Predicting seizures using non-spiking and spiking artificial neural networks in sequence

Abstract

The problem of seizure prediction from electroencephalograms is a longstanding problem within medicine, as seizures can be mitigated if predicted. While several seizure prediction algorithms exist, they have limitations, such as short timeframes, low sensitivities, or high false positive rates. A model based on a combination of traditional convolutional and spiking neural networks that can separate out preictal (before seizure) segments is presented and evaluated. Spiking neural networks are newer, run more efficiently, and more closely model how the brain learns than traditional networks. The relative effectiveness of spiking neural networks at complicated tasks such as seizure prediction is assessed by using a combination of traditional and spiking networks. Testing the neural network models on a prediction timeframe of 30 minutes shows that replacing traditional layers with spiking layers caused the overall accuracies (as measured by the area under the receiver operating characteristic curve) to decrease, falsifying our hypothesis. This provides crucial information for creating an device to automatically detect and suppress seizures.

Introduction

Artificial neural networks (referred to here as ANNs or just “neural networks”), are a loose mathematical model of how the brain functions. They can be used to form remarkably good algorithms for problems that hand-designed algorithms cannot practically solve, such as recognizing complex features in images and signals. An ANN is a network of artificial neurons, which each perform a simple computation, which varies based on the type of neural network. Some of these are input neurons, which take input from the outside world. All other neurons take their state from other neurons in the network. Some neurons serve as outputs, which take on values that encode the solution. These networks become useful when they are trained, a procedure that gives example inputs so that the network “learns” to correctly classify outputs (Schmidhuber, 2015).

ANNs are a large class of very different models. While all ANNs are composed of connected neurons, they differ by the connections between those neurons (*topology*), and in the behavior of the neurons themselves. These differences enable a specific *architecture* to be tailored to a specific application (Schmidhuber, 2015).

Feed-forward and *recurrent* neural networks are two of the simplest ANN topologies. A feed-forward neural network consists of a number of “layers” of neurons. Each layer is connected only to the previous layer as input and the next layer as output. Recurrent neural networks, on the other hand, are less strictly defined. Neurons still have inputs from the previous layer, but also loop back on themselves. This makes them strictly more powerful than the simpler feed-forward neural networks (Schmidhuber, 2015).

Another topology is the convolutional neural network, even more complex than feedforward and recurrent neural networks. In contrast to the mostly homogeneous layers of feed-forward and recurrent neural networks, a convolutional neural network is made up of two distinct stages: a set of layers that perform a convolution and a feed-forward or recurrent network. A convolution, conceptually, takes a large number of small sub-samples of the data. Applying a convolution reduces the volume of data, and also allows the network to better ignore small differences in the position of inputs that have no relevance to the outcome. This is especially useful for multidimensional inputs, like images (Schmidhuber, 2015). Multiple time-varying signals (such as EEGs) can also be used as inputs, as each signal can be treated as a separate dimension (Ren and Wu, 2014). This transformed data is then passed along to the second stage, where it goes through the network as described above.

The previous sections discuss the layout of the neural networks, but make no reference to how the neurons themselves function. There are two broad categories into which neurons fall: traditional and spiking. Traditional neurons take in a single value from each input; all of the inputs together form the input vector. This is then combined with a vector of weights (values that determine how important inputs from certain neurons are), usually by using the dot product, to get a single value. The *activation function* is applied to this value. Common choices are sigmoid functions, hyperbolic cotangent, and a simple $f(x) = max(x,0)$, known as ReLU (Schmidhuber, 2015). Each of the output neurons then receives this value. This process continues, cascading throughout the network, until the values are read out from the last layer, the output neurons.

