SeizNow: A Highly Accurate Model for Automated Pediatric Seizure Diagnosis using Neural Networks

Nadia Lach-Hab

Abstract

The purpose of this experiment is to examine the mathematical relationships that exist within electroencephalogram (EEG) data and to determine if those relationships can help diagnose pediatric seizures. There is currently no cost-efficient automated way to detect seizures solely based on EEG data. This research aims to find a reliable way to detect seizures by determining the relationship between the discrete energy differences of pediatric seizure EEG data and pediatric non-seizure EEG data. A neural network was coded to analyze the discrete energy differences and classify EEG data into seizure and non-seizure groups with an 87% accuracy. The discrete energy differences between the two groups were statistically different, so the null hypothesis was rejected. Non-seizure data had higher discrete energy values, indicating that the EEG graphs for the seizure group's discrete energy differences were smoother overall and had less distinct changes between the relative minimums and maximums. This project highlights the importance of examining mathematical properties, such as discrete energy, to indicate seizure activity. This project was the first to successfully apply discrete energy to medical research. This neural network could be expanded to help automate seizure diagnosis in pediatric patients in real-time, assisting healthcare professionals. Notably, since the project was developed at no cost, it can also be applied to low-income communities, ensuring broader access to essential healthcare technology.

Introduction

An electroencephalogram (EEG) is a test that measures electrical activity in the brain (Mayo Clinic, 2024). A seizure is a sudden burst of electrical activity in the brain that can cause spasms or changes in awareness (Epilepsy Foundation, n.d.). The EEG detects the electrical activity of the brain through uniformly arranged electrodes on the scalp. An EEG channel is defined by the difference between potentials measured at two electrodes, which captures the summed potential of millions of neurons. Shortly after the onset of most seizures, but sometimes after a prolonged period following seizure onset, a group of EEG channels develops rhythmic activity, often containing multiple frequency components. The identity of the EEG channels involved and the structure of the rhythmic activity is different across individuals, making it difficult to diagnose seizures (Tran et al., 2022) . Diagnosing pediatric seizures solely based on EEGs can be challenging due to several factors. Some seizures may not produce distinct EEG patterns, making it difficult to confirm a diagnosis (Panayiotopoulos CP., 2005).

Furthermore, various non-seizure conditions can mimic seizure symptoms, complicating the interpretation of EEG results (Nationwide Children's, n.d.). Pediatric patients may also have trouble remaining still during the procedure, affecting the quality of the EEG recording (Stanford Medicine Children's Health, 2024). Seizure characteristics can differ significantly between patients. This makes it necessary to conduct individualized analyses beyond the EEG when diagnosing seizures (Saab et al., 2020). Seizure characteristics can also vary based on the

patients, which is why individualized analysis is required when examining seizures and diagnosing epilepsy. These challenges exemplify the need for advanced automated detection systems to improve accuracy and efficiency in diagnosing pediatric seizures.

A time series is a sequence of data points indexed in time order, often used for analyzing trends or patterns over time. These time series have properties, such as fractional Brownian motion. Fractional Brownian motion (fBm) is a random walk process characterized by its Hurst parameter, H, which determines the correlation of increments (Quilez, n.d.). The quantity of the Hurst parameter helps quantify the persistence in EEG signals, providing insights into neural dynamics and possible abnormalities (Janušonis et al., 2020). Literature has indicated that EEG signals often exhibit fractal-like behavior, which can be conveyed using fBm due to its ability to model self-similarity, visualize and model patterns, and its statistical properties (Worcester Polytechnic Institute, n.d,). This experiment wanted to exploit the fractional Brownian motion traits of the EEG data to determine if they could be indicators of a seizure.

