Prediction of the Dosage of the Electric Stimulus Needed for Electroconvulsive Therapy (ECT) Based on Patient's Pre-Ictal EEG Using Artificial Intelligence

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Abstract. One of the most effective and rapid treatments for MDD is Electroconvulsive Therapy (ECT). However, cognitive adverse effects remain a great risk among patients undergoing ECT. These side effects are robustly tied to the dosage of the electric stimulus given to the patient. Two methods are currently used to determine an accurate dosage: the age-based method and the titration method. Furthermore, electroencephalograms (EEG) are done during an ECT session, to assess the adequacy of the treatment. Therefore, Artificial Intelligence (AI) could offer a third way, by analyzing the EEG before the shock is administered (called the pre-ictal EEG), using deep learning algorithms, to determine the adequate dosage of the electric stimulus needed. Once the EEG signals were decomposed using Fast Fourier Transform (FFT), we fed them into the Fuzzy Causal Effect Variational Auto Encoder (FCEVAE) deep learning algorithm. We implemented an FCEVAE model to identify patterns in patients' pre-ictal EEGs that lead to positive or negative outcomes of the ECT session. These outcomes were determined by the clinician in charge of the ECT session, based on the EEG assessment. A total of 470 EEGs were collected. The FCEVAE seems able to predict individualized ECT dosages based on the patient's pre-ictal EEG. The FCEVAE model had an overall accuracy of 90.33%, as measured by the root mean square measure. The use of FCEVAE seems promising in the field of EEG analysis and ECT, although further research is needed to optimize the model and its clinical applications.

Keywords. Artificial Intelligence, Electroconvulsive therapy, ECT, Causal transformers, Electroencephalogram, EEG.

1. Introduction

Major Depressive Disorder (MDD) became the leading cause of disability worldwide in 2012 [1]. Even if a good share of patients will respond adequately to an antidepressant medication, about one third will be considered treatment-resistant [2]. Moreover, MDD can lead to some life-threatening situations, like catatonic syndrome or active suicidal ideations that need rapid-acting treatments. Electroconvulsive therapy (ECT), one of the oldest therapies in the field of psychiatry, remains the most effective treatment for severe depressive disorder, especially in the case of treatment-resistant or life-threatening depression [3].

The principle of this therapy is to induce a generalized seizure with the administration of an electric current that passes into the brain, using electrodes that are placed on the scalp. The generalized seizure induced and the dose of electricity used have various and lasting effects on the central nervous system [4]. However, a seizure alone is not sufficient to produce a therapeutic effect, and generalized seizures can be induced without generating any antidepressant effects [5]. The seizure threshold is defined as the minimum charge that will induce an unambiguous generalized seizure. This threshold depends on the patient and several factors: age, sex, current medications, electrode placement, pulse width and recent ECT treatments [6]. A therapeutic seizure will be obtained when the delivered electric charge is above the seizure threshold, using a multiplier that depends on the various sites on the scalp where the stimulus is delivered. Additionally, one of the major drawbacks of this treatment is the possibility of the occurrence of cognitive adverse effects that can result in cognitive impairment and memory loss [7]. Now, these cognitive side-effects are proportional to how much the stimulus dose is above a patient’s threshold [8]. Hence, there is a constant need to assess the adequacy of the charge delivered, with a trade-off between efficacy and cognitive side-effects.

Presently there are two main techniques to assess the amount of charge to deliver: the age-based method and the titration method. In the age-based method, the electric charge is simply determined according to the patient’s age, depending on the site of the stimulus (e.g., 2.5 times the age for bitemporal stimulation). The amount of the charge is supposed to be around the adequate suprathreshold ratio. In the titration method, the seizure threshold is determined using increasing charges, starting with the lowest, so as to find the minimal charge that induces a seizure. Then a multiplier is applied, depending on the site of the stimulus, to get the adequate suprathreshold ratio (e.g. 2 times for bitemporal stimulation). Each method has advantages and drawbacks, and there is still some debate about the best method to use [9].

Finally, ECTs are performed under anesthesia. Electroencephalograms (EEGs) are recorded during the ECT session, to assess the adequacy of the seizure, from the beginning of the anesthesia until the end of the seizure. Recently, mental healthcare professionals, in collaboration with Artificial Intelligence (AI) researchers, started using machine learning algorithms to predict successful and unsuccessful ECT sessions [10]. Hence the aim of the present study is to assess if AI is able to predict the adequate dose to deliver to the patient, analyzing the pre-shock EEG (called the pre-ictal EEG).

2. Method

Ethics approval was first obtained from the ethics committee of the Centre intégré universitaire de santé et de services sociaux de la Mauricie-et-du-Centre-du-Québec. We first anonymized data gathered from ECT sessions at the Ste-Marie Hospital in Trois-Rivière, Quebec, Canada. EEGs that were recorded during the ECT sessions were used to train IA. To extract the underlying elements in EEGs causing successful and unsuccessful ECT sessions, we performed data pre-processing, and applied causal deep learning algorithms to the pre-ictal data.

To prevent obtaining dense- and low-dimensional latent space, which would negatively influence the DL's performance [11], we used CNN-LSTM architecture [12]. Next, to remove the noise from the EEGs, which occurs when an electric charge is applied to the patient's skull, we used Moving Average Technique [10]. We then divided the EEGs into pre-ictal EEG and after-shock parts. EEGs contain some hidden patterns that DLs cannot process [10]. In our case, Fast Fourier Transformation (FFT) was the best technique that revealed the frequency and amplitude of the components hidden in EEGs to DLs. Then we feed the FFT's output to an autoencoder variational-based DL called Fuzzy Causal Effect Variational autoencoders (FCEVAE) [11]. FCEVAE is a Fuzzy version of Causal Effect Variational autoencoders (CEVAE) [13]. We added Causal fuzzy rules to CEVAE to create Fuzzy CEVAE or FCEVAE [14]. We first used FCEVAE to detect good and bad EEGs. These outcomes were determined by the clinician in charge of the ECT session, based on the EEG assessment. In our next step, we used FCEVAE to predict the amount of charge to be applied to the patients' skulls.

3. Results

A total of 470 EEGs were collected. Out of these, 350 were used to train the FCEVAE model, while 120 were reserved for testing. The FCEVAE model had an overall accuracy of 90.33%, as measured by the root mean square measure. However, it takes about 30 minutes for FCEVAE to predict the charge to be applied to the patient's skull. This is a big flaw as mental healthcare professionals cannot wait 30 minutes before applying the shock to the patient's skull. One reason for FCEVAE being slow is that it is small compared to bigger DLs such as Transformers which have billions of neurons.

The use of FCEVAE seems promising in the field of EEG analysis and ECT, although further research is needed to optimize the model and its clinical applications. In our future work, we will be using Transformerbased DLs such as GPTchat architecture.

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