**Convolutional neural network for needle-electromyography diagnosis in comparison with physicians: A retrospective study**

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**Abstract**

**Background**

It has been demonstrated that deep learning shows good performance in reading a surface electromyography (EMG), needle EMG in resting state. However, it is not well elucidated whether deep learning can be applied to reading the needle EMG in contraction state, which plays more important role in differentiating among myopathy, neuropathy, and normal. We investigated whether convolutional neural network (CNN) algorithm can identify the abnormality of needle electromyography.

**Methods and findings**

We classified needle EMG data (58 patients; 382 muscles) stored in Seoul National University Hospital database from June 2015 to July 2020 among myopathy, neuropathy, normal by using the CNN algorithm.

Based on the classified results by CNN algorithm, the accuracy, sensitivity, specificity, positive predictive value and F1 score were 0.820, 0.820, 0.904, 0.820, and 0.820, respectively; mean values of the results electro-diagnosed by physicians were 0.537, 0.527, 0.770, 0.582, and 0.511, respectively. The performance of CNN algorithm for predicting myopathy, neuropathy, and normal was also evaluated with area under the receiver operating characteristic curve, and the results were 0.898 (95% confidence interval [CI] 0.884–0.912), 0.840 (95% CI 0.838–0.841), and 0.948 (95% CI 0.928–0.968), respectively.

**Conclusions**

This study demonstrated that the CNN algorithm is valuable in interpreting needle EMG of patient with neuropathy or myopathy on behalf of physicians and assisting physician’s decision making in diagnosing patients with suspected neuromuscular disease. Large, prospective cohort studies with more diverse neuromuscular disease are needed in the future.

**Keywords**: Electromyography, Machine learning, Neuromuscular disease, Convolutional neural network**Author summary**

**Why was this study done?**

Needle electromyography (nEMG) has established as an important electro-physiologic test widely performed when diagnosing patients with neuromuscular disease.

Despite the importance of nEMG in diagnosis, the accuracy of electromyography readings is not yet high enough and there are often discrepancies among examiners, so more objective and accurate reading means are needed.

**What did the researchers do and find?**

We found the

**What do these findings mean?**

The findings of this study

**Introduction**

Needle Electromyography (nEMG) is a type of electromyography, an electrophysiological test that records electrical activity generated from nerves, muscles, and neuromuscular junctions through a needle inserted into the muscle or surface electrode during resting and volitional state. [1-6] It is used to identify disorders of the peripheral nerves or muscles based on abnormalities in nEMG signals that reflect the anatomical and physiological characteristics of peripheral nerves and muscles. [1-6] Among the nEMG signals, the signal recorded during muscle contraction is called motor unit action potentials (MUAPs); Through this, it is possible to determine whether the subject is has neuropathy or myopathy or not. It has been known that the nEMG signals seen when examining a subject with peripheral neuropathy commonly show characteristics of large amplitudes, long durations, and reduced recruitments, whereas the nEMG signals seen when examining a patient with myopathy show characteristics of small amplitudes, short durations, and early recruitments. These differences in nEMG signals have been reported as important and useful information when diagnosing peripheral neuropathy and myopathy in previous studies. [1, 5-12]

Although nEMG plays an important role in diagnosing normal, neuropathy and myopathy, it has some limitations in that there are discrepancies among examiners, and the accuracy of nEMG relies to a lot extent on proficiency of the examiner. Previous studies have reported that sensitivity of nEMG in the diagnosis of neuropathy, myopathy, and normal is 47–83%, specificity is 73–81% and inter-rater reliability is 62–81%. [13-15] Additionally, to recognize abnormalities of nEMG signals accurately, considerable time and efforts are needed. As the prevalence of neuropathy and myopathy continues to increase, the frequency of nEMG for diagnosing it, the time it takes to interpret it, and the workload of the examiner are bound to increase. [16-19] A new approach may be helpful in clinically diagnosing neuropathy or myopathy through nEMG more efficiently and accurately in a shorter time.