Spiking neural networks are another class of neurons that more closely model how the brain works, and have recently outperformed traditional neural networks in some situations, because they require less power to compute (Lee, Delbruck, and Pfeiffer, 2016). Spiking neurons use a different model. Instead of taking a single value as input, it takes a time-varying value with rapid increases, called a *spike train*. The most common model for a spiking neuron is an *integrate-and-fire neuron*. Integrate-and-fire neurons are modeled as an exponentially decaying signal, with weighted inputs from other neurons added on (Lee et al., 2016).

Most spiking neural networks are single-spiking. Single-spiking means that for every input transmission a neuron in the network receives, the neuron outputs one spike at most. However, Ghosh-Dastidar and Adeli (2009) have described a multi-spiking neural network where each neuron can output more than one spike for every input transmission it receives. In a single-spiking neural network, a single connection (called a synapse) links each neuron to the layers next to it. In a multi-spiking neural network, each connection between neurons is made up of multiple synapses, and when a neuron outputs, it outputs along each of the synapses. Each of the synapses in a multi-spiking neural network have different weights and delays determining when the output is received and how much of an effect the output has on internal state of the receiving neuron. The internal state is what determines when a neuron fires. Ghosh-Dastidar and Adeli (2009) found that the multi-spiking neural network outperformed the single-spiking neural network with an accuracy of 92.3% while the single-spiking neural network achieved only 82% correctly detected seizures.

The network architecture alone does not account for any results it can achieve. A neural network must be *trained* in some way to become useful. Aside from the architecture of the network, which the network designer preselects, the only parameters the network has are the weights. These weights are present in slightly different forms in both spiking and traditional neural networks. This can be treated as a multi-dimensional optimization problem, with each weight being a dimension, and the quantity to minimize is a function measuring how far the predictions are from correct (also known as a *loss function*). What “correct” means is often solved by first running through *training data*, data which has been pre-classified (Schmidhuber, 2015).

One highly useful technique for solving this optimization problem is known as *backpropagation*, which uses techniques from calculus to attempt to find an area where the slopes downward on the cost function (measures of how much of an improvement a nudge in that direction could make) are low. Gradient descent consists of taking large steps in the decreasing direction on the graph where there are large improvements to be made, and small ones where there are not (Schmidhuber, 2015).

Many older models of spiking neural networks, such as Cao et al. (2015), use looser variants of this basic backpropagation algorithm, because the derivative is not strictly defined where the spikes occur, as there is an instantaneous jump down in membrane potential. These models resort to training the network on traditional-neuron ANNs, or training with another algorithm entirely. Cao et al. (2015) used a traditional convolutional neural network, trained with backpropagation, and then transformed the weights for use on a spiking neural network.

Lee et al. (2016) more recently described a spiking neural network with single spikes, which therefore can support training directly on the spiking neural network, without the need for any transformation. They accomplished this by ignoring the discontinuities, which they found did not unduly reduce the network’s accuracy. Also, while Cao et al. (2015) found that the spiking network was about 2% less accurate than the traditional network at detecting cars, Lee et al. (2016) found that the spiking network performed about 0.4% better at the related task of classifying handwritten digits (they are both image classification problems, so they should have similar solutions).

Neural networks have been used to predict epileptic seizures. Ramgopal et al. (2014) compared a number of previous attempts at predicting and detecting seizures. These techniques ranged from simple linear regression to multiple chained machine learning techniques, with varying accuracy, sensitivity, and false positive rates. Most studies in the field focus on detecting seizures, though there has been success at predicting them ahead of time, as discussed below. Many approaches use EEGs (electroencephalograms). EEGs are recordings of electrical activity in the brain; specifically, the differences in voltage between pairs of electrodes on the head.

The amount of time we will be able to predict seizures in advance remains unknown. Le Van Quyen et al. (2001) claimed to anticipate seizures on average seven minutes in advance based on scalp EEG recordings, by using a statistical analysis on the wave to determine (loosely) how chaotic the waves were. However, De Clercq (2003) tried and failed to replicate those results, so they should be examined skeptically. Entirely disregarding EEGs, Mula and Monaco (2011) state that one third of epilepsy patients have premonitions hours or even days in advance. Therefore, the theoretical upper bound on prediction length is very long.