The Hausdorff Dimension is the measure of roughness or the fractal dimension. For example, a point has a Hausdorff Dimension of 0, a square has a Hausdorff Dimension of 2. In fBm, the Hausdorff dimension is calculated by subtracting the Hurst exponent from 2 (Schaefer et al., 2013). Fractals, such as EEG data, have a non-integer Hausdorff Dimension. Fractional Brownian motion also has discrete energy values that can be calculated as shown below. When graphed over time, these discrete energy curves should converge to the value of the Hausdorff Dimension, if the data behaves like fBm (Betti et al., 2022).

$$I_s(P_n) = \frac{1}{n^2} \sum_{p \neq p' \in P_n} |p - p'|^{-s}$$

Assessing these properties can provide useful insight about the EEG data, it serves as a useful comparison between seizure and non-seizure data. It is still unknown if EEG data behaves like fBm, however, the discrete energy calculation is not dependent on fBm, making it suitable for research. One way to assess if EEG data behaves like fBm is calculating what number the discrete energy curve converges to and subtracting the Hurst exponent from 2 (Betti et al., 2022). If the EEG data does behave like fBm, assessing fBm's traits and applying it to EEG data could be very beneficial. For example, fBm's self similarity trait could help predict seizures and their behavior on the EEG.

Procedure/Methodology

The EEG data used in this experiment was taken from the CHB-MIT Scalp EEG Database. There were 22 subjects from which EEG data was collected from at the Children's Hospital Boston. All signals were sampled at 256 samples per second with 16-bit resolution, and the international 10-20 system of electrode positioning and nomenclature was used to record the data (Shoeb, 2010). Each file had been labeled when the seizure occurred which made it seamless to process the data through the computer algorithm. All code was done in Jupyter Notebook in Python.

The EEG .edf files had to be read in as numpy arrays to make the data easier to work with mathematically. The EEGs were split into times when the patient was seizing and

experienced regular neurological activity and these arrays were stored and labeled accordingly. The arrays were then normalized using the min-max normalization, so every data point was divided by the maximum value in the EEG array. Min-max normalization was chosen so that it scales data to a consistent range, thereby improving model performance and convergence in machine learning algorithms. This process was repeated for every subject, the array consisted of 1 second of EEG data values seizing and when they were experiencing normal neurological activity was processed for 1 second. The discrete energy quantities were then calculated for the arrays and the S parameter was 25. Code for calculating the discrete energy values is below given a numpy array, P, and the S parameter.

```
def DiscreteSEnergy(P, s):
    n = np.shape(P)[0]

    [Rows, Columns] = np.indices((n,n))

    VecDiff = np.abs(P[Rows,:] - P[Columns,:])

    MagDiff = np.power(np.sum(np.power(VecDiff,2), axis=2),1/2) #here we use L2 norm (Euclidean distance in Rd) to find vector magnitude

    Diff= np.triu(MagDiff) #remove duplicate differences by considering only those differences above the main diagonal
    MaskedDiff = ma.masked_where(Diff==0, Diff, copy=True) #mask all zero differences so we are not dividing by zero

    SumMat = np.ma.power(MaskedDiff, -s)
    sum = np.sum(np.sum(SumMat))

    discSEnergy = np.power(float(n), -2)*sum

    return[discSEnergy, s]
```

Figure 1: Discrete Energy Calculation Code

The top and bottom 10% of the data values, or the outliers, were removed from the arrays of discrete energy dataset to maximize accuracy. The minimum and maximum discrete energy values of the seizure and non-seizure data arrays were stored in a separate list and analyzed. The average off each of these lists was taken. T-tests were run on both the minimum dataset of the seizure and non-seizure data and the maximum of the seizure and non-seizure data to determine the statistical significance of the data. Below is the code for the discrete energy minimum/maximum calculations for the seizure data. The same process was applied to the non-seizure data.

```
#discrete energy ranges

#maximum for seizure
seizmaxavg=0
newl=[]
for i in de_seiz:
    if type(i)==list:
        newl.append(i[0])

newl = np.array(newl)
newl = newl[(newl>np.quantile(newl,0.1)) & (newl<np.quantile(newl,0.9))].tolist() #removes upper and bottom 10% of discrete energy values for outliers
seizmaxavg=sum(newl)/len(newl)


#minimum for seizure
seizminavg=0
newl=[]
for i in de_seiz:
    if type(i)==list:
        newl.append(i[1])


newl = np.array(newl)
newl = newl[(newl>np.quantile(newl,0.1)) & (newl<np.quantile(newl,0.9))].tolist() #removes upper and bottom 10% of discrete energy values for outliers
seizminavg=sum(newl)/len(newl)


print(seizminavg,"-",seizmaxavg,"is the range of the discrete energy for the seizure data")
```

