Epileptic Spike Detection with EEG using Artificial Neural Networks

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Abstract— **Epilepsy is a neurological disease that causes seizures in its victims that can lead to physical injury or even death in some circumstances. It is caused by excessive, synchronous abnormal firing of neurons in the brain. This chronic disease has no known cure and affects millions of people worldwide but can be managed through various methods. The successful treatment is dependent upon correct identification of the origin of the seizures within a brain. One major challenge for doctors is the analysis of the immense amount of data collected by electroencephalogram (EEG) devices. In order to identify a region of the brain that causes epileptic seizures, millions of samples must be analyzed manually by a trained eye to find interictal spikes that emanate from the afflicted region of the brain. This paper presents a method for automatic interictal spike detection while minimizing false positives. In this way, it eliminates the lengthy, manual process currently used by doctors. Analyzing real world data, the presented Neural Network Epileptic Spike Detector (NNESD) showed a PPV of 72.67% and sensitivity of 82.68% on average over 300 trained networks on a single channel of EEG.**

Keywords—EEG, Interictal Spike Detection, Epilepsy, Neural Network

I. Introduction

Epilepsy is a neurological disorder that affects millions of people across all age groups and has no known cure. People who have epilepsy experience debilitating seizures that come without warning, interrupting their daily life and potentially endangering them. It is caused by an abnormal firing of a cluster of neurons in the brain [22,23]. With the invention of electroencephalography (EEG), doctors have been able to analyze the electromagnetic radiation given off by the brain, commonly called brainwaves.

The EEG device consists of numerous electrodes that are placed in strategic locations around the patient's head. Each electrode is used to measure the voltage potential across the brain, giving a voltage over time readout, as shown in Figure 1. The EEG readings can be used to identify abnormal brainwave patterns, such as an epileptic seizure, or in the case of this study, an interictal spike. An epileptic seizure is characterized in the EEG by a period of very high amplitude, short duration pulses. An interictal spike, however, is a high amplitude short duration pulse that occurs sporadically, as opposed to in a quick series.

These interictal spikes, while not seizures themselves, are generated by the same group of neurons that cause the patient's seizures [24,25]. Therefore, if neurologists can identify where in the brain these spikes are coming from, they have likely found the source of the patient's seizures as well. To identify these spikes, a neurologist must manually analyze the EEG output across multiple channels. An EEG reading session can range from a few hours to dozens of hours, giving an immense amount of data to analyze [29-31]. The interictal spike lasts about 100ms, therefor the neurologist must examine in fine detail a multi-hour session millisecond by millisecond to find the spike pattern. Once enough spikes are identified, they can start to piece together which electrodes exhibit the spike pattern and identify where they are coming from within the brain.

This process is incredibly time consuming, taking many hours of a neurologist's valuable time away from other important tasks. If this process were automated, it would save many physician man-hours per patient. This paper presents a simple, automated method of identifying epileptic spikes in EEG using a single layered artificial neural network, and compares the results to an autocorrelation baseline, that seeks to approximate the neurologist's visual pattern recognition. It is important to note that the datasets used in this study were chosen specifically because the interictal spike features were very difficult to visually discern from the surrounding data. The system uses datasets with epileptic spikes pre-annotated by a neurologist to provide ground truth. The presented method shows promising results, with a 72.67% PPV and 82.68% sensitivity.

This paper is organized as follows: Section II takes a look at related works in the field studying both epileptic spikes as well as epileptic seizures. Section III details information regarding how EEGs work and discusses epileptic spikes further. Section IV analyzes the preprocessing steps utilized to prepare the data. Section V details the presented Neural Network Epileptic Spike Detector (NNESD) algorithm. Section VI presents the results and analysis of the research. Finally, Section VII concludes the paper with some closing comments and future work to be done.

II. RELATED WORKS

Machine learning and epileptic research have been closely tied for many years. Some of the first successful automated identification of both seizure and spike features started to come out in the mid 1970's.

Automated seizure and spike detection has been researched thoroughly for the past two to three decades. Earlier automated systems looked at neural networks by themselves as a tool for analysis, [2,11]. [9,10] utilized a self-organizing map (SOM) with neural networks to classify seizures. The early results had varying degrees of success, with more success in identifying seizures than interictal spikes.

