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

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**Abstract**

**Background**

Electromyography

**Methods and findings**

We used

**Conclusions**

In this study, we found that

**Author summary**

**Why was this study done?**

Diagnosing neuropathy is difficult job

**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] As a result of the study of 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] We retrospectively reviewed nEMG waveforms, which were examined in subjects with neuropathy or myopathy or normal, analyzed those by using convolutional neural network, and compared the classification results of nEMG signals by deep learning and 6 physicians.

**Methods**

**Study design and population**

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 obtained because this study is retrospective analysis. nEMG was performed with a monopolar needle electrode from the subject’s muscles. (Viking Quest, Natus, Middleton, WI). 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. 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.

The results of the waveform data of patients stored numerically in the electromyography machine were extracted, and they were made into a waveform through the MATLAB software (version R2020b) program. Among the created waveform data, artifacts occurring 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 some 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. After slicing, total segments were composed of 2700 segments from subjects with myopathies, 3664 segments of subjects with neuropathies, and 1706 segments of subjects without neither neuropathy nor myopathy. Consequently, rest of the numerical data was used for analysis.

**Classification of nEMG signals by deep learning and Validation**

nEMG signal was classified into 2 stages through nEMGNet. First, the nEMG signals of individual muscles were classified regardless of the subject, and the individually classified nEMG signals of each muscle were collected for each subject, considering together, and then the subjects were classified. And the performance of nEMGNet was evaluated with the accuracy, sensitivity and specificity.

We used feature visualization to identify the characteristics of each classified waveform learned through nEMGNet. The accuracy of nEMGNet was calculated by cross entropy, and since the number of subjects was small, the actual diagnosis and the predicted diagnosis for each subject were compared with 5-fold cross-validation.

In order to evaluate the applicability of nEMGNet to clinical practice, the nEMG signal numerical data were transformed to waveform data, which similar to the actual test screen shown on the screen of the nEMG machine, and the waveform that provided to the 6 residents of the Department of Neurology and Rehabilitation medicine who currently conduct and interpret nEMG. (S1 Figure) The classified results by 6 residents were compared with results by nEMGNet. The degree of agreement between physicians and nEMGNet and accuracy were obtained.

**Statistical analysis**

Statistical analyses were performed using R statistical software (version 4.1.0; R Foundation for Statistical Computing, Vienna, Austria). Inter-rater reliability was analyzed and presented with value of Fleiss kappa. 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. 파이썬으로 정확도 등 구했다. (김동민연구원 내용주면 추가)

**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 results of filtering the entire nEMG segment through a convolutional block were plotted through a method called uniform manifold approximation and projection (UMAP). While the data had been passed through convolutional block, the dimension gradually decreased, neuropathy and myopathy were well distinguished, and the normal was located between the two groups. (S2 Figure) 

S2 Figure. Dimension reduction of signal segments after passing through convolutional layers of nEMGNet. (a) Initial state, state after passing through (b) 2nd block, (c) 4th block, (d) 6th block, (e) 9th block, (f) 12th block. z1 and z2, reduced dimensions; M, myopathy; N, neuropathy; NL, normal. 유재성연구원 그림 바꿔서 주면 변경

The classified results were depicted as a heatmap and a 3-dimensional plot. (Figure 3) The predicted result with the largest value among the muscle signal prediction scores through the DiVote pipeline is expressed in 3 different color, and the highter the probability, the darker the color. In the muscle signal prediction score, the predicted result with the largest value among the subject prediction scores that passed through the DiVote pipeline again was denoted by N for neuropathy, M for myopathy, and NL for normal. (Figure 2A) The subject prediction score was depicted as a 3-dimensional plot with the probability of being classified as myopathy, neuropathy, and normal as each axis. (Figure 2B) The classifier measured using logistic regression and argmax function was added as a decision boundary that distinguishes myopathy, neuropathy, and normal. (Figure 2B) Neuropathy and myopathy were distinguished relatively well, however, normal was directed toward the center and not well differentiated. (Figure 2C) The decision boundary was shifted using the classifier measured by adding the location information of the muscles divided into proximal or distal muscles, and as a result, the normal was better distinguished than the classifier measured without location information of the muscles. (Figure 3D) 

