Real Time Seizure Recognition via EEG, AI, and Nonlinear Dynamics

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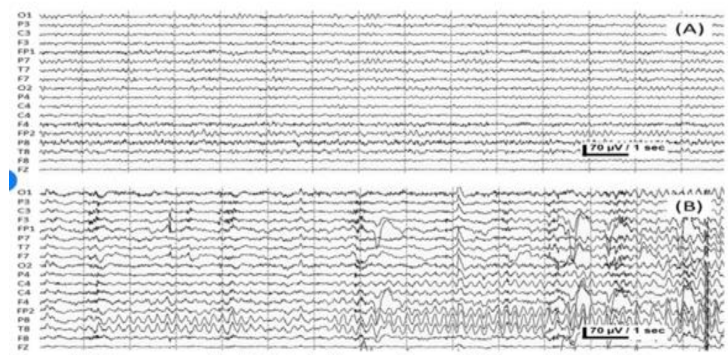
Abstract

EEGs have some technical challenges. These challenges can increase patient, patient family, and hospital staff stress levels and costs. This paper will give a synopsis of those challenges and show that they can be overcome by taking in the brain's real time electrical activity via EEG and use AI and concepts from Nonlinear Dynamics to provide real time seizure recognition for families and hospitals. The benefits of real time seizure recognition would increase patient quality of life and save tremendous amounts of money for hospitals and insurance companies. Additionally, real time brain electrical activity processed through AI could also be utilized in many other areas with applications to PTSD, decision making, military training, and more.

Introduction

EEGs are limited. The brain generates electrical activity through movement of ions across neurons' membranes. The electrical activity in the brain is very low in amplitude, measured in microvolts (millionths of a volt), and ranges from a few to a few hundred microvolts. EEGs receive these very small measurements, amplify them, and displays them in the form of waves on a monitor. These waves are then used as only a tool for doctors to decide if it fits the pattern of a seizure and, along with other tools (video, audio, family history, etc.), decide if a patient is an Epileptic. This process is full of challenges, the most noticeable of which is the loss of information and noise between the generation of the electrical activity through its amplification process. Other problems are, but not limited to:



Normal EEG compared to EEG including a seizure: (A) Normal EEG of 15 seconds; (B) EEG of the same patient having an epileptic seizure visible as rhythmic activity starting on electrodes P8 and T8.

Figure 1: Fürbass, Franz. (2017). EEG monitoring based on automatic detection of seizures and repetitive discharges.

- the length of time patient families wait for a doctor to interpret the readings, human error in reading them,
- the inability to discern electrical signals that are generated in the deep brain,
- the challenges in interpreting results from brains that have suffered injuries or have been altered via surgery. Even the blinking of an eye can alter an EEGs recording,
- EEG leads picking up ambient electrical activity that other leads are also registering.

So how can seizures (or any unique brain activity) be recognized amid the chaos of any thought or movement? EEGs have one very powerful advantage: they produce arrays of numerical values, and within this array of values lies the information needed to make the wave patterns on a monitor: therefore, this array can be interpreted as a one-to-one encoding of the brain's current state within a finite moment in time. A system's state in a moment in time is the foundation of dynamics: the study of how systems changes over time. Because the interactions within the brain are nonlinear, the brain's current state in real time would fall under the branch of mathematics called Nonlinear Dynamics.

In fact, the Clay Mathematics Institute has several Millennium Prizes, one of which is to prove or disprove whether the Navier-Stokes equations have a smooth solution that is valid for all time, or whether they can break down and develop singularities in finite time, the reward for which is a million dollars. Epilepsy, and specifically, the brain as a closed system, falls into this category of mathematics, and therefore research into the brain's electrical activity could lead to a million dollar prize. For those not familiar with this idea of fluids and turbulence outside of a glass of water or a bumpy airplane ride, fluids take many forms in nature, the air flowing over the wing of an airplane, the water crashing over the rocks (whirlpools might be a visual example of a singularity, although it mathematically isn't) the emergence of photons eventually being spit out into space from the plasma in a star, and that same photon millions of years later being swallowed by a true singularity of a black hole after traveling on the sea of solar winds. Air, water, plasma, solar winds, spacetime itself, and the bowels of a black hole are examples of fluids in some sort of system that can exhibit turbulence, smoothness with respect to time, and singularities. And the brain is no different. The movement of the brain's electrical activity, rising and falling like waves in the ocean occur within the brain's closed system over time. Is the brain's activity "smooth" over all time, or does the brain ever form a "singularity:" a place where any mathematical description of the brain fails.