Seizure detection is important because it allows medical intervention to minimize harm. For example, Ramgopal et al. (2014) discuss one system which alerts caregivers when a seizure is detected, and another that could automatically administer drugs or an apparatus to stimulate the brain in case to halt the seizure. Seizure prediction opens up more opportunities for intervention, because there is a longer period where the patient or a caregiver can take corrective action; the person affected could be taken to a hospital during the several minutes of pre-predicted time if the epilepsy was particularly severe.

To use EEG data as inputs to a convolutional neural network, the data must first be transformed. Ren and Wu (2014) describe one method to preprocess EEG data so that it can be fed into a neural network, albeit non-spiking (though the methods could be adapted to spiking neural networks). A Fourier transform (which converts a signal to a representation of the frequencies of the sine waves which form it) is applied to the data, in order to pull out the more-relevant frequency components. Specifically, Ren and Wu (2014) chose the frequency band 8-30 Hz, which Darcey and Williamson (1985) found was a highly predictive band. The resulting signal still has a large number of dimensions, while a convolutional neural network can only handle a few. Principal component analysis is used to reduce the number of dimensions to a more manageable number. At this point, one of the methods described below can be used to convert the waveform into a series of spikes, which make up the input to the network.

Previous studies also considered support vector machines (SVMs). Pure support vector machines consider inputs to be vectors in a high-dimensional space. They then use hyperplanes to separate the inputs in a way that minimizes error (Cortes & Vapnik, 1995). We plan to use a variant of SVM that has warped decision boundaries, as described in Boser, Guyon, and Vapnik (1992).

There are many other methods which can be used to transform the raw EEG data to use as an input for a convolutional neural network. Kasabov and Capecci (2015) used an AER (Active event representation) encoding method to transform the EEG data into discrete spikes. In the AER method, the spikes are determined by the times when the derivative of the EEG signal goes above or below a threshold. Nuntalid, Dhoble, and Kasabov (2011) used filters to strip the EEG signals down into spikes. Filters remove unwanted features from a signal, usually certain frequencies. These methods would probably also have to be used along with principal component analysis to reduce the number of dimensions to a number a convolutional neural network can handle.

We plan to test whether a multi-spiking neural network trained using backpropagation forms a better model for predicting epileptic seizures based on EEG data than the traditional machine learning methods of SVM and CNN. We plan to use a model based on the work of Ghosh-Dastidar and Adeli (2009) who used a multi-spiking neural network to detect seizures, showing that spiking neural networks can be used effectively on EEG data. Our research differs because we plan to predict the seizures ahead of time, rather than detect them when they have already begun. We plan to compare the SVM and CNN to the multi-spiking neural network described in Ghosh-Dastidar and Adeli (2009). We will be using the University of Pennsylvania and Mayo Clinic (2014) as the source of our data. The data contains a number of studies with annotated EEG recordings of epileptic and healthy patients totalling up to month of EEG data when combined.

Method

<u>Data and preprocessing</u>

We took input data from the IEEG database. The database has a large number of EEG records; however, not all of them are annotated properly. Through investigation, we found that the entries with IDs of the form “Study XXX”, where “XXX” are three digits, had seizure annotations. We selected only one study (Study 005), because Freestone et al. (2017) found that pooling data across patients is ineffective. We selected one channel (LTD4) from this study to take samples from that seemed to best represent the channels as a whole. We selected 151 5-minute positive samples 30 minutes before each seizure, and negative samples from anywhere else in the EEG recording at least 30 minutes before or after an annotated seizure event. We ran FFT on the samples and took 135 amplitudes at frequencies between 8-30 Hz for inputs to the convolutional neural network.

