG recordings, the conditions under which the EMG was acquired, the sampling frequency, the procedure of segmentation, and the division of the obtained samples into training, validation, and test set. Special emphasis is placed on subject independent data partitioning, so that the model can be tested on signals which were not used in the training phase.

Then, the training setup of ALSNet is introduced; optimization strategy, loss function, learning-rate adaptation, batch size, number of training epochs and computational environment. The behavior and convergence of the proposed model is also studied by analyzing training and validation loss curve. Finally, the overall accuracy, sensitivity, specificity and balanced accuracy are calculated for the independent test set to assess the performance of ALSNet. The predictions by the model are derived as probability values and transformed to binary decisions based on the threshold value of 0.5. The ground truth labels are compared to the predictions obtained using a confusion matrix, and the results of ALSNet are compared to those reported previously. This comparison shows the efficacy of the suggested technique to differentiate ALS EMG signals from normal EMG signals and the advantages and disadvantages of the proposed technique compared to the existing techniques.

4.1. Dataset

The EMG signals collected for the present work were the clinical signals from the publicly available N2001 EMGLAB dataset. The N2001 EMGLAB dataset contains three different subject groups which are Normal, Myopathy, and Amyotrophic Lateral Sclerosis (ALS). In the current research only Normal and ALS datasets were used to construct a binary classification task. The Normal dataset included 10 healthy people with four females and six males aged from 21 to 37 years. The ALS dataset included eight patients consisting of four females and four males aged from 35 to 67 years. All EMG signals were acquired under the same standard experimental protocol which is common for MUAP study. The signals were collected during low-level voluntary and constant muscle contraction being slightly above the contraction threshold. Feedback (visual and audio) was applied to provide assistance in monitoring EMG signals acquisition. Standard concentric needle electrode was used to collect EMG signals. The EMG signals were acquired from five different muscle regions at three insertion levels (deep, medium and low). During EMG signal acquisition the cut-off frequencies of the high-pass and low-pass filters of EMG amplifier were set to 2 Hz and 10 kHz respectively.

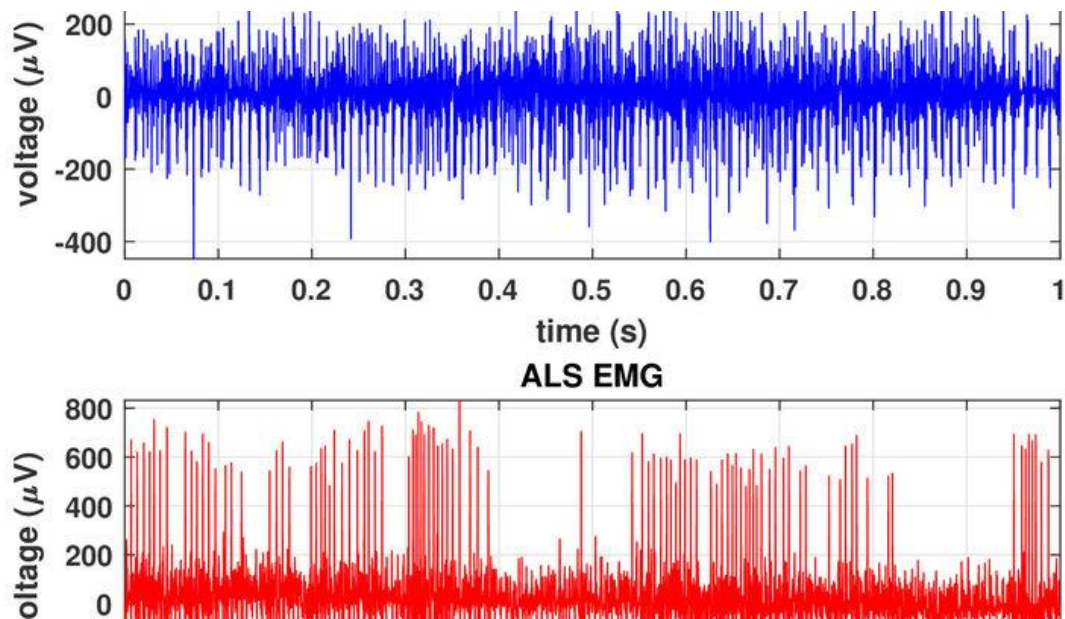


Figure 2: Arbitrary segments of Normal and ALS EMG signals

All EMG signals were sampled at 24 kHz and were recorded for about 11 seconds. A total of 302 EMG signals recorded from the brachial biceps and medial vastus muscles were used in this experiment. Of these, 151 signals were in the Normal group and 151 signals were in the ALS group. Each of the 302 EMG recordings was segmented into 11 short clips with fixed-length inputs of 1 second to enhance the number of training samples and to address the length of the inputs for the proposed model. Thus, there were 3,322 one-second EMG segments for this dataset (302 segments x 11 repetitions). For comparison, two one-second portions of a Normal EMG signal and an ALS EMG signal are shown in Figure (2). The resulting data set was then partitioned into training, validation and test sets with a subject independent partition method. In particular, the training set consisted of 2,125 segments, the validation set of 532 and the test set of 665 segments. These numbers represent about 63.97%, 16.01%, and 20.02%, of the full data set, respectively. Importantly, the signals in the training, validation and test sets were from different subjects. The subject-independent partitioning avoids the occurrence of signals from same subject in more than one subset, which leads to a more reliable evaluation of the ability of the proposed ALSNet model to generalize. The distribution of the data is summarized in Table 1.