This paper shows that a "volcano" pattern emerges at the onset of a seizure, complete with a cauldron, and while the process takes less than 1/256th of a second, the math does not break down; therefore it is smooth, if you zoom in far enough. It goes on to show that the baseline electrical activity before the seizure onset is different from the activity after.

This suggests that a seizure should be able to be recognized in real time.

Background

For decades, my wife's deep frontal lobe seizures were misdiagnosed by doctors who at one point admitted her to a mental hospital even though her mother was a diagnosed epileptic, and at other points accidentally overdosed her. Last year, my wife had brain surgery to attempt to correct her Epilepsy. We now know that the main cause of these misdiagnoses was the inability for an EEG to detect "deep brain" seizures.

Diagnosed with brain cancer at the 20-week anatomy scan after finding a mass in her brain, our daughter, Nicolette, wasn't born with cancer, rather Ohtahara Syndrome, a very deadly syndrome indeed, and Cortical Dysplasia. Nicolette's first pediatric neurologist misdiagnosed her, and her only solution was to add more dangerous meds. One of these meds blinded Nicolette in one eye. This specialist would ignore our attempts to help find solutions via our personal research and quickly put us in our place, never hesitating to let us know she was the expert, and we were not. Finally, Nicolette was correctly diagnosed when this doctor traveled to a conference, and in short order and at 6 months of age, a neurosurgeon removed half of Nicolette's brain, and her condition was so unique, we were asked to donate the removed brain to science.

Unfortunately, this was only one part to Nicolette's story, but of the many trials and tribulations, one had a lasting impact on us, and it dealt, again, with EEGs. Ohtahara patients, if they live, generally develop Lennox-Gastaut Syndrome (LGS), Dravet Syndrome, or West Syndrome. This diagnosis depends on a known pattern in an EEG. Because half of Nicolette's brain was removed, changing her brain anatomy, this pattern was not there, so any medications that could treat these conditions were denied by insurance companies. This created tremendous stress for my family, and we lived for quite some time fearing we were going to lose her after all we'd already been through, and Nicolette would have died from an untreated condition stemming from a lapse in technology: the inability for an EEG to find a known pattern in the electrical output of a brain. Needless to say, these experiences affected me profoundly. I learned and tutored higher mathematics and went back to school to get a Data Science Certification for the sole purpose of preventing my experiences from happening to other families, hospital staffs, and even insurance companies.

Surely AI can automate much of this, and luckily it can.

I initially had two goals that changed over time, leading me to the solution:

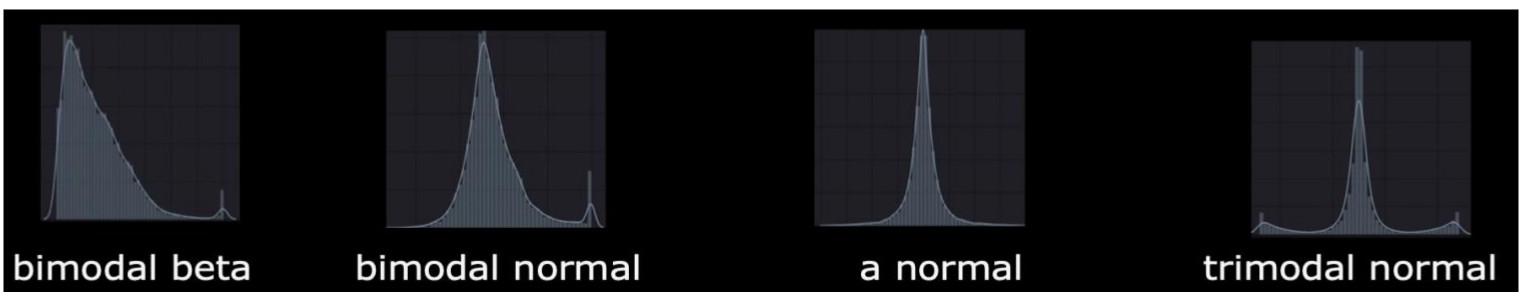
1. Predict Seizures in the future.
2. Find the known EEG pattern for Lennox-Gastaut Syndrome (LGS), Dravet Syndrome, or West Syndrome from Ohtahara children who had their brain anatomy changed with surgery.