Many researchers have utilized neural networks in conjunction with other statistical analysis methods. Correlation methods, [1,3], use various filtering and thresholding to identify abnormal regions of EEG data. Zerifia et al. in [7] used a genetic algorithm to optimize these thresholding values to achieve accurate results on data that humans failed to accurately classify. James et al. in [13]. They analyzed epileptic spikes in patients using a neural network along with a fuzzy logic system that added spatial information to their process.

Many papers use wavelet transforms to break down the voltage signal into frequency values for further analysis. Various methods of implementing these wavelet transforms have led to good results in classification. Approximate entropy of wavelet transformed data was used in [15,17]. In [8,14,16], a neural network utilized wavelet data as input for classification. [12] explored the use of superparamagnetic clustering of wavelet data while [5] analyzed the difference in accuracy between using continuous and discreet wavelet transforms (CWT vs DWT).

Recent years have led to newer methods of analysis. [20] examined EEG data using a convolutional deep belief neural networks, and [27] explored unique feature vectors for neural
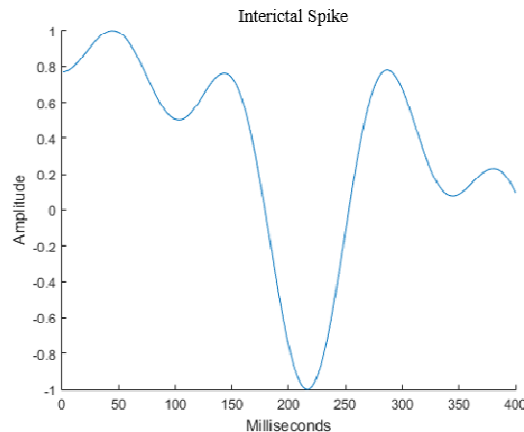

Figure 2: A sample interictal spike. Characterized by a fast, large amplitude drop followed by a fast, large amplitude rise. Voltage values are normalized.

network classification. The use of principal component analysis was compared in [18]. Slow waves patterns in EEG were examined in [6] and used along with the Adaboost classifier to identify spikes. In [4], Barkmeier et. al validated the use of these automated systems by showing the accuracy of their method was at least as good as the human reviewers they used for comparison.

A recent survey in automated epileptic feature detection by Tzallas et. al [26] discussed many successful methods in extracting the desired features from EEG recordings. However, as seen in the previously discussed works and in the survey paper, there is no method which clearly outperforms all others. No consensus has been found regarding which system, if any, to employ in a commercial environment, and there has been little to no penetration of these systems into the medical community.

III. EEG AND INTERICTAL SPIKES

A. Electroencephalography

EEG measures voltage differences across the brain from numerous electrodes placed around the head. These electrodes can be placed directly on the brain itself, requiring invasive surgery, or directly on the scalp using electrically conductive gel to help increase the sensitivity of the electrodes. Figure 1 shows an example of raw EEG voltage data from a single electrode.

Each electrode of the EEG network outputs its own voltage reading over time. Different thought patterns, muscle movements, and even emotions [19] can cause a voltage differential detectable by the device. Artifacts in the data can be caused by excessive muscle movements, like smiling or blinking, as well as external sources, such as high-voltage power lines, cell phones or anything that generates electromagnetic radiation.

B. Interictal Spikes

Epileptic seizures are characterized by excessive, synchronous abnormal firing of neurons in the brain [22,23].
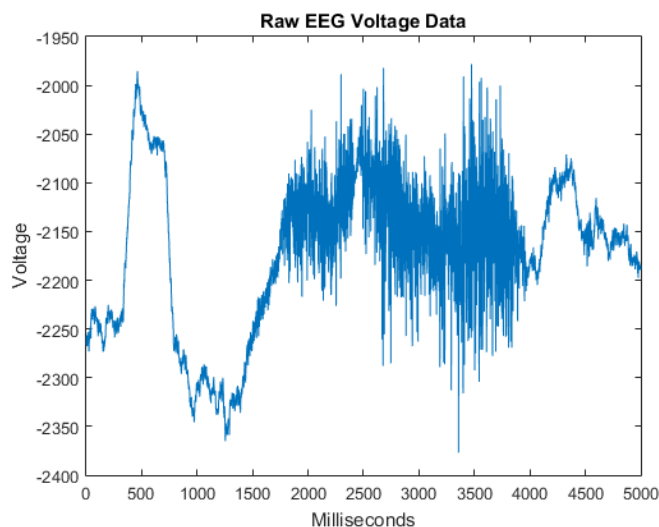

Figure 1: Single channel of raw EEG data showing high frequency noise from samples ~2000 to ~4000.

