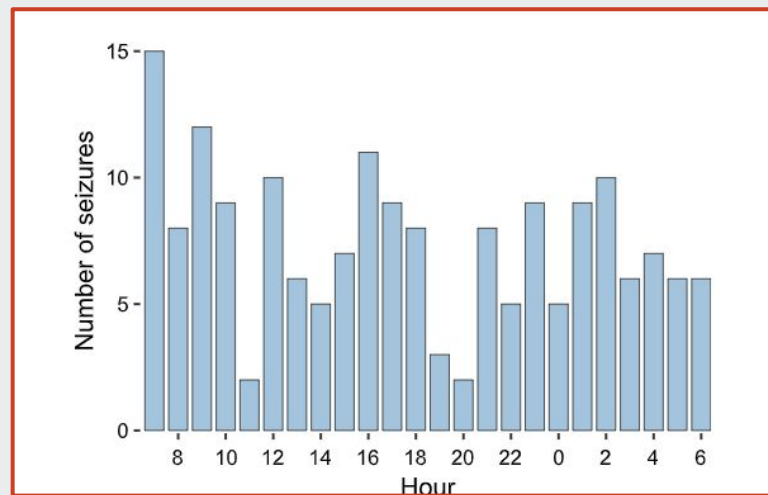


Convolutional Neural Networks for Seizure Prediction using Intracranial and Scalp Electroencephalogram

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Background

- Abstract: Proposes generalized seizure convolutional neural network predictive model for iEEG and sEEG datasets
- Materials:
 - Datasets: Freiburg Hospital Dataset, CHB MIT dataset, American Epilepsy Society Seizure Prediction Challenge (Kaggle)
 - Python 2.7, Tensorflow 1.4.0
- Seizure predictive algorithms' accuracy and success metrics are compared to a random chance predictor

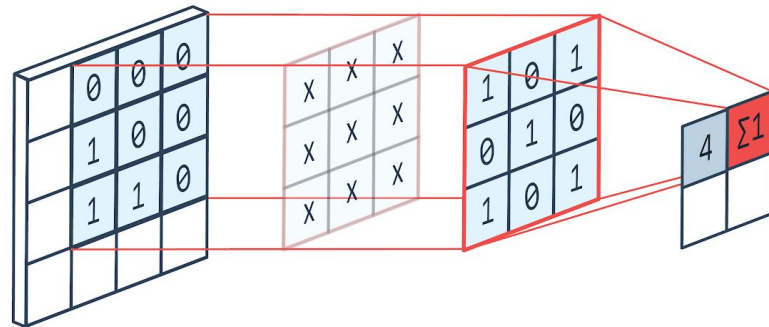
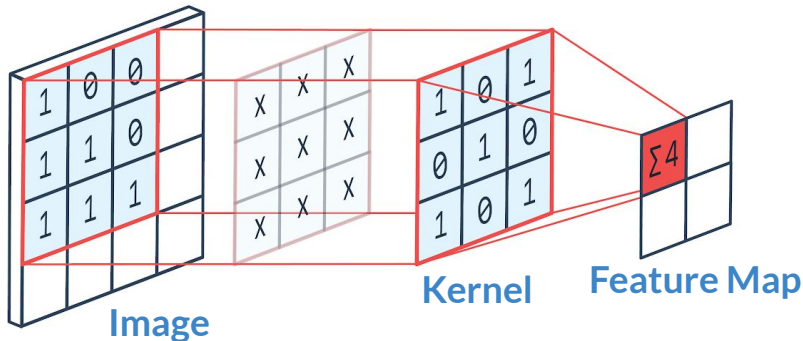
Table 1
Summary of the three datasets used in this work.

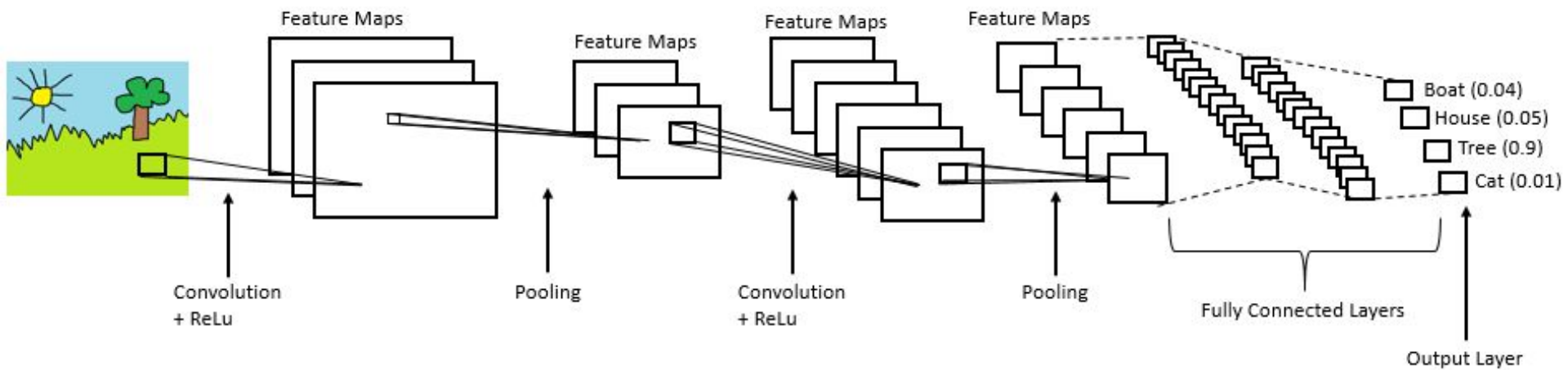
Dataset	EEG type	No. of patients	No. of channels	No. of seizures	Interictal hours
Freiburg Hospital	Intracranial	13 patients	6	59	311.4
Boston Children's Hospital-MIT	Scalp	13 patients	22	64	209
American Epilepsy Society Seizure Prediction Challenge (Kaggle)	Intracranial	5 dogs, 2 patients	16	48	627.7