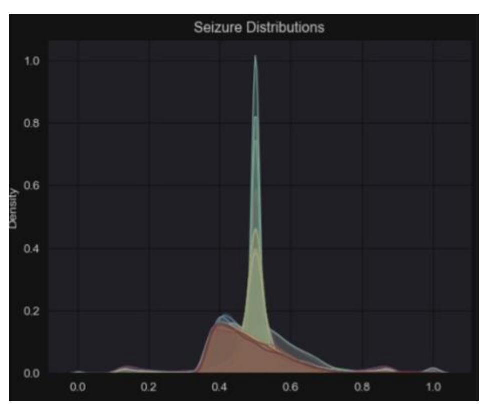
For 1: I planned on using Bayesian inference to predict seizures. The process was as follows: a posterior probability distribution would give a probability that any EEG reading in any moment in time was a seizure or not via bayes Theorem. In Bayesian terms, I wanted the conditional probability that given the data, it was a seizure:

$$\mathrm{P(S|D)} = \frac{\mathrm{P(S)} * \mathrm{P(D|S)}}{\mathrm{P(D)}} : \text{where}$$
$$\mathrm{S} = \text{Seizure EEG data}, \mathrm{D} = \text{ any random EEG data},$$
$$\mathrm{P(S|D)} \text{ is the posterior}, \mathrm{P(S)} \text{ is the prior},$$
$$\mathrm{P(D|S)} \text{is the liklihood}, \mathrm{P(D)} \text{ is a normalizing constant, if needed.}$$

In words, the probability that this is a seizure given new data is equal to the probability of a seizure times the probability that this data is a seizure given known seizure data divided by the sum of probabilities of all the possible outcomes. This inferred that the patient would already have EEG data on file from previous EEGs with a known seizure event. As the equation continued to take in real time data, the probabilities would update, based on the previous data, and be able to say the seizure was imminent in the future. Two problems surfaced:

1. the system always went to zero, which could be interpreted as a singularity where math breaks down, making prediction impossible. To combat this I began playing with the probability distributions in order to get the numerators and denominators that would prevent this while preserving the data's information, which is when problem two surfaced.
2. EEG data did not fit into any known distributions for modeling. Because so many things in nature have normal distributions, I tried many times to get a normal distribution from the data, but this couldn't be forced, or the resulted would be biased. The following picture shows 4 of the distinct distributions found in the data.





And to the right, a collage of the feature distributions seen during the seizure. In the end, I determined that seizures, like the weather and earthquakes, cannot be predicted due to the mathematics of Chaos Theory, a branch in Nonlinear Dynamics. Chaos shows that 2 otherwise identical systems (a brain in this case) can vary wildly in their long term behaviors depending on the initial conditions when the system begins. I could take it to its logical beginning and say it's impossible to know the initial conditions when an epileptic is born, or when the ideal conditions coalesce in such a way that a seizure at some point in the future will occur.

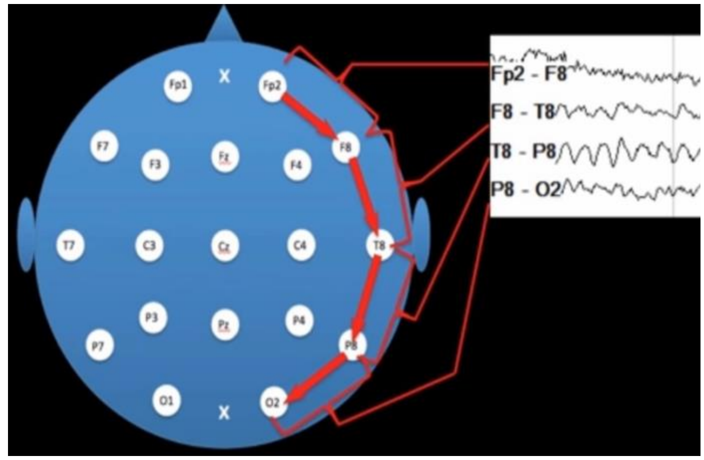
Abandoning Bayesian Inference couldn't be avoided. Thus began a new process of running all types of models on the data to attempt to find a pattern that could lead down a new path.