Monitoring the brain for extended durations can show various patterns that arise as the patient is observed. One of these patterns, the interictal spike, tends to occur in the region of the brain where seizures emanate from, but the spike itself is not a seizure [24,25]. These interictal spikes are useful for doctors since they provide information about the regions of the brain where seizures originate. With this information, neurosurgeons attempt to pinpoint the region of the brain where seizures propagate from and surgically remove it.

While spikes may differ from patient to patient, the general characteristics include a sharp change in amplitude of the voltage in a relatively short amount of time, much like a high frequency pulse. Figure 2 shows an example of an interictal spike after being run through a low pass filter. The feature itself is approximately 100ms in duration, exhibits a sharp drop in amplitude followed by an equally sharp rise in amplitude. This sharp change in amplitude is uncharacteristic of the surrounding region, making it stand out enough for a doctor's eye to identify.

Figure 3A-B shows two interictal spikes as seen in the surrounding environment. They can be seen as the sharp, negative pulses just before samples highlighted by the red line. This plot also shows the subtlety of the spike in the surrounding signals and how hard it can be to detect with an untrained eye.

C. Current Detection Methods

To detect these epileptic spikes, neurologists manually (by eye) analyze the time-domain voltage waveform across multiple electrodes (256 electrodes). This process is both time-consuming and potentially inaccurate [4, 29-31]. The doctor is prone to fatigue, boredom, and any number of psychological effects that occur when performing repetitive, monotonous tasks. Thus, the standard approach for spike detection is still performed by physician inspection of frequency filtered EEG data.

The EGI Dense Array EEG has 256 electrodes that record the voltage differential across the brain from their specific location on the scalp. Visually identifying these spikes requires a trained observer who knows what a "normal" EEG reading

Table 1: Signal processing parameters.

Filter Order	6
Passband Frequency Low (Hz)	1
Passband Frequency High (Hz)	30
Passband Ripple (dB)	0.5
Sample Rate (Hz)	1000

looks like at any given time. The doctor must be able to differentiate patterns from noisy interference, such as muscle artifacts, and patterns from normal brainwave activity, such as sleeping or a normal alert state. Identifying the subtle spike pattern amidst the range of EEG patterns provides an opportunity to ease the workload of the doctor by automating this process. Furthermore, robust detection of epileptic spikes may improve the efficiency of surgical interventions by more accurately pinpointing the spike source.

IV. DATA PREPROCESSING STEPS

A. Raw EEG Data

The data used in this experiment came from an EGI Dense Array EEG [28] used in clinical study at VCU's MCV Department of Neurology. EEG data from six different patients was analyzed for this study. A single patient reading could last on the order of 5 to 24 hours. The sampling rate of the EEG was 1000 Hz, or one sample every millisecond. This translates to roughly 20 million data points for *each* electrode on the lower end of the time scale. With 256 electrodes and 20 million data points, the scale of the data is immense, using roughly 25 GB of hard drive space per patient for the raw data alone. For this reason, only small portions of the data were actually analyzed. The size of the analyzed sections ranged from approximately 70,000 to 250,000 samples, or roughly one to five minutes of continuous EEG data. The selected regions were chosen due to their high frequency of doctor-annotated interictal spike activity