Recently, deep learning has been used to analyzing big data in many field, and it is also applied to clinical data including waveform, time series data. [20, 21] Convolutional neural network, one kind of deep learning techniques, has applied to analyzing time series data and waveform data such as electrocardiography, electroencephalography. [20, 22, 23] Based on a result of the study on reading the results of electrocardiography and electroencephalography using deep learning, the accuracy was similar to or superior to that of medical students or residents, and detect nonobvious abnormalities easily overlooked. [24] Previous studies that analyzed nEMG signals using machine learning were mostly those that analyzed surface nEMG or needle nEMG signals during resting state. [25-29] To our knowledge, few studies have been reported analyzing nEMG signals during volitional state.

To overcome the limitations of nEMG, we developed a deep learning model, which are known to show good performance in image analysis. [30, 31] The development of deep learning-based nEMG analysis could lead to the development of faster and more accurate automated nEMG interpretation. The present study was attempted to verify that deep learning could carry out electrophysiologic diagnosis of nEMG on behalf of physicians and to prove that it could help decision-making in diagnosis of patients. For that goal, we retrospectively reviewed nEMG waveforms, which were examined in subjects with peripheral neuropathy or myopathy or normal subjects, analyzed those by using convolutional neural network (CNN) algorithm, and compared the classification results of nEMG signals with classification results by 6 physicians.

**Methods**

**Study design and preparation**

In this study, nEMG signal data of 58 subjects who visited Seoul National University Hospital from June 2015 to July 2020 were used for analysis by dividing them into peripheral neuropathy, myopathy, and normal based on the final diagnosis. This study was approved by the Internal Review Board of Seoul National University Hospital (No. 2008-055-1147) and conducted according to the Declaration of Helsinki and its later amendments. Informed consent was not necessary because this study is retrospective analysis and all nEMG signal data was anonymized before analysis.

nEMG was performed with a Nicolet EDX EMG system and monopolar needle electrode from the subject’s muscles. The filter setting was set at 20 Hz (low-cut) and 10 kHz (high-cut). The results of the last 10 seconds of the nEMG were recorded and used for analysis.

The results of the waveform data of patients stored numerically in the electromyography machine were extracted, and they were made into waveform data through the MATLAB software (version R2020b). Among the created waveform data, artifacts which occurred in the cases including move of the needle electrode or patients moving, among the data at the beginning and at the end were excluded, and all of the noise in the middle portion was preserved.

The raw nEMG data, which was originally sampled at 48 kHz, was downsampled to 10 kHz to reduce computational complexity, and sliced in fixed window length of 0.4 seconds units and hop size of 0.1 seconds units that were likely to be the most optimal length for post-experimental analysis. Dataset consisted of different numbers of muscle nEMG data because the number of muscles tested was different for each subject. After slicing, total segments were composed of 2700, 3664, and 1706 segments extracted from subjects with myopathy, neuropathy, and normal subjects, respectively. Based on the elbow joint of the upper extremity and the knee joint of the lower extremity, the muscles close to this joint were classified as proximal muscles and distal muscles.

**Classification by physicians**

The nEMG numerical data were extracted from EMG machine after certified neurologist and rehabilitation medicine doctor reviewed and confirmed the diagnosis of all subjects. By de-identifying the number of patient identification as a random number, the nEMG numerical data were transformed to waveform data similar to the actual result displayed on the screen of the nEMG machine; That was stored in the storage space of the web-based labeling platform so that residents belonging to different organizations can participate and provided to 2 neurology residents and 4 rehabilitation medicine residents for classification. (S1 Figure)

Six physicians classified EMG signal data without any clinical information such as symptoms or age of the subject. When the physician pressed the randomly assigned number of the subject, the EMG waveform was simultaneously played with sound and showed both real-time waveform data and waveform data stacked for 500 microseconds; Physicians were allowed to be able to change the amplitude of wave not just 100, 200, and 500 microvolts, but also 1 and 2 millivolts. Physicians first annotated the muscles, and then diagnosed the subjects by considering the results of the muscles annotation. After the physician completes diagnosis, the diagnosis was stored within the platform as well as aggregated and compared with the actual labeling.