Table 1: Summary of the dataset

Dataset	No. of segments	Percentage
Training	2,125	63.97%
Validation	532	16.01%
Test	665	20.02%
Total	3,322	100%

4.2 ALSNet Model Training

The proposed ALSNet model was built in the Keras and TensorFlow frameworks, and trained with a GPU accelerator offered by the Kaggle computing environment. With that task, a binary classification task was used with the loss function of binary cross-entropy with the Adam optimization algorithm and an initial learning rate of 0.001. The learning rate was decreased by 10x for every two epochs if the validation loss was not decreasing or it started to increase over consecutive epochs during training. The lowest learning rate was established as 10^{-10} . Further, an early stopping approach was implemented to stop training when validation loss did not decrease significantly from one epoch to the next. The key training parameters and computational setup used for ALSNet are summarized in Table 2 and the training and validation loss curves are shown in Figure (3).

Table 2: Summary of the training configurations of ALSNet

Parameter	Configuration
Deep learning framework	Keras / TensorFlow
Hardware accelerator	GPU (Kaggle)
Loss function	Binary Cross-Entropy
Optimizer	Adam
Initial learning rate	0.001
Learning-rate reduction factor	10
Minimum learning rate	10^{-10}
Learning-rate adjustment	Based on validation loss
Early stopping	Based on validation-loss improvement
Number of training epochs	67
Batch size	48
Training execution time	721.7 s

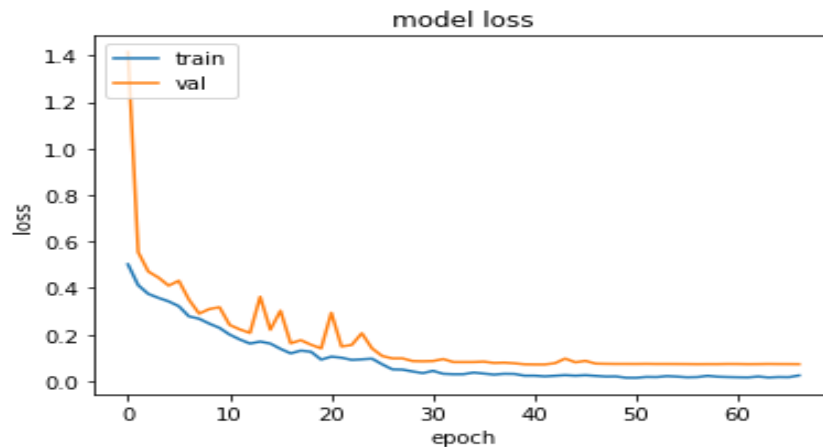


Figure 3: Training and validation loss curves

4.3 Test Samples

The confusion matrix was further employed to validate the classification ability of the proposed ALSNet model with the independent test set as shown in Fig.4. The confusion matrix was used to determine the normal and ALS EMG segments classes: it represents a detailed representation of the agreement between the classes predicted and the labels in the ground truth. The model correctly classified 350 Normal segments and 300 ALS segments, with 650 correct classifications out of the 665 test segments. Of those that were misclassified, 10 ALS segments were misclassified as Normal (false negatives [FN]), and 5 Normal segments were misclassified as ALS (false positives [FP]). So, there are 350 true negatives, 5 false positives, 10 false negatives and 300 true positives. From these values, the overall accuracy of ALSNet can be estimated to be around 97.74%. The sensitivity (recall)

of the ALS detection is about 96.77%, which means that most segments of ALS was detected correctly. The specificity is about 98.59%, which shows that there is a very good recognition of Normal EMG segments. The accuracy rate is about 98.36%, with the majority of the segments that were predicted as ALS being correct. The F1 score is around 97.56%.