B. Signal Preprocessing

The information output from the EEG data is a voltage signal propagating over time. Figure 1 shows the raw voltage as a function of time from a single electrode of EEG data.
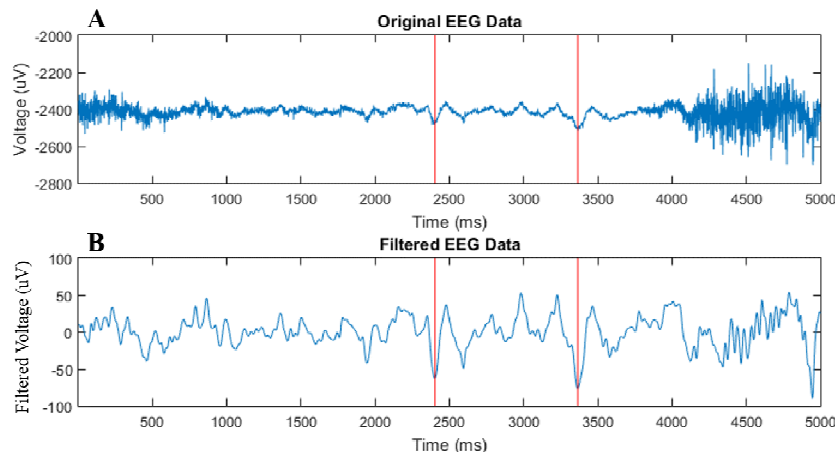

Figure 3: Original EEG data plotted with EEG data after being run through the bandpass filter.
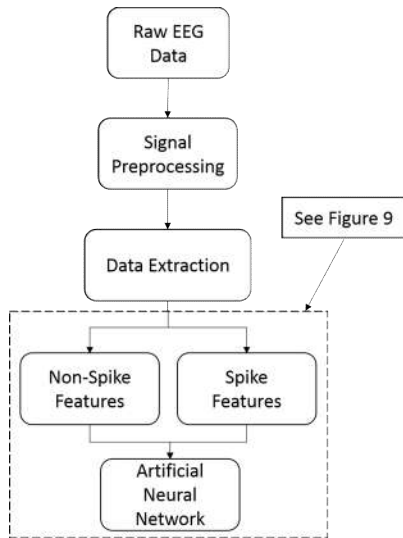
Figure 4: Flow diagram documenting the overall design of the process.

Figure 6: Overlay of all annotated spikes used in the autocorrelation method. Red represents all annotated spikes, blue represents the mean of all spike data.

Immediately obvious from samples ~2000 to ~4000 is a section of very noisy data. This noise may come from muscle artifacts, a strong, errant EM wave from some source within the hospital, or something similar. Any patterns exhibited in this noisy area would be impossible for a human eye to discern. To reduce the high frequency noise, the raw data is run through an infinite impulse response (IIR) Butterworth band pass filter from 1-30 Hz [21]. In effect, this band pass filter cuts off most frequencies below 1 Hz and above 30 Hz. To best approximate the neurologist's filtering process, the parameters chosen are displayed in Table 1.

The high pass filter cutting off any frequencies below 1 Hz acts as a de-trending tool. Any low frequency shift that occurred across the electrodes over time was eliminated by this filter.. Figure 3A-B shows a comparison between the raw voltage values and the filtered voltage values before normalization. To standardize the range of the data, the max
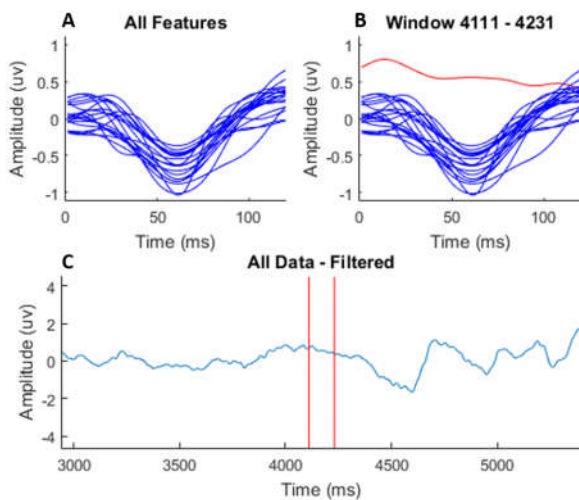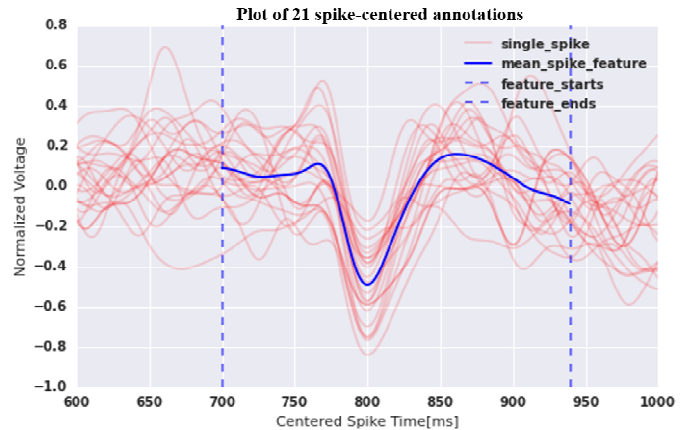

