Age prediction using scalp Electroencephalography and Deep Learning

Group 37
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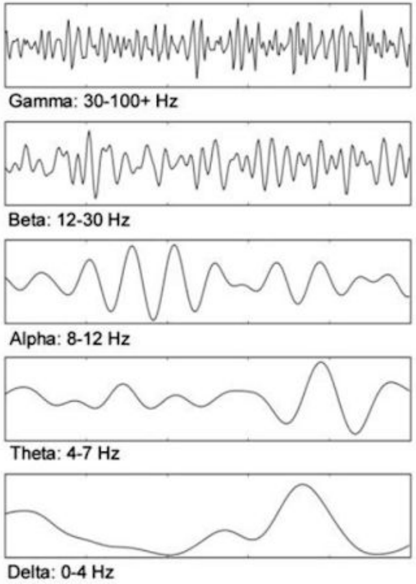
Background

- Goal: Predict age groups using raw EEG with deep learning to investigate the brain developmental level of children and adolescents.
- Traditional brain development evaluation methods include developmental and behavioral screening, and brain imaging evaluation.
- Electroencephalography (EEG):
  - Non-invasive
  - Real-time brain activity monitoring
  - High temporal resolution
- Common EEG analysis method:
  - Event related potentials (ERPs)
  - Spectral analysis
  - Event related spectral perturbation (ERSP)
  - Component analysis



Literature survey

EEG-based age-prediction models as stable and heritable indicators of brain maturational level in children and adolescents. (Vandenbosch, M. et al. (2019) *Human Brain Mapping*)

- Input features: 12-ch EEG power spectra from 2667 subject (851 child)
- Machine learning approach: random forest, support vector machine, and relevance vector machine

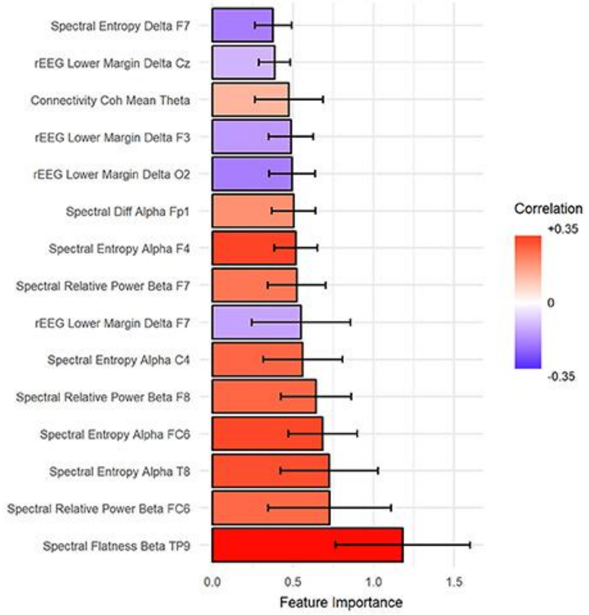
	Type of classification	Child	Adolescence	% of correct classification
RF				
	Correct	736	1,768	93.9
	Incorrect	115	48	
RVM				
	Correct	748	1,792	95.2
	Incorrect	91	36	

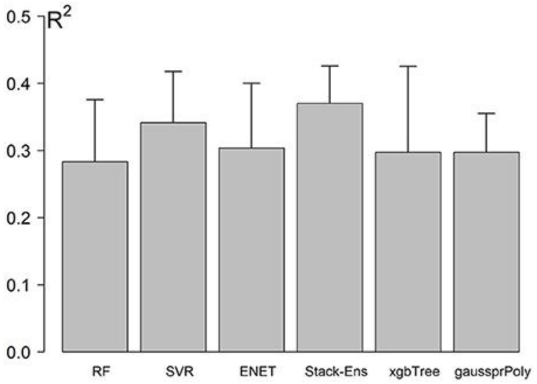
RF = random forest; RVM = relevance vector machine.

Literature survey

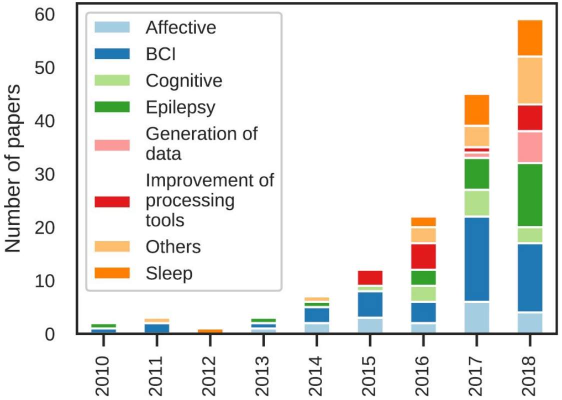
Predicting age from brain EEG signals -- a machine learning approach. (Zoubi, O. et al. (2018) *Frontiers in Aging Neuroscience*)

- 468 subjects (mean age: 34.8 years, 297 females), extracted EEG features from particular channels and bands
- Machine learning approach: Elastic Net (ENET), Support Vector Regression (SVR), Random Forest (RF), extreme gradient boosting tree (XgbTree), and Gaussian Process with Polynomial Kernel (gaussprPoly)