Figure 2: Code for the discrete energy minima and maxima values

Discrete energy values were then plotted against their corresponding times (in seconds) to measure qualitative data and for comparisons.

```
def energy_graph(data, s):
    d_e_list = []
    x_list = []
    maxN = data.shape[1]
    for i in range(1, maxN // 10):
        d_e_list.append(discrete_energy(data[:, ::i], s))
        x_list.append(maxN // i)
    print(d_e_list)
    plt.subplot(2,1,1)
    plt.plot(x_list, [i for i in d_e_list])
    plt.yscale('log')
    plt.title(f"s = {s}")
    plt.show()
```

Figure 3: Code for the discrete energy graphs

After the graphs were analyzed, the differences of the discrete energy values were computed. The higher discrete energy differences meant that the discrete energy graphs had more variability and drastic changes. This can be seen when the discrete energy graph has a higher oscillation and thus leads to less predictable data. Discrete energy differences were then stored in arrays for both seizure and non-seizure data. T-tests were also run between the discrete energy differences for those values to determine their statistical significance.

```
#discrete energy graph 1 second with the seizure data
#discrete energy graph 1 second with the non-seizure data
mne.sys_info()
seizdiff_max=[]
nonseizdiff_max=[]

de_seiz=[]
#de_min_seiz=[]

de_noseiz=[]
#de_min_noseiz=[]

for i in seizures:
    file = "/Users/nevenapuletic/Downloads/chb-mit-scalp-eeg-database-1.0.0/chb"+str(i[3:5])+"/"+str(i[6:])
    data = mne.io.read_raw_edf(file)
    raw = data.get_data()
    count=False
    for j in seizures[i]:
        raw_seizure = raw[:,j[0]*256:j[1]*256]
        seizdiff = raw_seizure[1:len(raw_seizure)]-raw_seizure[0:len(raw_seizure)-1]
        seizdiff_max.append(np.max(seizdiff))
        for s in range(23, 26):
            de_seiz.append(energy_graph(raw_seizure[:, 2000:2256], s))
            print("siezure for patient "+str(i[6:]))
        if (2000<j[0]*256 and 2256<j[1]*256) or (2000>j[0]*256 and 2256>j[1]*256):
            de_noseiz.append(energy_graph(raw[:, 2000:2256], s))
            print("non siezure for patient "+str(i[6:]))
        else:
            print("find a new way")
        if count == False:
            nonseizdiff = raw[1:len(raw)]-raw[0:len(raw)-1]
            nonseizdiff_max.append(np.max(nonseizdiff))
            count=True
```

Figure 4: Code to calculate the discrete energy differences for the seizure and non-seizure data.

A neural network with three layers was developed to examine the discrete differences between the seizure and non-seizure values. It took in two 1-D numpy arrays of the discrete energy differences, consisting of the seizure and non-seizure arrays. The data was split so that 80% of the data was used for training and 20% was used for testing, and the accuracy of the model was evaluated at the end of testing. The purpose of this neural network was to determine if the algorithm could classify whether or not it could be determined if the EEG belonged to the