Figure 2. The results of subject classification through DiVote pipeline and decision boundary (A) Heatmap of the most probable diagnosis among muscle signal prediction scores. Each square box represents the most probable diagnosis value in color after aggregating the signal segment prediction scores predicted by nEMGNet. (B) The subject prediction scores as dots in a 3-dimensional plot. (C) Decision boundary calculated through simple argmax function. (D) Shifted decision boundary after adding the information on location of muscles. M, myopathy; N, neuropathy; NL, normal; P, proximal muscle; D, distal muscle. 유재성연구원 그림 바꿔서 주면 변경

The accuracy of total prediction over all, myopathy, neuropathy, and normal segments without processing of DiVote pipeline was 62.35%, 71.58%, 63.2%, and 52.26%. As a result of applying the DiVote pipeline, the accuracy improved to 76%–81%, and the accuracy was further improved to 76%–83% when the location of muscle was also considered. As a result of comparing the accuracy of 4 versions with different number of residual blocks among nEMGNets, nEMGNet-B, which included 2 residual blocks between spatial blocks, showed the best accuracy, while nEMGNet-A, which included no residual block, showed the poorest accuracy. (Table 2)

|  |  |  |  |
| --- | --- | --- | --- |
| nEMGNet subtype | Accuracy (%) | | |
| No classifier | Classifier using from subject features without muscle location | Classifier using from subject features with muscle location |
| A | 67.17±10.75 | 76.06±4.90 | 76.57±10.23 |
| B | 73.64±7.27 | 81.92±4.83 | 83.69±5.28 |
| C | 69.95±7.77 | 81.26±6.35 | 81.87±6.80 |
| D | 75.35±6.93 | 81.26±6.35 | 80.81±5.31 |

Table 2. The accuracy of subject classification according to nEMGNet version with and without DiVote (Divide and Vote) pipeline processing and additional information of muscle location. All values are expressed as mean ± standard deviation.

In the process of classifying with nEMGNet-B with muscle location information added, the weight values of myopathy, neuropathy, and normal were obtained by dividing them according to proximal and distal muscles. Five-fold cross validation was performed, and each fold was repeated 3 times to obtain each weight value from a total of 15 classifiers, and then the average value of all weights was measured. (S1 Table) For example, if the proximal muscle is classified as myopathy just before the final classification, the weight value multiplied during the final classification as myopathy were 1.56±0.96. For final classification as myopathy, the weight value of myopathy (proximal muscle, 1.56±0.96; distal muscle, 1.32±0.76) was the largest, followed by normal (proximal muscle, -1.63±0.99; distal muscle, -1.10±0.87) and neuropathy (proximal muscle, -1.76±0.94; distal muscle, -1.37±0.60), and among proximal and distal muscles, the weight value of proximal muscle myopathy (1.56±0.96) was larger than that of distal counterpart (1.32±0.76). For final classification as neuropathy, the order of the weight values was neuropathy (proximal muscle, 1.76±0.78; distal muscle, 1.29±0.83), myopathy (proximal muscle, -1.08±0.58; distal muscle, -1.06±0.80), and normal muscle (proximal muscle, -1.67±1.11; distal muscle, -2.12±1.28), and the weight value of proximal muscle neuropathy (1.76±0.78) was larger than that of distal counterpart (1.29±0.83). The results of other weight values are shown in S1 table.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Classified results | Input | | | | | |
| Proximal muscles | | | Distal muscles | | |
| M | N | NL | M | N | NL |
| M | 1.56±0.96 | -1.76±0.94 | -1.63±0.99 | 1.32±0.76 | -1.37±0.60 | -1.10±0.87 |
| N | -1.08±0.58 | 1.76±0.78 | -1.67±1.11 | -1.06±0.80 | 1.29±0.83 | -2.12±1.28 |
| NL | -1.53±1.18 | 0.17±0.98 | 1.53±1.05 | -0.78±0.92 | -1.31±0.97 | 1.93±1.13 |

S1 Table. Total results of weight values. All values were averaged over 15 weight values and are expressed in mean±standard deviation.

M, myopathy; N, neuropathy; NL, normal.

The accuracy of nEMGNet-B is depicted as confusion matrices by muscle prediction results and subject prediction results for each diagnosis. (Figure 3)



Figure 3. Confusion matrices of prediction by nEMGNet-B. Left; Accuracy of predicted results for each nEMG waveform, Right; Accuracy of predicted results by considering all nEMG of each patient together. Missing value는 제외했다는 내용 추가

Based on the results of training through nEMGNet, 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. (Figure 5)



S3 Figure. Trained waveforms of myopathy, neuropathy, and normal based on nEMGNet.