**Classification by CNN algorithm**

Current CNN was used to sequentially classify the subject in 2 stages (S1 Figure); First, it received the nEMG signals of each muscle tested for each subject as an input and elicited one of myopathy, neuropathy, and normal as an output. Then, the final output was presented as one of myopathy, neuropathy, and normal by considering all the probability values belonging to myopathy, neuropathy, and normal of the tested muscles to the subject. The results were compared after deriving the output when only the nEMG signal was given as input without clinical information with those when both the proximal or distal and the nEMG signal, which are the location information of the tested muscle, were given as inputs.

This CNN comprised of 7 spatial reduction blocks and 5 residual blocks with 1 and 2 convolutional layers, respectively. (Fig 1) Spatial block and residual block consisted of convolutional layers, batch normalization, and a rectified linear unit (ReLU). Hyper-parameters were determined empirically. Learning rate, batch size, and epoch was set to 10-3, 32, and 100, respectively.

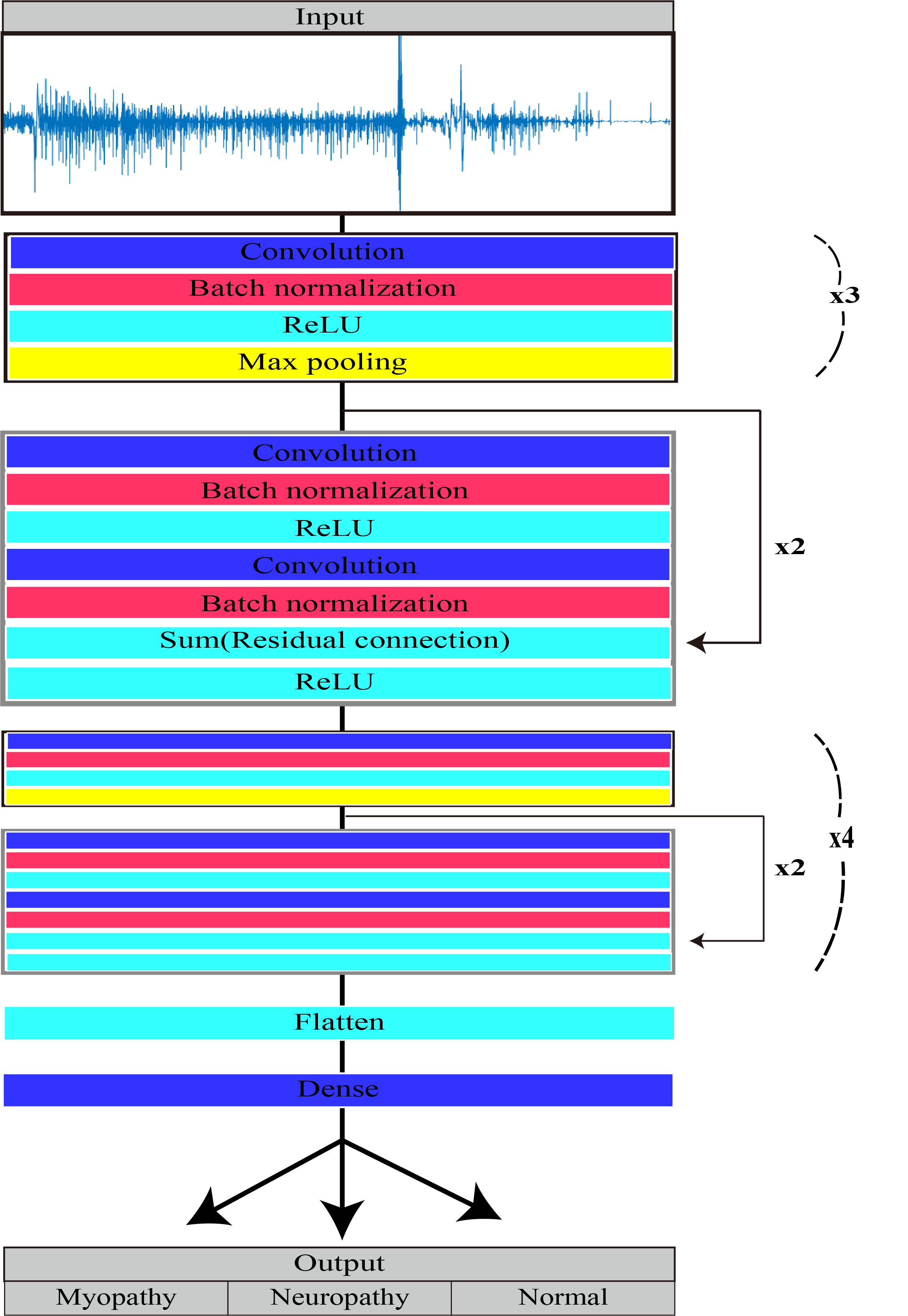


Figure 1. Structure of current CNN algorithm. 7 spatial reduction blocks and 5 residual blocks with 1 and 2 convolutional layers, respectively

**Assessing the performance of CNN algorithm**

The performance of deep learning was evaluated with the accuracy, F1 score, area under receiver operating characteristic curve (AUROC), positive predictive value (PPV; precision), sensitivity (recall) and specificity. Since the number of subjects was small, the accuracy of this algorithm was calculated by cross entropy with 5-fold cross-validation. Based on the results of accuracy, and F1 score as well as PPV, sensitivity, and specificity, we compared the result classified by current CNN algorithm with results by physicians; also measured the degree of agreement between physicians and that between physicians and current CNN algorithm.