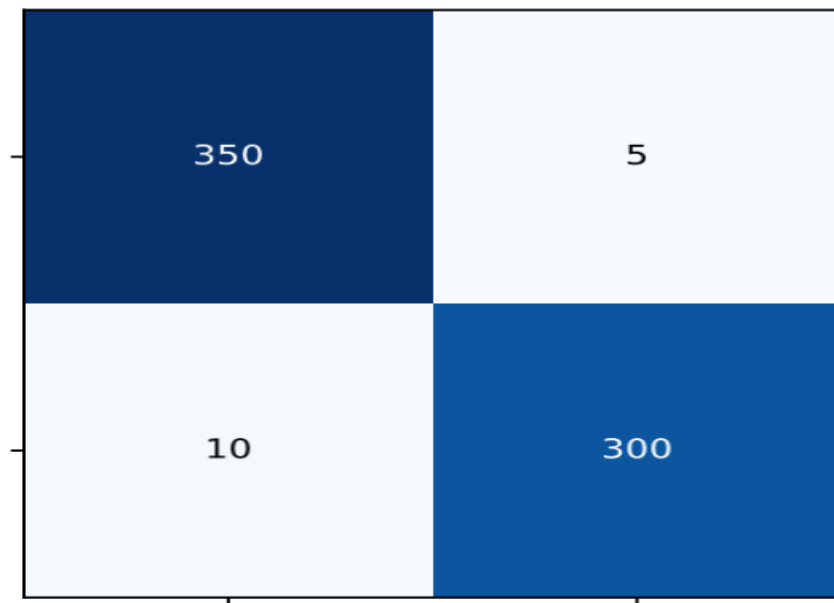


Figure 4: Confusion matrix

4.4 Metrics Analysis

Various performance metrics were used to give an all-around analysis of the ALSNet model in discriminating between ALS EMG segments and Normal EMG segments. Some of the metrics used include accuracy, sensitivity, specificity, precision, F1 score, and balanced accuracy. All these help in giving a complete picture of the performance of the model as a whole, detection of the ALS case, correct identification of the Normal case, and the reliability of positive prediction by the model. The results obtained using these metrics are given in Table 3.

Table 3. Performance evaluation of ALSNet on the test set

Performance Metric	Value
Accuracy	97.74%
Sensitivity	96.77%
Specificity	98.59%
Precision	98.36%
F1-Score	97.56%
Balanced Accuracy	97.68%

The classification performance obtained from the independent test set in Table 3 shows that ALSNet has obtained a high classification performance. Results for the model achieved an overall accuracy of 97.74% which means that the vast majority of the 665 test segments were accurately classified. The sensitivity of 96.77% indicates that ALSNet successfully identified most of the ALS EMG segments. This outcome is especially significant for clinical disease diagnosis since it decreases the proportion of ALS misdiagnosed as Normal when a test is conducted to detect disease. The model also had superior specificity of 98.59%, showing its excellent ability to correctly classify Normal EMG segments and reduce false-positive classifications.

This accuracy of 98.36% also shows that most segments that were labeled as ALS were indeed ALS segments. This indicates that the model has a low rate of false ALS predictions. Furthermore, the F1 score of 97.56% indicates a good balance of the model's performance in identifying ALS patients and its accuracy in

predicting ALS. Last, the balanced accuracy (97.68%) shows that the performance of ALSNet is stable across the two classes (Normal, ALS). The difference between the sensitivity and specificity is not large, which means that there is not a significant bias toward one class. In general, the results show that ALSNet is able to discriminate the EMG segments of Normal and ALS with the reliability as a promising tool of automated ALS detection.

5. Conclusions

This study assessed the feasibility of the ALSNet deep learning model in automatic diagnosis of Amyotrophic Lateral Sclerosis based on electromyography signals. This study used processed EMG recordings from the N2001 EMGLAB and classified Normal and ALS signals as a binary classification problem. A total of 302 EMG recordings were segmented into 1-second samples (3,322), and a subject-independent partitioning strategy was used to partition the training, validation, and test sets. This partitioning ensured that all signals of the same subjects were not shared between the different subsets, allowing for a more accurate evaluation of model generalization. The classification results on the independent test set showed that ALSNet could obtain high classification accuracy. In the test set, 97.74% of the test segments were correctly classified and 650 segments were correctly classified by the model. Furthermore, ALSNet achieved a sensitivity of 96.77% and a specificity of 98.59%, precision of 98.36%, F1-score of 97.56% and balanced accuracy of 97.68%. The result shows high consistency of the model to distinguish the Normal and ALS EMG segments. The high sensitivity is relevant when considering the detection of ALS; most ALS segments were detected correctly with high sensitivity, and the high specificity shows that Normal EMG segments can be correctly recognized.

In summary, the results demonstrate that it is feasible to implement deep learning to detect ALS using EMG signals, proving the potential of using this technique for the automatic detection of ALS. It also shows that ALSNet is able to learn the discriminative patterns from the processed EMG representation without relying heavily on the manually designed features. Study limitations are, however, that it is based on the N2001 EMGLAB data set, which has a relatively small sample of subjects and controlled recording conditions. Thus, more studies are needed on larger, more independent and more diverse clinical EMG datasets to assess the robustness and generalizability of the approach. Further research is possible to study other signal-processing techniques, optimizing the threshold and external clinical assessment of automated EMG-based ALS diagnosis.

Compliance with ethical standards

Disclosure of conflict of interest

The authors declare that they have no conflict of interest.

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