(A), (C) and (E), waveform based on learned features by nEMGNet; (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.

The prediction results of muscle and subject classification by not only nEMGNet but also 6 physicians were compared. The mean accuracies of the former were 53.66% and 52.01%; those of the latter were 68.67% and 81.03%, 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 nEMGNet were 0.249 and 0.256, respectively. (Table 3)

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | Classification results | | | |
|  | Physician | | nEMGNet | |
|  | Muscle | Subject | Muscle | Subject |
| Accuracy (%) | 0.54\* | 0.52\* | 0.69 | 0.81 |
| Sensitivity |  |  |  |  |
| Specificity |  |  |  |  |
| Inter-rater reliability (Fleiss κ) |  | | | |
| Overall | 0.26† | 0.26† | 0.25‡ | 0.26‡ |
| Myopathy | 0.35† | 0.36† | 0.34‡ | 0.40‡ |
| Neuropathy | 0.28† | 0.26† | 0.28‡ | 0.25‡ |
| Normal | 0.18† | 0.20† | 0.16‡ | 0.17‡ |

Table 3. The results of classification by physicians (mean result of 6 physicians) and nEMGNet. Result was shown with sensitivity, specificity, inter-rater reliability.

\* Mean value of 6 physicians’ results.

† Fleiss κ value between physicians’ results

‡ Fleiss κ value between nEMGNet’s result and physicians’ results

**Discussion**

The aim of this study was to evaluate the accuracy of detecting the presence of peripheral neuropathy or myopathy by analyzing nEMG waveform data using machine learning, and to confirm its applicability in clinical practice. For that purpose, we applied deep learning named nEMGNet to interpreting the nEMG waveforms, and assess the performance and compare the accuracy with classification by 6 physicians. As a result of analysis with nEMGNet, the time required was shorter, and the accuracy was superior to accuracy of the physician’s analysis.

While nEMGNet is capable of extracting complex signal features, it only accepts a fixed number of signal samples. However, the number of muscles tested for each subject and the length of nEMG signal for each muscle is different. DiVote pipeline was used to overcome these limitations and contributed to the improved accuracy. Additionally, considering that peripheral neuropathy mainly shows abnormalities in the distal part muscle, whereas, myopathy mainly shows abnormalities in the proximal part muscles, addtional information on muscle location, which means whether the muscles are located close to the trunk or not, was added to the nEMGNet and this contributed to improved accuracy. Training the deep learning model with muscle type information may bias the model to make predictions based on the muscle type information, not the signals. This process was prevented by leveraging the information of muscle location in generating subject features. When creating subject features, muscle signal prediction scores were soft voted within each group divided by muscle location, and missing muscle signal prediction score was substituted with equal prediction probabilities of a third. Thus, subjects whose only proximal or distal muscles were measured are not biased during the prediction process.

Previously, there have been reports that machine learning showed good performance when applied to image analysis, surface nEMG, 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] For the purpose of diagnosing neuromuscular disorders, needle nEMG is useful rather than surface nEMG, 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]. After minimal noise were removed at the beginning and the end of the nEMG data, the rest nEMG data as the 1-dimensional numerical data during the volitional state for minimizing the data loss that may occur while using the 2-dimensional data as in the previous studies. To confirm the clinical applicability of nEMGNet, the diagnostic accuracy of physicians was measured and compared with that of nEMGNet. Finally, we found that the accuracy and time-taken of diagnosing neuropathy, myopathy, and normal were 83.69% and 40 seconds in using only nEMG data by nEMGNet, which is better than that of the machine learning model found in previous studies or physicians.

Interestingly, 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. Additionally, when myopathy and neuropathy were classified with nEMGNet, the weight values given to proximal and distal muscles were greater in both cases. In the case of myopathy, the weight value of proximal muscle is greater than that of distal counterpart, which is usually consistent with the more common proximal involvement in myopathy. On the other hand, in the case of neuropathy, the weight value of proximal muscle is greater than that of distal counterpart, which is slightly different from the previously reported result that distal involvement is more common in neuropathy.

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. Decision support의 장점도 있다.

**Contributor and guarantor information**

YIH and KKW conceptualized this work.

**Supporting information**

S1 Fig.

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