**Statistical analysis**

Statistical analyses were performed using R statistical software (version 4.1.0; R Foundation for Statistical Computing, Vienna, Austria) and Python 3. The differences among the groups for categorical variables were assessed using the Fisher’s exact or Pearson’s χ2 tests and those for continuous variables were assessed using the Kruskal–Wallis tests or one-way analysis of variance tests. Data are expressed as means ± standard deviation for continuous variables and number (%) for categorical variables. A *p* value less than 0.05 was regarded as statistically significant. For assessment of algorithm, an ROC (receiver operating characteristic) analysis was used with one versus other method, sensitivity plus specificity were measured with binary decision for each label, and PPV plus recall were calculated and are depicted with PPV-recall curve. Inter-rater reliability was analyzed and is expressed with value of Fleiss kappa.

**Results**

The data of the subjects used for the analysis were 20 subjects with normal and 19 subjects with neuropathy with whom the diagnosis was radiculopathy, motor axonal polyneuropathy, motor neuron disease, etc., myopathy was 19 subjects with whom the diagnosis was muscular dystrophy and inflammatory myopathy. The number of nEMG signal data used for analysis was 125, 161, and 97, respectively, length was 204.31 seconds, 423.12 seconds, and 204.31 seconds. (Table 1)

Table 1. Demographic characteristics of subjects

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | Myopathy | Neuropathy | Normal | p-value |
| Number of Subjects | 19 | 19 | 20 |  |
| Female, n (%) | 14 (73.7) | 12 (63.2) | 13 (65) | 0.761 |
| Age (mean±SD) | 52.2±20.1 | 58.4±15.1 | 60.2±16.9 | 0.329 |
| Proportion of nEMG according to location of muscle (%) |  | | <0.001 | |
| Distal muscles | 60 (48.4) | 97 (60.2) | 80 (82.5) |  |
| Proximal muscles | 64 (51.6) | 64 (39.8) | 17 (17.5) |  |
| Number of nEMG (mean±SD) | 6.53±3.82 | 8.47±4.59 | 4.85±1.93 | 0.006 |
| Total signal length (sec) | 313.54 | 423.12 | 204.31 |  |