Figure 5: A shows all labeled spikes from patient 1. B shows all the features plotted along with a sample of non-spike data. C shows the filtered data with the bars representing the area plotted in B. All voltage values normalized.

and min values were normalized to 1 and -1 respectively.

C. Data Extraction

Out of the multiple hours of EEG reading and subsequent millions of data points, proportionally very few features were identified by a neurologist as interictal spikes. However, these spike features did not occur on every electrode at every labeled time step. These annotations were spread out across the entire data sets, with clusters of spikes occurring in various regions of data. Due to memory and processing limitations, the data sets were cropped to include smaller sections of data representing the regions of high spike frequency.

Figure 5 shows a visual representation of the data extraction process. To capture the feature, a sliding window technique was used to analyze each section of data. The sliding window was set to the size of the feature spike, 120. These windowed sets of data were extracted from the continuous dataset to be analyzed separately. To compare the spike features to the rest of the signals, the window-sized chunk allows a direct comparison of each feature at a discrete time step along the signal.

V. NEURAL NETWORK EPILEPTIC SPIKE DETECTOR

A. Neural Network Design

The neural network design, shown in Figure 8, followed the standard feed forward algorithm using the back propagation algorithm and was implemented using Matlab's neural network toolbox. The neural network contained a single hidden layer with 10 neurons. The output layer consisted of one binary neuron, determining whether the individual feature being analyzed was a spike or not a spike. The input layer of the neural network contained 120 neurons. The input to these neurons was the 120 values from the windowed datasets. This allowed the neurons to learn on the individual values that represented each window. Figure 5-A shows a sample of windows that contained spike features. While the distribution of amplitudes is not tightly bound, there is a clear pattern in the amplitude drop. Figure 5-B shows a windowed feature from a non-spike region. The non-spike pattern clearly does not exhibit the drop in amplitude of the spikes. This difference in
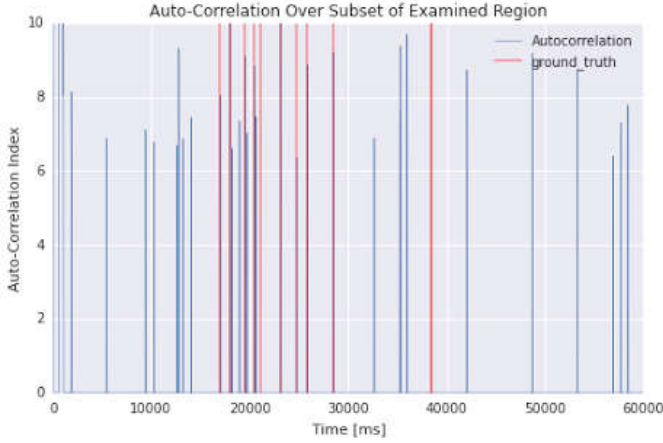
Figure 7: Output of the autocorrelation convolution.

Figure 8: Design of the feed forward artificial neural network using error back propagation.

pattern is what the neural network learns, and classifies each pattern accordingly.

B. Training and Testing Datasets

Figure 9 shows the process used to select training and testing features for the neural network. The data was first split into both spike sets and non-spike sets. All windows that included spike data were removed from the non-spike data to prevent contamination of the training set. Of the annotated spike windows, 50% were used for training, and the other 50% for testing. A continuous set of 2000 random non-spike samples were used for training, and a continuous set of 5000 random non-spike features were used for testing.