<u>Classification models</u>

The convolutional network is structured with layer sizes 135, 45, 15, 5, and 1. The hidden layers use a square 1x1 convolution and an ReLU activation function while the output neuron is linear. The model was trained for 500 epochs on 80% of the preprocessed EEG data. The model was then tested on the remaining 20% of the preprocessed EEG data to obtain the ROC curve.

The MuSpiNN model is structured with layer sizes 21, 5, 1 and 61, 15, 4, 1 for MuSpiNN (1) and (2), respectively. MuSpiNN (1)'s inputs are taken from the last hidden layer of the CNN while MuSpiNN (2)'s inputs are taken from the second to last hidden layer of the CNN. We encoded the real numbers in the CNN output into spike times by taking the height of the intersections with various Gaussian distributions, as described in Ghosh-Dastidar and Adeli (2007). This model simulates how biological sensory neurons process input. The MuSpiNN layers are fully connected and the network is trained on 100 epochs and learns through back propagation via gradient descent.

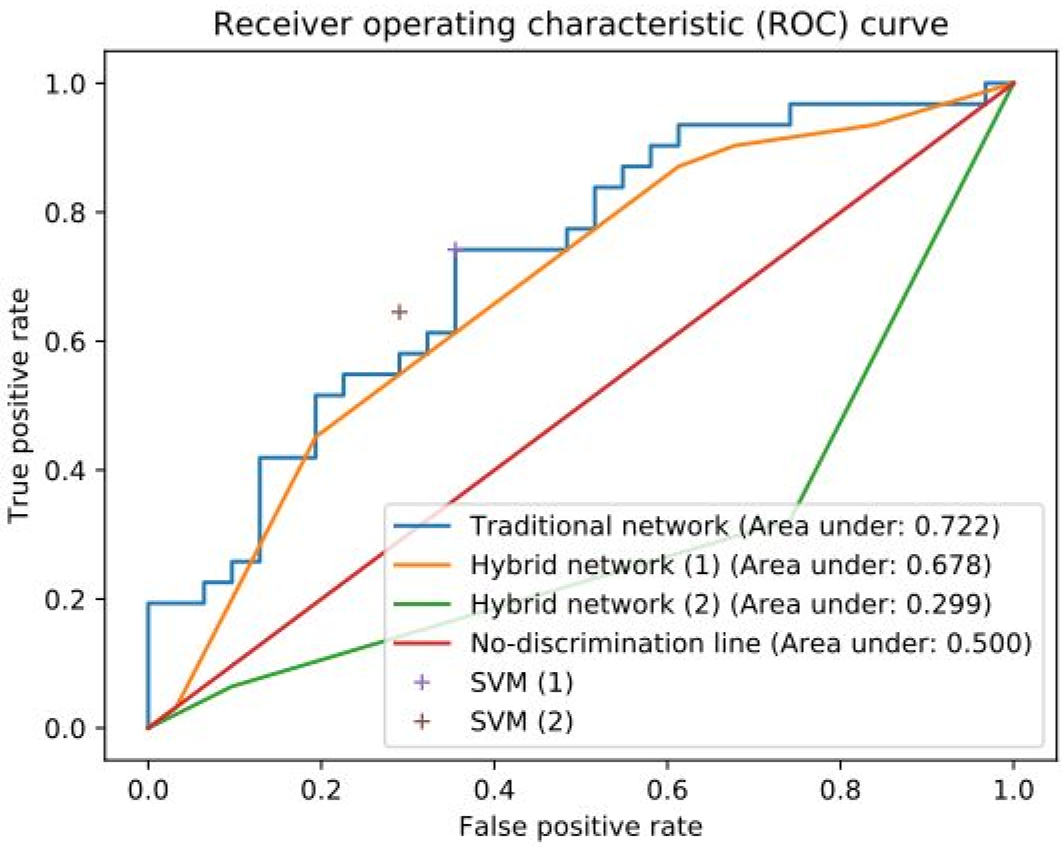
The SVM (1) and (2) use the same inputs as the MuSpiNN (1) and (2), respectively. The SVM is run with a no limit radial basis function (RBF) kernel.