The accuracy, sensitivity, specificity, PPV, and F1 score of the CNN algorithm calculated by excluding the results of 8 subjects and 10 muscles, which were missing values, were 0.880, 0.825, 0.908, 0.825, and 0.825, respectively, in contrary, the counterparts of physicians were 0.691, 0.527, 0.770, 0.582, and 0.511, respectively. (Table 2) ROC curve and PPV-recall curve is depicted. (Figure 1)

The prediction results of muscle and subject classification by CNN algorithm were compared those by 6 physicians. The accuracies of the former were 0.710 and 0.820; those averaged of the latter were 0.542 and 0.537, respectively. The inter-rater reliabilities for classifying each muscle nEMG and subject nEMG between physicians were 0.258 and 0.260 expressed in Fleiss κ; the inter-rater reliability between physicians and CNN algorithm were 0.249 and 0.256, respectively. (Table 2)

|  |  |  |
| --- | --- | --- |
|  | Classification results | |
|  | Physicians | CNN algorithm |
| Accuracy | 0.537\* | 0.820 |
| Sensitivity (recall) | 0.527\* | 0.820 |
| Specificity | 0.770\* | 0.904 |
| PPV (precision) | 0.582\* | 0.820 |
| F1 score | 0.511\* | 0.820 |
| Inter-rater reliability (Fleiss κ) |  | |
| Overall | 0.26† | 0.26‡ |
| Myopathy | 0.36† | 0.40‡ |
| Neuropathy | 0.26† | 0.25‡ |
| Normal | 0.20† | 0.17‡ |

Table 2. The results of classification by physicians (average result of 6 physicians) and CNN algorithm (weighted average result). Result was shown with accuract, sensitivity, specificity, positive predictive value (PPV, precision), F1 score and inter-rater reliability.

\*Average value of 6 physicians’ results.

† Fleiss κ value between physicians’ results

‡ Fleiss κ value between CNN algorithm’s result and physicians’ results



Figure 2. ROC and precision-recall curves according to neuropathy, myopathy, normal.

Area under receiver operating characteristic curve on myopathy, neuropathy, and normal are 0.898, 0.840, and 0.948, respectively. (Fig 2)

The accuracies of this machine learning algorithm were calculated except missing values (n=8 for subjects, n=10 for muscle signals) are depicted as confusion matrices by muscle prediction results and subject prediction results for each diagnosis. The results of measuring the prediction accuracy by group of each muscle and subject are as follows; Myopathy was 71.58%±8.06% and 81.11%±14.74%, neuropathy was 63.20%±14.09% and 80.00%±18.71%, and normal was 52.26%±21.74% and 91.11%±15.65%. (Figure 3)