Using a variety of models from Deep Learning in Tensorflow-Probability and Tensorflow to supervised and unsupervised models in sci-kit learn and even forecasting models in stats models and scipy, I failed to find a pattern.

Approach and Solution 1:

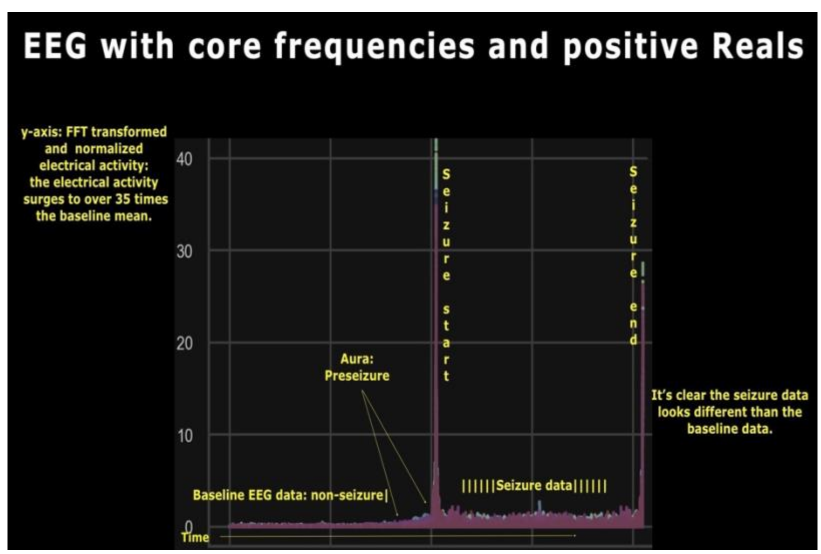
Given a previous EEG, whose data has been preprocessed and run through a clustering algorithm, produce a warning system for the family and hospital in real time.

A return to the drawing board, effectively erasing all assumptions, allowed me to begin to consider feature engineering. Could I use the EEG data to create new features to put into a model. First, it’s important to know exactly how data in an EEG is acquired and recorded. The electrical activity is acquired through leads attached to the skull. Each individual lead is not what is recorded, rather the values that are the differences between two consecutive leads as seen on the photo on the right. Lead Fp2 – lead F8 = the value recorded by the EEG. The leads are arranged in such a way that the part of the brain is identified (outer left hemisphere, inner left hemisphere, center line, inner right hemisphere, and outer right hemisphere), and the difference of two leads effectively provides a rate of change from one moment to the next. If you are familiar with the Calculus, knowing a rate of change from one moment to another is valuable information. It could create a vector field through which the brain’s information flows from one moment to another, like a fluid. If a function could be found that described a particle in motion through a vector field and integrated, one would have the function that, at least in theory, would describe the brain’s past, present, and future, and probably a million dollars for Nicolette’s future courtesy of the Clay Mathematics Institute.



Another problem with this proverbial vector field would be the noise contained in it, and how much did this affect the vectors magnitude and direction. How could I rid myself of the noise: the eyeblinks, arm movements, etc.?

Thanks to a French Mathematician, Joseph Fourier, the process of eliminating noise and reducing information down to its core frequencies is well known: Fourier Transforms, and in this particular case, Fast Fourier Transforms (FFT). After passing the known non-seizure and seizure data through the FFT transform, taking the absolute values of the complex number to simplify graphing, extracting the core frequencies, passing it through the inverse FFT to return to the time dimension, and normalizing the data, a striking and obvious pattern was revealed (photo to the right).

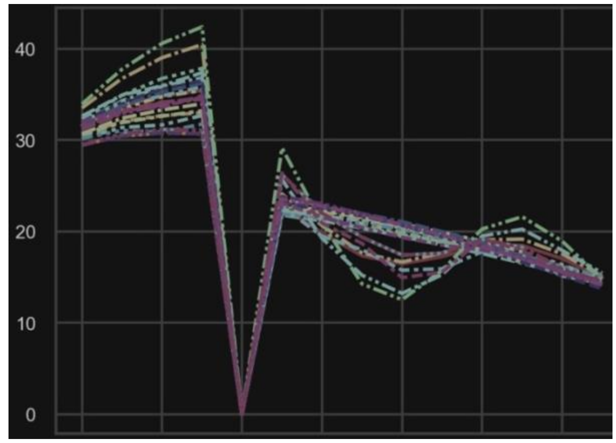


The baseline, non-seizure data is ‘smooth’ with low amplitudes until an increase in electrical activity becomes unstable and more chaotic resulting in an exponential increase in energy, a exponential decrease in energy, then an ‘rougher’ seizure baseline with varying amplitudes until a final explosion in energy and fall that marks the end of the seizure. Look at this data in an array and in a graph:

