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Letter to the Editor

Artificial intelligence in the field of electrodiagnosis – A new threat or heralding a new era in electromyography?

We read with great interest the recently published paper by Nodera et al. (2019). They have introduced a deep learning model that could identify different electromyography (EMG) signals, including complex repetitive discharges and fasciculation potentials with high levels of accuracy. The following are some suggestions we would like to share with the authors and others interested in artificial intelligence for EMG.

First, while the authors had developed a deep learning model, it was not validated prospectively with a different external data set. In addition, whether their model can be generalized in other data sets is an issue that needs to be resolved.

To maintain a fine balance between the complexity of a deep neural network and information gain from a training set is a challenging task in deep learning. Failing to do so often results in overfitting or underfitting. In consideration that it would be difficult to accrue thousands of needle EMG sounds in real clinical settings, future researchers in EMG are likely to face similar overfitting issues. Small training sets, as presented in this study (Nodera et al., 2019), may lead to overfit of the network, which leads to the loss of its generalization capability. To solve the overfitting factor, the authors had employed techniques of data augmentation and the use of pre-trained weight (Nodera et al., 2019). Although both techniques are good practice as regularization, "dropout" is a more direct method which helps the model to learn a feature that is generally helpful to solve a task. In this dropout process, overfitting is prevented by randomly omitting half of the feature detectors during the training session (Baldi and Sadowski, 2014). To overcome such obstacles, we recommend the employment of diverse dropout techniques (Orr and Müller, 1998).

Second, while the authors had proposed a model that identifies the pathological needle sounds, sounds from normal insertional activities were not included in their analysis. In clinical practice, it is always pertinent to identify the pathological from the normal. Therefore, for the model to be clinically applicable, in conjunction with the model proposed by the authors (Nodera et al., 2019), a classification model that identifies the normal insertional activities from the pathological needle denervation sounds would be a prerequisite. In addition, denervation potentials are always detected among a continuous background noise generated from other sounds. Thus, a deep learning model that can identify pathological denervation potentials amidst a background of diverse noise, including normal insertional activities, endplate potentials or motor action unit potentials (MUAPs) would be needed.

Third, in the work by Nodera, various deep learning models were employed, and the accuracy of these models was estimated as single models (Nodera et al., 2019). Surface EMG studies on pattern recognition in human upper limb joint angles have suggested that a combination of the repetitive and convolutional neural network show better performance than the application of a single model. Whether the combination of such different models can be applicable in needle EMG and show more robust performance is another topic that may be pursued in the future.

Another technical aspect that requires attention is the use of pre-trained weights from known image classification models, such as VGG16 or ResNet50. These two networks are widely used for image object detection and sound pattern recognition. The performance from these networks was impressive with high accuracy rates in the work by Nodera et al. (2019). However, the task of classifying mere patterns from spectrogram obtained through acoustic signals is essentially different from pattern recognition represented through visual object recognition tasks. In the light of depth of transferred feature detectors, training only one additional layer is conducted to classify spectrogram with the pre-trained visual object classification tools. To achieve task-specific feature detectors, one can fine-tune transferred weights in the earlier layers with small learning rates. On the other hand, training from scratch can also perform better if the model implements carefully defined initial weights such as Xavier or He initialization (Adam et al., 2014). Therefore, future deep neural networks that integrate and meet the unique characteristics and patterns of the Mel-spectrograms converted from audio signals is warranted.

Finally, disease diagnosis through electrodiagnosis and needle EMG is more complex, and the process cannot be performed through the identification of the pathological needle sounds alone. In order to make a correct clinical diagnosis, electromyographers need to identify denervation potentials, and at the same time interpret different recruitment patterns, and make estimations of changes in MUAP amplitudes and durations during needle EMG. However, the accurate interpretation of these needle sounds can be challenging. For example, whereas 90.6% agreement is present for fibrillation potentials or positive sharp waves, only 60.4% agreement is found in the interpretation of reinnervation, such as increased rate of polyphasic MUAPs, or long duration and large-sized MUAPs (Narayanaswami et al., 2016).

For artificial intelligence to be applicable in clinical practice, a deep learning model on these needle EMG parameters known to have modest levels of reliability levels (Narayanaswami et al., 2016) is needed. The development of such models on these parameters would reassure that artificial intelligence complements in areas of electrophysiology where human interpretation may be prone to error or misinterpretation and help in making a more accurate and reliable diagnosis. In the future, the development of a deep learning model that can help detect subtle early MUAP changes and predict disease outcome as biomarkers would be most promising.

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Artificial intelligence can, by no means, threaten the role of the electromyographer. The results of needle EMG and the final diagnosis should be interpreted in the context of the patient's unique clinical presentation, and of other information, such as nerve conduction study results. However, needle EMG studies, even when being performed and interpreted by an expert, has its own specific weaknesses and challenges. More future work from other keen electromyographers on integrating deep learning to the field of electrophysiology is needed. We hope that the pioneering work by Nodera et al. (2019) will open a new era of research for implementing artificial intelligence in EMG.

Declaration of Competing Interest

None of the authors has any conflicts of interest or financial ties to disclose.

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