Once the neural network was trained, it was tested 100 times on separate continuous sets of 5000 random non-spike features along with the remaining test spike features. This process of training and testing over 100 regions was repeated a total of 300 times, with each network being trained on randomized spikes and randomized non-spike features. The total number of tested samples was 500,000 for each trained network.
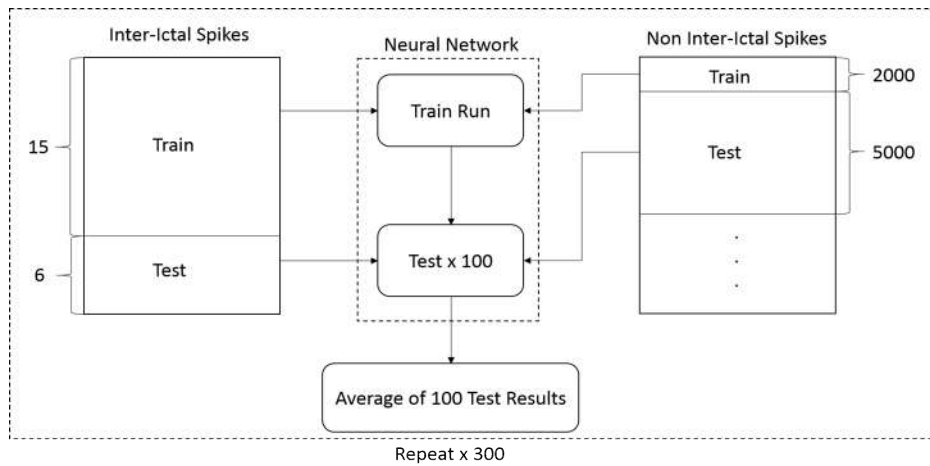
VI. EXPERIMENTAL RESULTS

A. Evaluation Metrics

To evaluate the performance of the NNESD algorithm alongside the autocorrelation algorithm, the positive predictive value (PPV) and sensitivity were used as metrics.

PPV is a measurement of how many positively predicted values are correctly predicted compared to the total number of positive identifications. It is defined as:

$$PPV = \frac{TP}{(TP + FP)} \tag{1}$$

where TP is true positives and FP is false positives. This determines how accurate the system is at filtering out actual spikes from falsely classified spikes.

Sensitivity is a measurement of how many true positives are correctly identified out of the total number of true positives. It is defined as:

Figure 9: Shows feature selection for testing and training for the artificial neural network.

$$Sensitivit\,y = \frac{TP}{(TP+FN)} \qquad (2)$$

where TP is true positives and FN is false negatives. This determines how accurate the system is at accurately identifying real spikes that are occurring in the dataset.

B. Results

In order to provide a comparative analysis, a frequently used technique, autocorrelation, was used as a baseline. To develop a mean spike feature from the spikes in the region, all annotated spikes were centered about their minimum value as shown in Figure 6. This was performed separately for each patient. Once all the spikes were trough centered by time-shifting, a time-wise mean voltage amplitude was computed, shown by the blue line in Figure 6. The mean voltage feature was convolved with itself over a 1600ms window, producing an autocorrelation index. From this feature autocorrelation, a threshold value was chosen to exclude signals with low correlation. Finally, the mean feature was convolved with the entire filtered electrode data, outputting an autocorrelation index of the mean feature for the entire sample recording. The thresholded autocorrelation index (>6) was plotted alongside the physician annotated spike locations, see Figure 7 for an example plot.

Figure 10 shows the averaged PPV and sensitivity of the neural network and autocorrelation tested over all 6 patients. NNESD shows better PPV results than the autocorrelation method on all but patients five and six. The autocorrelation performs much better in the sensitivity metric, while NNESD still performs poorly on patients five and six. What can be gathered from these results is that NNESD is better at accurately filtering out false positives, while still performing quite well at correctly identifying labeled true positives. The autocorrelation is much less consistent across all patients, but does perform better on patients five and six, where NNESD's performance drops quite substantially.

It is important to note that NNESD's performance is very subjective to the training region. After analysis of the results, it was found that certain regions trained the network worse than others. For this reason, the median result from the neural network was calculated to compare when statistical outliers are not taken into account. This difference is more pronounced in the sensitivity metric, where the median sensitivity for patients two, three, and four are all 100%. The difference between the mean and median result is likely due to a non-uniform/suboptimal distribution of annotation quality. In addition, an analysis of the location of network errors showed these regions of poor classification were non-random (data not shown).