Convolutional Neural Networks (CNN)

Convolution: mathematical operation on 2 functions that produces another which expresses how the shape of one function affects/modifies the other

- **CNN:** deep learning algorithm used for images
 - **Image Dimensionality Reduction:**
 - Allows for use of multilayer neural network
 - **Kernel:** a $H \times W \times D$ matrix that functions as a filter for image dimensionality reduction
 - **Convolutional Operation:** used to extract high level, features from input image via $\text{dot}(\text{kernel}, \text{image})$





MLA Seizure Predictive Algorithm Procedure & Implementation

Implementation



1. Clean, convert and process input image data

- a. Short time Fourier Transform (STFT) of input data
- b. **Convolutional network:**
 - i. 3 convolution blocks w/rectified linear unit activation function and max pooling layer
 1. 1st convolution layer: w/ $16 \times n \times 5 \times 5$ kernel (where n is number of EEG channels), stride $1 \times 2 \times 2$
 2. 2nd convolution layer: w/ 32 convolution kernels, kernel size 3×3 , stride of 1×1 and max pooling over 2×2 region
 3. 3rd convolution layer has 64 convolution kernels, kernel size 3×3 , stride of 1×1 and max pooling over 2×2 region

2. Batch normalization

3. 2 fully connected neural network layers

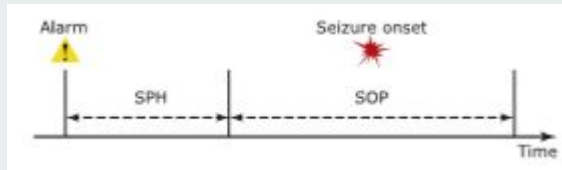
- a. 1st neuron: w/sigmoid activation, drop out rate of 0.5 & an output size of 256
- b. 2nd neuron: w/softmax activation function, drop out rate of 0.5 & output size of 2

Procedure

$$P \approx 1 - e^{-\text{FPR} \cdot \text{SOP}}$$

$$p = \sum_{i \geq m} \binom{M}{i} P^i (1 - P)^{M-i}$$

Random Chance Predictor



1. Compute predicted seizures
2. Compare to nonspecific random chance predictor
 - a. P = approximation of the probability of alarm in an SOP given the FPR
 - b. p = probability of predicting at least m of M independent seizures by chance
 - i. Calculated for each patient
3. If $p < 0.05$, can conclude prediction method is “significantly better” in comparison to the random predictor
4. Leave-one-Out Cross-validation performed twice and average results w/ standard deviation were recorded

Results

- CHB-MIT: Sensitivity 81.2%
w/ FPR 0.16/h

Patient	No. of seizures	Interictal hours	Sensitivity (%)	FPR (/h)	p
Pat1	7	17	85.7 ± 0.0	0.24 ± 0.00	<0.001
Pat2	3	22.9	33.3 ± 0.0	0.00 ± 0.00	<0.001
Pat3	6	21.9	100 ± 0.0	0.18 ± 0.00	<0.001
Pat5	5	13	80 ± 0.0	0.19 ± 0.03	0.010
Pat9	4	12.3	50 ± 0.0	0.12 ± 0.12	0.067
Pat10	6	11.1	33.3 ± 0.0	0.00 ± 0.00	0.025
Pat13	5	14	80 ± 0.0	0.14 ± 0.00	<0.001
Pat14	5	5	80 ± 0.0	0.40 ± 0.00	0.004
Pat18	6	23	100 ± 0.0	0.28 ± 0.02	<0.001
Pat19	3	24.9	100 ± 0.0	0.00 ± 0.00	<0.001
Pat20	5	20	100 ± 0.0	0.25 ± 0.05	<0.001
Pat21	4	20.9	100 ± 0.0	0.23 ± 0.09	<0.001
Pat23	5	3	100 ± 0.0	0.33 ± 0.00	<0.001
Total	64	209	81.2 ± 1.5	0.16 ± 0.00	

Freiburg results are only marginally better than the random predictor.