seizure or non-seizure groups solely based on the discrete energy differences. The sequential neural network model was used with the sigmoid and ReLU activation functions to improve the speed of the neural network. The model was then compiled, trained, and tested. During compiling, the Adam optimizer and the binary cross entropy loss were used.

```python
#neural network for detecting if a person has a seizure or not based on the discrete differences of the data
import numpy as np
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler

# Example 1D data (replace with your actual data)
# For simplicity, assume each sample is a 1D array of length 100
X_seizure = np.array(x)  # 100 samples of 1D data
X_non_seizure = np.array(y)  # 100 samples of 1D data

# Combine data
X = np.concatenate((X_seizure, X_non_seizure), axis=0)
y = np.concatenate((np.ones(len(X_seizure)), np.zeros(len(X_non_seizure))), axis=0)

# Split the data into training and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Reshape the data to 2D before scaling - Each sample is a row, and there's one feature column
X_train = X_train.reshape(-1, 1)
X_test = X_test.reshape(-1, 1)

# Optional: Standardize the data
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)

# Define the model
model = Sequential([
    Dense(64, activation='relu', input_shape=(X_train.shape[1],)),  # Input shape for 1D data
    Dropout(0.5),
    Dense(32, activation='relu'),
    Dense(1, activation='sigmoid')  # Binary classification
])
```

```python
# Compile the model
model.compile(optimizer='adam',
              loss='binary_crossentropy',
              metrics=['accuracy'])

# Train the model
model.fit(X_train, y_train, epochs=10, batch_size=32, validation_split=0.2)

# Evaluate the model
loss, accuracy = model.evaluate(X_test, y_test)
print(f"Test Loss: {loss:.4f}")
print(f"Test Accuracy: {accuracy:.4f}")
```

Figure 5: Neural network used to determine if the patient was experiencing a seizure based on their discrete energy differences.

The Hurst exponents of the data were also calculated and analyzed.

```python
def get_hurst_exponent(time_series, max_lag=20):
    """Returns the Hurst Exponent of the time series"""

    lags = range(2, max_lag)

    # variances of the lagged differences
    tau = [np.std(np.subtract(time_series[lag:], time_series[:-lag])) for lag in lags]

    # calculate the slope of the log plot -> the Hurst Exponent
    reg = np.polyfit(np.log(lags), np.log(tau), 1)

    return reg[0]

print(2 - get_hurst_exponent(channelData))
```

Figure 6: Code used to calculate Hurst exponents of the timeseries EEG data.

Results

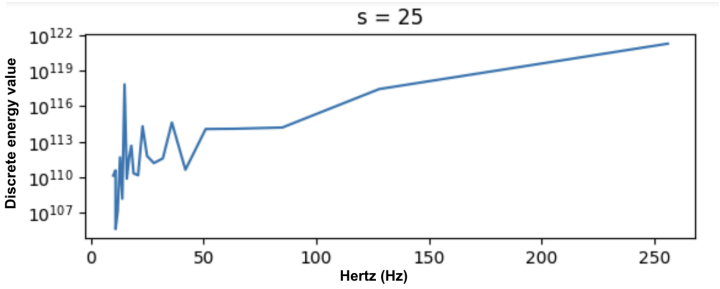
The discrete energy values for the seizure data generally ranged between 9.00×10^{96} to 8.78×10^{116} while the discrete energy values for the non-seizure data ranged between 2.48×10^{104}

to 1.79×10^{124}, after the removal of outliers. On average, the discrete energy values for the seizure EEG data with all 23 channels was higher than the discrete energy values for the non-seizure EEG data.

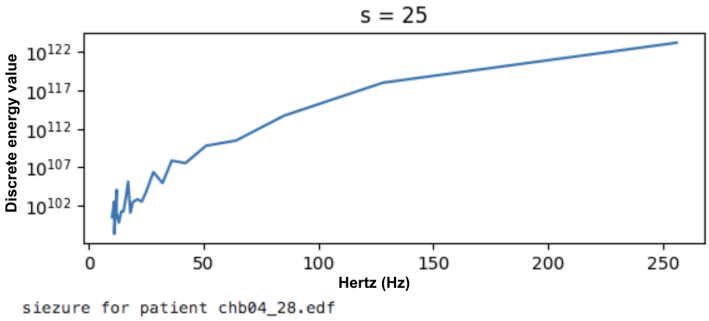
```
9.001246757345378e+96 - 8.777881417578864e+116 is the range of the discrete energy for the seizure data
2.4790236109105207e+104 - 1.7909608544528335e+124 is the range of the discrete energy for the no seizure data
```

Figure 7: Computation of the thresholds for seizure and non-seizure data's threshold

Discrete energy graphs were also made for each subject's seizure and non-seizure discrete energy values. The non-seizure discrete energy graphs tended to have higher oscillations and amplitudes, especially in the beginning of the graph. The non-seizure data also had higher discrete energy values than the seizure data, as could be explained by the higher threshold for discrete energy in the non-seizure data. The seizure discrete energy graphs were more predictable and often converged to a certain value, while the non-seizure discrete energy data were less reliable and oscillated more. Discrete energy graphs generally had a short period of instability and distinctive behavior towards the beginning. All discrete energy graphs were only read in EEG data spanning 1 second.