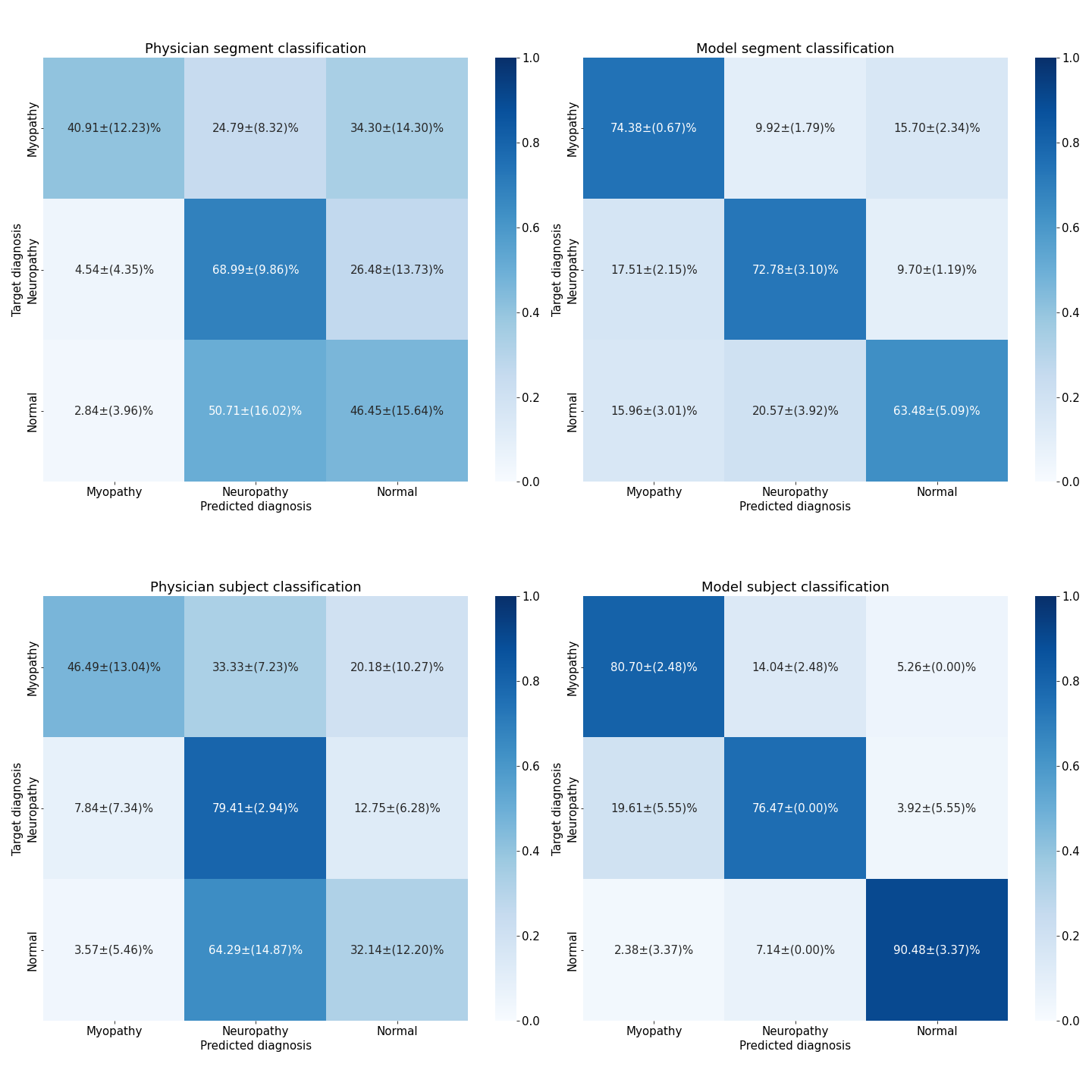


Figure 3. Confusion matrices showing the accuracy of classification by current machine learning algorithm and that by physicians, excluding missing values. (n= 10 muscles and 8 subjects) Left; Accuracy of predicted results for each nEMG waveform, Right; Accuracy of predicted results by considering all nEMG of each patient together. Physician confusion matrix추가.

Proximal, distal의 정보가 있는것과 없는것의 정확도 차이를 비교한 table. S1 table.

Based on the results of training through CNN algorithm, the characteristics of the waveform of myopathy, neuropathy, and normal were similar to characteristics of the actual nEMG waveforms. The waveform of myopathy showed small amplitude as well as short duration and counterpart of neuropathy showed high amplitude as well as long duration. (S2 Figure)



S2 Figure. Trained waveforms of myopathy, neuropathy, and normal based on CNN algorithm.

(A), (C) and (E), waveform based on learned features by CNN algorithm; (B), (D) and (F), actual waveform

(A) and (B), myopathy; (C) and (D), neuropathy;(E) and (F), normal.

Note that (A), (B), (E), (F) were plotted with 5mV y-axis limit and (C), (D) was plotted with 20mV y-axis limit to show the overall shape of the nEMG signal from neuropathy subjects which has characteristic of high amplitude.