Patient	No. of seizures	Interictal hours	Sensitivity (%)	FPR (/h)	p
Pat1	4	23.9	100 ± 0.0	0.00 ± 0.00	<0.001
Pat3	5	23.9	100 ± 0.0	0.00 ± 0.00	<0.001
Pat4	5	23.9	100 ± 0.0	0.00 ± 0.00	<0.001
Pat5	5	23.9	40 ± 0.0	0.13 ± 0.00	0.032
Pat6	3	23.8	100 ± 0.0	0.00 ± 0.00	<0.001
Pat14	4	22.6	50 ± 0.0	0.27 ± 0.00	0.078
Pat15	4	23.7	100 ± 0.0	0.02 ± 0.02	<0.001
Pat16	5	23.9	80 ± 0.0	0.17 ± 0.13	0.001
Pat17	5	24	80 ± 0.0	0.00 ± 0.00	<0.001
Pat18	5	24.8	100 ± 0.0	0.00 ± 0.00	<0.001
Pat19	4	24.3	50 ± 0.0	0.16 ± 0.00	0.033
Pat20	5	24.8	60 ± 0.0	0.04 ± 0.00	<0.001
Pat21	5	23.9	100 ± 0.0	0.00 ± 0.00	<0.001
Total	59	311.4	81.4 ± 0.0	0.06 ± 0.00	

- Freiburg: Sensitivity: 81.4%
w/ FPR 0.06/h

- American:
Sensitivity 75%
and FPR 0.21/h

Participant	No. of seizures	Interictal hours	Sensitivity (%)	FPR (/h)	p
Dog1	4	80	50 ± 0.0	0.19 ± 0.02	0.053
Dog2	7	83.3	100 ± 0.0	0.04 ± 0.03	<0.001
Dog3	12	240	58.3 ± 0.0	0.14 ± 0.09	<0.001
Dog4	14	134	78.6 ± 0.0	0.48 ± 0.07	<0.001
Dog5	5	75	80 ± 0.0	0.08 ± 0.01	<0.001
Pat1	3	8.3	100 ± 0.0	0.42 ± 0.06	0.009
Pat2	3	7	66.7 ± 0.0	0.86 ± 0.00	0.693
Total	48	627.7	75 ± 0.0	0.21 ± 0.04	

Conclusion:

1. Generalized CNN is good approach for iEEG and sEEG data sets
2. Perfect prediction is not yet available: Current predictions can, at minimum, provide for precautionary warnings for seizures

Future:



- FDA defines *International Medical Device Regulators Forum (IMDRF) software* “as a medical device as software intended to be used for one or more medical purposes that perform these purposes without being part of a hardware medical device” (FDA).
 - Reviewed through **premarket pathway Clearance 510K**
 - *Any updates/modifications to software as medical device must go through approval process*
 - **Was not designed for AI and MLA**
 - FDA has proposed and requested enhancements on premarket approval specifically for AI and ML software as Medical Devices (SaMD)
- Currently any medical devices w/ AI and ML have to go through a long outdated pre approval process for pre market integration and modifications

Resources

- <https://www.fda.gov/medical-devices/software-medical-device-samd/artificial-intelligence-and-machine-learning-software-medical-device#transforming>
- <https://towardsdatascience.com/batch-normalization-in-neural-networks-1ac91516821c>
- <https://medium.com/@amarbudhiraja/https-medium-com-amarbudhiraja-learning-less-to-learn-better-dropout-in-deep-machine-learning-74334da4bfc5>
- <https://peltarion.com/knowledge-center/documentation/modeling-view/build-an-ai-model/blocks/2d-convolution-block>
- <https://medium.com/data-science-bootcamp/understand-the-softmax-function-in-minutes-f3a59641e86d>
- <https://towardsdatascience.com/a-comprehensive-guide-to-convolutional-neural-networks-the-eli5-way-3bd2b1164a53>
- <https://buzzrobot.com/whats-happening-inside-the-convolutional-neural-network-the-answer-is-convolution-2c22075dc68d>
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- <https://www.hopkinsmedicine.org/health/treatment-tests-and-therapies/electroencephalogram-eeeg>
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- <https://www.sciencedirect.com/science/article/abs/pii/S0893608018301485?via%3Dihub>
- <http://clik.dva.gov.au/ccps-medical-research-library/sops-grouped-icd-body-system/e-g/epileptic-seizure-f050-7803>
- <https://medium.com/@RaghavPrabhu/understanding-of-convolutional-neural-network-cnn-deep-learning-99760835f148>