Graph 1: Discrete energy graph for chb04_28, no seizure



Graph 2: Discrete energy graph for chb04_28, seizure

The accuracy of the neural network that predicted whether the subject was seizing or not based on their discrete energies was computed and then analyzed. The highest accuracy recorded was 86.79% and its corresponding test loss was 36.48%.

```
Test Loss: 0.3648
Test Accuracy: 0.8679
```

Figure 8: Computed test loss and accuracy of neural network

Inferential Statistics

T-tests were conducted between all experimental groups. The data for the differences of discrete energy ranges in seizure and non-seizure data was statistically significant. The p-value for the comparisons between the minimum discrete energies for the seizure and non seizure values was 2.33×10^{-5}. The p-value for the comparisons between the maximum discrete energies for the seizure and non seizure values was 2.82×10^{-8}.

All discrete energy differences values for seizure and non-seizure data were recorded and stored. A t-test was run to compare these two groups and the p-value was 5.25×10^{-29}. The data was statistically significant.

The Hurst exponents for seizure and non-seizure data were recorded and stored. A t-test was run to compare these two groups and the p-value was 0.908. This data was not statistically significant.

Discussions/Conclusions:

Discrete energies were a very useful quantity when comparing seizure and non-seizure EEG data and are very promising in locating seizures on EEG data. By analyzing and locating seizures on the EEG through this machine-automated algorithm, diagnosing epilepsy could become easier for healthcare professionals compared to traditional manual methods. Overall, discrete energy values for seizure EEG data was lower than the non-seizure EEG data. This is an additional factor that can assist people in differentiating between seizure and non-seizure EEG data. This property can also be seen in Graph 1 and Graph 2, where Graph 1, modeling seizure discrete energy values, contained more unstable and distinctive behavior, which resulted in greater discrete energy values and greater discrete differences.

The neural network is also a very promising tool for analyzing EEG data. It had a high accuracy of 86.8%, meaning that the discrete energy values for the seizure and non-seizure EEG data were effective at determining whether the EEG data belonged to the seizure or non-seizure group. Another advantage to this model was its speed. Results were obtained in less than seconds, which is crucial in medicine where the speed of making a diagnosis could make the difference between life and death. Pediatric seizure data is also easier to misinterpret due to the many factors that can result in misdiagnosis. Currently, there are no foolproof methods for diagnosing seizures using solely an EEG (Sirven et al., 2013). This pioneering study was one of the first to successfully apply discrete energy values to medical research. Given the potential of discrete energy in classifying pediatric EEG seizure data, this new mathematical concept warrants further exploration in medical and neuroscience research. The neural network is an encouraging tool that can aid healthcare professionals in their diagnosis and treatment plans.

Comparing the Hurst exponents of the seizure and non-seizure EEG data was ineffective, as the data was not statistically significant. This shows that fBm and its properties could not be used to successfully compare the two groups. This experiment was also developed at no cost,

meaning that it can be easily accessible by everyone, regardless of income or access to a medical provider.

Due to the nature of this experiment, there were no ethical or safety concerns that this experiment needed to address. A possible limitation of this experiment was that only 1 second of EEG data was analyzed. This 1 second interval either took place during the time the patient was seizing, or at a time where the patient was not seizing, depending on what group they belonged in. Only 1 second of EEG data was analyzed due to the computer processing time that it would take to analyze a larger amount of data. On the contrary, this could be a strength of the project as the algorithm was able to detect a seizure over the span of one second, making it both effective and efficient. The length of time for the processed data is also an important constant that was kept uniform throughout the experiment. In the future, larger amounts of data could be analyzed to process the entire EEG and improve neural network accuracy as better technology becomes available.

This data can help enhance the accuracy of seizure diagnoses in children. The neural network was both efficient and effective in rapidly distinguishing between seizure and non-seizure EEG patterns.

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