<u>Performance evaluation</u>

All of the neural-network based predictors output some sort of prediction confidence. For the traditional neural network, this is straightforward, as the outputs vary within the range 0-1 (barring a few exceptions). For the spiking neural network, the output must be shifted and scaled, because its natural output range is from 15-20. We collect the these outputs, as well as the true labels from the annotations. We then iterate over each of the outputs, taking it as the cutoff for deciding between a positive or negative class and determining the false positive rate and true positive rate that result from that. The curve formed from these points is a receiver operating characteristic curve (ROC).

The area beneath this curve is the AUROC, which we used to evaluate the relative effectiveness of the neural network models. An ROC connecting the points (0, 0) and (1, 1) is called the *non-discrimination line*, and is achievable by random chance, while an ROC connecting (0, 0), (0, 1), and (1, 1) corresponds to a perfect classifier. Overall, higher ROCs signify better results. Since the SVMs do not output a prediction confidence, we could not generate ROCs using this method; therefore, we can assess where their single point lies. If the point lies strictly above and to the left of a given AUROC, it is unambiguously superior, as it has a higher true positive rate at a lower false positive rate than the other predictor.

Results



Discussion

The goal of this project was to find how well different machine learning models performed on a seizure prediction task. A multi-spiking neural network, convolutional neural network, and SVM were compared by using common preprocessing of FFT and convolutional neural network layers on EEG data. It was hypothesized that the MuSpiNN would outperform the traditional CNN and that both of these networks would outperform the SVM. Contrary to what was hypothesized, both hybrid neural networks performed worse than the traditional neural network with the hybrid network with more layers performing worse than chance, and the SVMs performed equivalently to or better than any other methods. The hybrid networks had the two lowest AUROC values of 0.678 and 0.299 for the 1 and 2 multi-spiking layer networks, respectively, while the traditional convolutional network had an AUROC of 0.722. The CNN also outperformed the Hybrid Network at nearly all false positive values with some exceptions around 0.2 and 1. The SVM(1) point lies on the traditional network curve meaning that for its false positive rate it performs equally to the traditional network, however the SVM(2) point lies above the traditional network curve meaning that for its false positive rate it outperforms the traditional network.

This seems to indicate that the SVM is better than the CNN since as we take off more CNN layers the SVM performs better. This is unlikely though as the CNN seems to be a necessary preprocessing step for high SVM accuracy. In fact, it is common in machine learning to use a pre-trained CNN as preprocessing for an SVM. There is likely an amount of CNN layers that produces a maximum SVM accuracy, and further research could be done in the future to determine this. Ultimately, the SVM with CNN as preprocessing seems to be the best model for seizure prediction as CNN and MuSpiNN had lower accuracies. The CNN's training time, however, is faster since the SVM requires a trained CNN to run in addition to the runtime of the SVM itself.

Even just one layer of the MuSpiNN, however, takes much longer to train than the entire CNN or CNN with SVM. This is because the MuSpiNN was coded in pure Python without the use of libraries. We could not find any libraries which supported this model, but we may continue optimizing to achieve higher accuracy. While the CNN with SVM seems like the best model though, the SVM didn't achieve very high accuracy. This could be because of the channel selection, as only one channel was chosen for training and testing as preliminary explorations showed that channels could give widely varying accuracies. The channel chosen was picked as it seemed most representative as the channels as a whole, but a channel choosing process might increase the accuracy of the prediction. Overall, the trends shown seem to indicate that unlike our hypothesis, the SVM outperformed all other methods. However, we cannot formally reject the hypothesis, not enough trials were run to be able to run any statistics on the data. But the ROC graph seems to strongly at least show that he MuSpiNN is not viable as a machine learning method for predicting seizures.

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