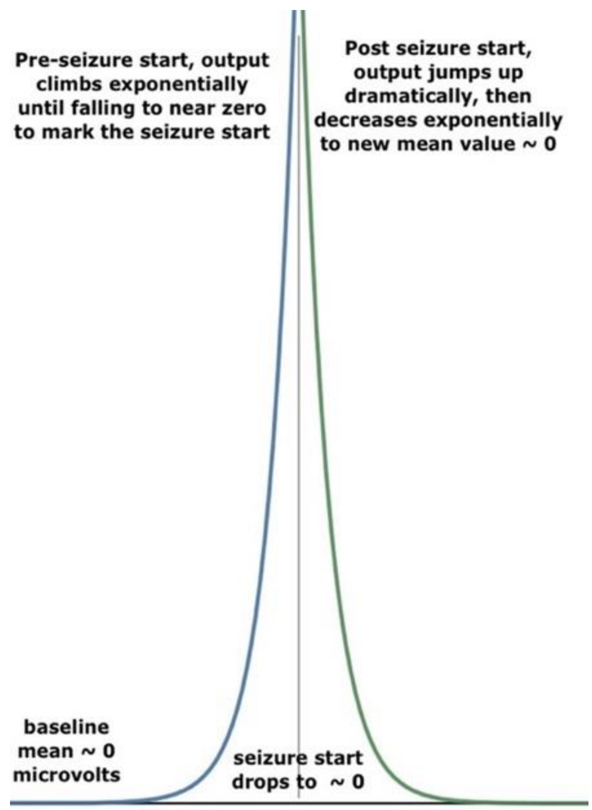
	FP1-F7	F7-T7	T7-P7	P7-01	FP1-F3	F3-C3	C3-P3	P3-01	FP2-F4	F4-C4	...
10233	22.308598	23.530069	23.654020	23.742293	20.757780	22.651415	22.717404	23.341978	19.386261	22.011902	...
10234	25.432541	26.149967	25.778174	26.309404	25.122121	25.790256	25.487630	25.902212	24.334235	25.619769	...
10235	28.669189	29.043821	27.848500	28.696904	29.484150	28.836210	28.192146	28.315532	29.314687	29.167735	...
10236	31.629114	31.579793	29.479894	30.680710	33.510780	31.466153	30.692076	30.485880	33.939171	32.337422	...
10237	33.708997	33.243740	30.444402	32.016235	36.751413	33.460409	32.397207	31.909040	37.774925	34.898700	...
10238	34.843117	34.151906	30.768939	32.676646	39.038424	34.758680	33.302897	32.622349	40.607076	36.749754	...
10239	35.425091	34.491160	30.692781	32.991932	40.473440	35.438399	33.964128	33.199653	42.413717	37.865077	...
START	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	...
10241	22.706046	22.153794	23.834506	22.805812	24.098736	23.708124	22.906869	22.447269	29.141551	22.312318	...
10242	19.825963	21.361974	23.018960	22.080666	20.661425	22.868135	22.297515	21.666525	20.954133	21.461971	...
10243	17.334067	20.445016	21.933233	21.310456	17.637132	21.826972	21.524288	20.883771	14.255200	20.472858	...
10244	16.459263	19.537962	20.751027	20.250707	16.651512	20.815971	20.542393	19.875212	12.532384	19.626378	...
10245	17.238271	18.710014	19.568394	19.215535	17.658062	19.893522	19.393759	18.803833	15.736248	18.956105	...
10246	18.427276	17.872006	18.362029	18.187454	19.072326	18.938983	18.188856	17.801931	20.263371	18.246395	...
10247	18.462324	16.820853	17.033125	16.880916	19.159613	17.772454	16.890438	16.621152	21.605465	17.234100	...
10248	17.018945	15.595952	15.580265	15.495259	17.537438	16.345050	15.514006	15.333625	18.936342	15.851368	...
10249	14.925187	14.374228	14.092303	14.248046	15.094085	14.751012	14.175211	14.198160	14.776036	14.238801	...