Among the classified waveforms, there were waveforms whose accuracy was poor by CNN algorithm and physicians. CNN algorithm classified correctly, but the diagnostic accuracy of physicians was low in some cases, less than 2 in 6, and vice versa; There were also some waveforms that neither the CNN algorithm nor physicians couldn’t classify accurately. (S3 Figure)

S3 Figure. Examples of misclassified waveforms

**Discussion**

The aim of the present study was to evaluate the accuracy of classifying the nEMG waveform data using machine learning, and to demonstrate if it can support physician’s decision to enable more accurate and efficient diagnosis. For that purpose, deep learning was applied to classifying the nEMG waveforms, assessed the performance; additionally, the classified results were compared with electrophysiological diagnosis by 6 physicians. Based on the classified results by our CNN algorithm, the accuracy was superior to accuracy of the physician’s diagnosis.

Previously, there have been reports that machine learning showed good performance when applied to image analysis, surface EMG, and needle nEMG. [25-31] Previous studies that analyzed nEMG data as 2 dimensional data using machine learning were studies to analyze gestures using surface nEMG or signals during resting state using needle nEMG. [25-29] It is well known that needle nEMG is more useful than surface EMG for diagnosing neuromuscular disorders, and not only the signal during resting state but also the signal of during volitional state should be considered among needle nEMG signal. [1-6, 8, 32, 33]. However, there have been few studies that classify nEMG data in a volitional state using deep learning.

We analyzed nEMG data in volitional state, which is important for electrophysiological diagnosis of neuropathy and myopathy, and confirmed that it showed better performance than physicians. Moreover, in order to minimize data loss, nEMG data, which is one-dimensional numerical data, was used after minimal noise was removed from the beginning and end of the nEMG data. To confirm the clinical applicability of our CNN algorithm, the diagnostic accuracy of physicians was measured and compared with that of present CNN algorithm. Finally, we found that the accuracy and time-taken of diagnosing neuropathy, myopathy, and normal were 0.820 and 40 seconds in using only nEMG data by our CNN algorithm, which is better than that of physicians.

In order to finally diagnose a patient, the nEMG results of all tested muscles should be considered altogether. However, the number of muscles tested may be slightly different for each patient, and abnormalities may not be found in all muscles, but only in some. To consider these points, a newly devised method was used to determine final diagnosis of subject; it was that the data of each muscle were analyzed individually, the probability value for each label was divided as a result of the analysis by the number of muscles and averaged, and finally the label with the highest probability value was determined as the diagnosis. Additionally, considering that peripheral neuropathy mainly shows abnormalities in the distal part muscle, whereas, myopathy mainly shows abnormalities in the proximal part muscles, additional information about muscle location, which means whether the muscles are located close to the trunk or not, was added our CNN algorithm, and contributed to improved accuracy.

Interestingly, the waveform, generated by this CNN algorithm, were similar to that of typical myopathy, neuropathy, and normal waveforms. the diagnostic accuracy of physicians was lower than expected at 54%, which is thought to be due to 2 main reasons; first, in the data used in this study, the proportion of peripheral neuropathy and myopathy is out of distribution, which is much higher than the prevalence in population. Secondly, it is thought that the pre-test probability of diagnosing only with the nEMG data without clinical information such as the patient’s age and symptoms, as in clinical practice, may have worked.

Out study also has some limitations. First, this study deal with retrospective data from only 1 center study. Secondly, study number is not enough to demonstrate perfect usefulness of deep learning on nEMG classification. Finally, we focused only on dividing nEMG signal into neuropathy, myopathy, and normal. However, more specialized diagnosis could be identified with more concise machine learning algorithms. Future study with much more data from multicenter will show potential of applying machine learning to nEMG interpretation.

Until now, few studies on analyzing nEMG data of volitional state by deep learning have been documented. Our study suggest that machine learning has the possibilities to be embedded in nEMG machines, reducing errors in nEMG interpretation and the workload of physicians, and potentially preventing personal medial information leakage that can arise when nEMG data is uploaded online for nEMG analysis, so shed lights on diagnosis patient of suspected neuropathy or myopathy by machine learning which might help with nEMG signal classification. In summary, it is concluded that deep learning may play a significant role in the electrophysiologic diagnosis of patients with neuropathy or myopathy.

**Contributor and guarantor information**

YIH and KKW conceptualized this work.

**Supporting information**

S1 Fig.

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