While the reported PPV and sensitivity percentages do not approach consistently high values, analysis of the absolute number of errors provided useful information. The average number of false positives across all patients for NNESD was 2.34, while the median was only 1.82 with the number of labeled spikes in the regions tested ranging from 6 to 23. The autocorrelation had an average number of 8.83 false positives across all patients.

It is important to note the sparseness of the dataset used for this study. Physician annotated spikes represent less than 1% of the total dataset, very sparse by any measurement. Identifying these regions with potentially poor annotations and training on optimal regions of data is an area for improvement that requires additional feedback from neurologists.

VII. CONCLUSION AND FUTURE WORK

This paper presented a simple neural network design using only windowed voltage data from only a single channel EEG to accurately identify interictal spikes from the surrounding patterns. To provide a baseline comparison, an autocorrelation of a template epileptic spike was computed. The presented NNESD method achieved an average PPV of 72.67% and sensitivity of 82.68% over six test patients compared to the autocorrelation average PPV of 60.43% and sensitivity of 90.61%.

The autocorrelation performs well on the tested dataset, but requires manual analysis of the spikes to achieve a proper thresholding value. NNESD simply learns on the data
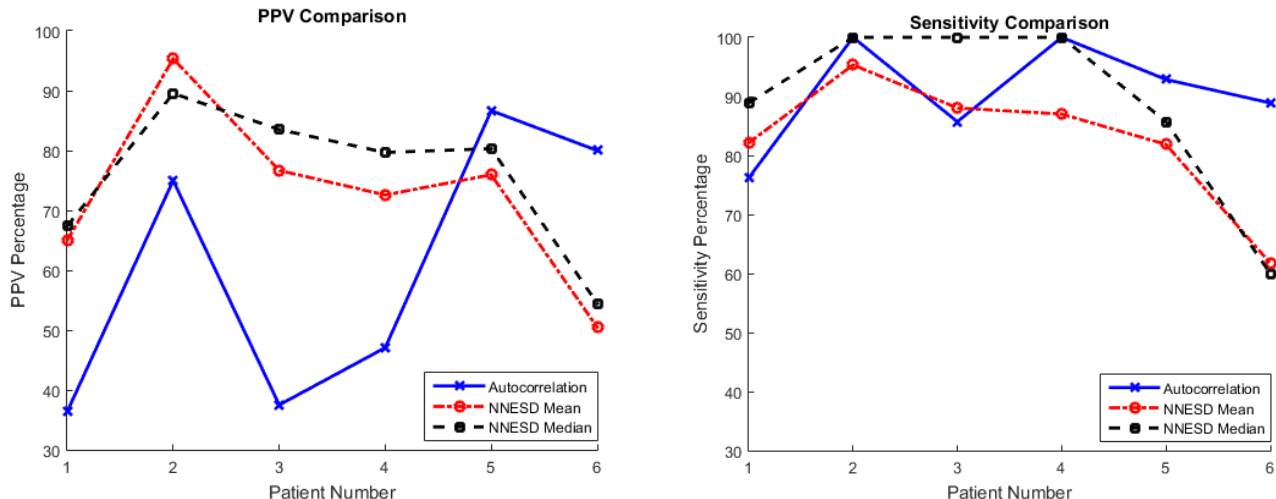

Figure 10: Plots show the PPV and sensitivity comparison between the tested algorithms

presented to it. In an implemented environment, the neural network would allow a more hands-off approach and simply point out which regions contain spikes without the need to optimize a thresholding value. The results clearly show that utilizing an automated system, while not able to 100% identify properly all spikes in a region, would be able to drastically reduce the amount of data a neurologist has to manually analyze.

This work is part of a larger study to identify patterns in various epileptic spikes and develop a single tool to automatically extract the spike-features of interest and label their location in the patient's brain. From this study, we were able to determine that information from a single channel EEG is probably not sufficient to identify interictal epileptic spikes from the surrounding data. A multichannel EEG approach is necessary to extract spatial information regarding the interictal spikes as well as reduce the number of false positives. This will be explored in future studies.

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