“START” is where the seizure officially begins.

Note the dive in electrical output, like a surge protector failing



In any of the columns, the increase in electrical activity is rising to an incredible 34 – 40 standard deviations from the baseline mean, before falling and rising again in 1/256th of a second. Note: the START of the seizure, highlighted in blue, are not actually zero, but very close to it. It was as though the brain’s surge protector was trying to prevent a seizure but failed. This is when I saw the ‘volcano’ effect, complete with a caldron that spewed forth the seizure. This was clearly a pattern, and surely the pattern in the underlying data could be found. An obvious start would be finding the difference between a non-seizure and a seizure that is seen in the graph above. I used a KNN clustering model to see if it could identify a “non-seizure” node and a “seizure” mode. Success!




```
Patient 1
Centroid 1: 0.10134668392412163 mV   Non-seizure
Centroid 2: 17.3674323319266 mV      Seizure

Patient one 18 months later
Centroid 1: 0.10280081187817895 mV   Non-seizure
Centroid 2: 19.03651032782568 mV     Seizure

Patient 18   Typo: this is Patient VNS’s data
Centroid 1: 0.11491301122255833 mV   Non-seizure
Centroid 2: 26.235263404230004 mV    Seizure
```

Three different datasets, the same result. The new path then percolated up from the most terrifying event that can happen to any family with epileptics: silent seizures in the middle of the night that kill Nicolette or my wife and the next morning, I wake up to find I’d slept through it. The current EEG process mandates that a family member watch the epileptic 24/7 and press a button attached to the EEG. When pressed, all overhead lights come on and hospital staff flood the room. My wife and I have lost a lot of sleep watching Nicolette 24 hours a day. I fainted at work from exhaustion after staying up for 5 straight days living on energy drinks. But when my wife loses sleep, her seizures dangerously increase. On a couple of occasions, hospital staff were working on my daughter to save her life and the ER team had come to the baby's room to rush my wife to the ER to save hers.

Why couldn't the EEG sound an alarm when it detected abnormal brain activity? Now it can. Given a patient's previous EEG data with a recorded seizure, its core frequencies extracted via FFT, and the patient-specific clusters identifying the baseline and seizure frequency nodes in microvolts, a simple python for loop allows parents to sleep and not worry about deadly, silent seizures.

```python
for (index, row) in p1_1.iterrows():
    if 0.1 < row.mean() < 1:
        print(f'WARNING SEIZURE POTENTIAL NOTICED AT TIME = {index}')
    if 1 <= row.mean() < 17:
        print('-------------------------------------------------------')
        print(f'WARNING SEIZURE LIKELY = {index}')
    if row.mean() > 17:
        print('-------------------------------------------------------')
        print(f'SEIZURE! SEIZURE! = {index}:\n\nvalue: {row.mean()}')
```

```
WARNING SEIZURE LIKELY = 10226
------------------------------
WARNING SEIZURE LIKELY = 10227
------------------------------
WARNING SEIZURE LIKELY = 10228
------------------------------
WARNING SEIZURE LIKELY = 10229
------------------------------
WARNING SEIZURE LIKELY = 10230
------------------------------
SEIZURE! SEIZURE! = 10231:

value: 17.641233734478295
------------------------------
SEIZURE! SEIZURE! = 10232:

value: 20.04229124050437
------------------------------
SEIZURE! SEIZURE! = 10233:

value: 22.85907370799915
------------------------------
SEIZURE! SEIZURE! = 10234:

value: 25.711757726566244
------------------------------
SEIZURE! SEIZURE! = 10235:
```

As the electrical activity climbs, the EEG would sound an alarm to alert or wake people in the room but would not necessarily alert the hospital. A family member can then choose to press the button and only then are hospital staff alerted and hospital resources allocated. This could be generalized to include a single EEG run. The EEG can be running the software in the background on a continuous basis and once a doctor identifies the seizure location, the software is then used for the remaining EEG run to sound the alarm that the brains electrical activity has dangerously increased. This could be done with an ambulatory EEG and even may have applications with deep brain stimulators that are inserted into the brain as a way to alert a family member in the home that seizure is occurring.

A Generalization of the Approach and Solution 1:
Could an EEG recognize a seizure in real time and with no previous recording of the patient?

I successfully used Python and Google's Deep Learning Tensorflow to write a propriety program that provides real time seizure recognition. There were three datasets, each of which included continuous EEG sampling at 256 times per second. These datasets were subset to include 40 seconds before and 40 seconds after the seizure start. The datasets were then manipulated via concepts in Nonlinear Dynamics, the Calculus, and Linear Algebra to create features that assist in finding the patterns in the original data. The model took almost an hour to train on a 2020 M1 MacBook Pro. The model trained on one of the patient datasets as a continuous time series. The model was tested on the other two datasets and the following results speak for themselves:

	predict_18	predict_vns	seizure
10231	0.007495	0.001059	0
10232	0.007275	0.001111	0
10233	0.006979	0.001038	0
10234	0.008031	0.001108	0
10235	0.007288	0.001097	0
10236	0.007066	0.001009	0
10237	0.006701	0.001046	0
10238	0.007291	0.001055	0
10239	0.993065	0.998915	1
10240	0.993027	0.998938	1
10241	0.992608	0.998902	1
10242	0.992848	0.998914	1
10243	0.993189	0.998980	1
10244	0.992444	0.998916	1
10245	0.992693	0.998951	1
10246	0.992696	0.998935	1
10247	0.992923	0.998947	1
10248	0.993075	0.998966	1
10249	0.992186	0.998876	1
10250	0.992641	0.998993	1
10251	0.993297	0.998971	1
10252	0.993166	0.998957	1
10253	0.992469	0.999001	1
10254	0.992167	0.998887	1
10255	0.992598	0.998931	1
10256	0.992196	0.998877	1
10257	0.993226	0.998976	1
10258	0.992843	0.998940	1
10259	0.992958	0.998955	1

The data the model trained on is not present in this photo. 'predict_18' is the same patient as the model's training set, but the data is from an EEG recorded 18 months later. 'predict_vns' is a separate patient with a Vagal Nerve Stimulator (VNS) surgically installed in the neck and chest to control seizures. Both my wife and daughter have this device. The last column, 'seizure' is there to show what moments in time is not a seizure (0) and what is a seizure (1). The numerical values are probabilities that the row is a seizure or not. The dataframes index values are moments in time transformed to integer values for simplicity. Index 10239 marks the seizure start.

High precision was necessary. An EEG sounding the alarm for a seizure, and it turns out not to be a seizure could have traumatic consequences on family members.

Implementation

I've eluded to several practical implementations throughout the paper. In practice, an EEG machine would simply have this program and trained models installed and run concurrent with the readings as they came in. It would not be costly since the hardware already exists. EEG manufactures, like Natus, would install and test the software, so collaborations with companies would be necessary although it's possible it could be done directly through the hospital. These collaborations would be important since accessing EEG data from real patients could be tricky with HIPPA laws. With more data to train more models, this program could be finetuned even more, making headway into many other areas where real time brain wave activity could be analyzed to make decisions.

Conclusion

Realtime Seizure Recognition for any person could dramatically reduce hospital costs, reduce family stress levels, shorten diagnosis times, improve patient-hospital relationships, and save lives in the home and in the hospital. It could open doors for further research into MRI data and mathematical solutions to Navier-Stokes equations. In fact, understanding the brain's underlying numerical patterns could open doors to understanding how Epilepsy drugs change the brain in small moments over time, or how changes in brain structures affect a person's ability to execute basic functions. In fact, the applications to finding patterns in the brain's electrical output is only constrained by the imagination.

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The original data was acquired from: https://physionet.org/content/chbmit/1.0.0/

Patient 1:
The patient's baseline (no seizure):
https://physionet.org/content/chbmit/1.0.0/chb01/chb01_02.edf
The patient's seizure:

https://physionet.org/content/chbmit/1.0.0/chb01/chb01_03.edf

Patient 1 but 18 months later:
The patient's baseline (no seizure):
https://physionet.org/content/chbmit/1.0.0/chb21/chb21_18.edf
The patient's seizure:

https://physionet.org/content/chbmit/1.0.0/chb21/chb21_19.edf

Patient 2, who had a VNS installed:
The patient's baseline (no seizure):
https://physionet.org/content/chbmit/1.0.0/chb09/chb09_18.edf

The patient's seizure:
https://physionet.org/content/chbmit/1.0.0/chb09/chb09_19.edf

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