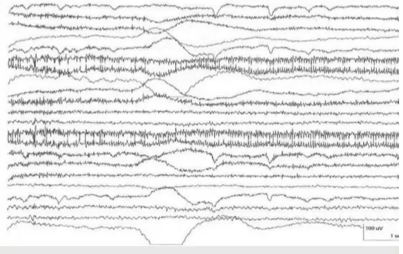


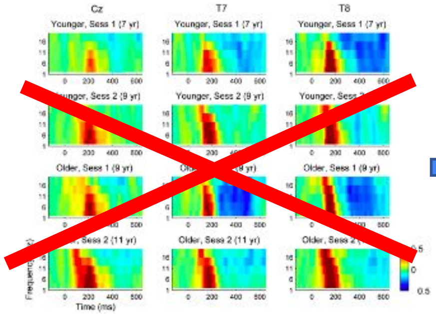


Deep Learning on EEG - A rising interest

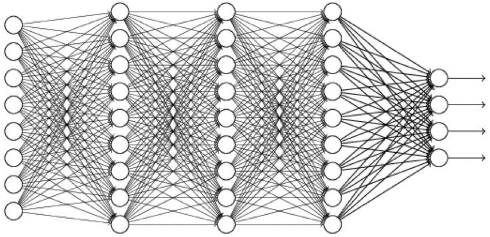


Roy et al. 2019





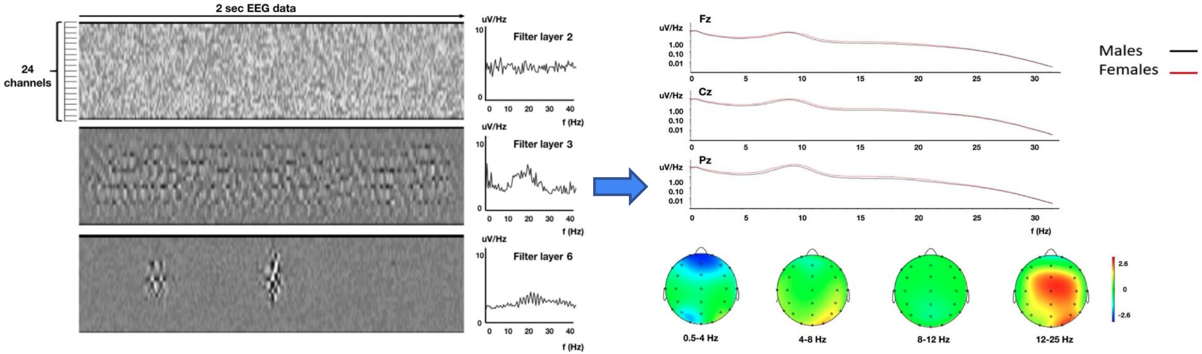
ERSP



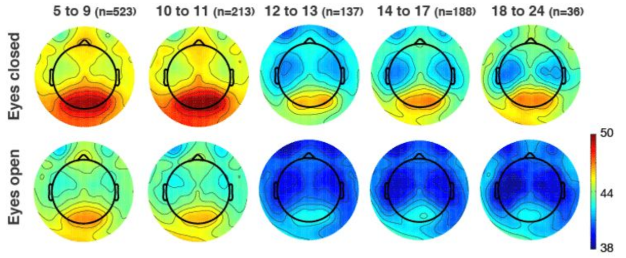
Emotion/Traits

Our Project

- Inspired by the approach of van Putten et al. (2018)
  - Trained a Convolutional Neural Network (CNN) to predict biological sex on scalp resting state EEG
  - > 80% accuracy
  - Applied visualization technique on trained model to generate scientific hypothesis
- Train CNN to predict child (5-11) vs. adolescent (11-23)



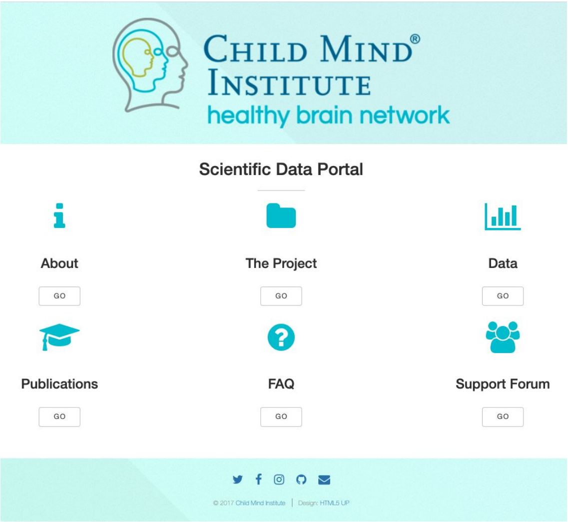
Van Putten et al. (2018)



Delorme et al. (2019)

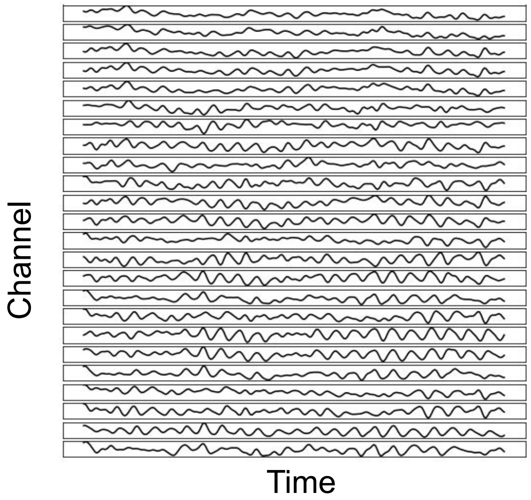
Dataset

- Healthy Brain Network Project
  - Alexander et al. (2017)
  - EEG, MRI, Behavioral data
  - 1574 subjects
  - Ages: min 5, max 23, mean 10
- Publicly available: http://fcon_1000.projects.nitrc.org/indi/cmi_healthy_brain_network/



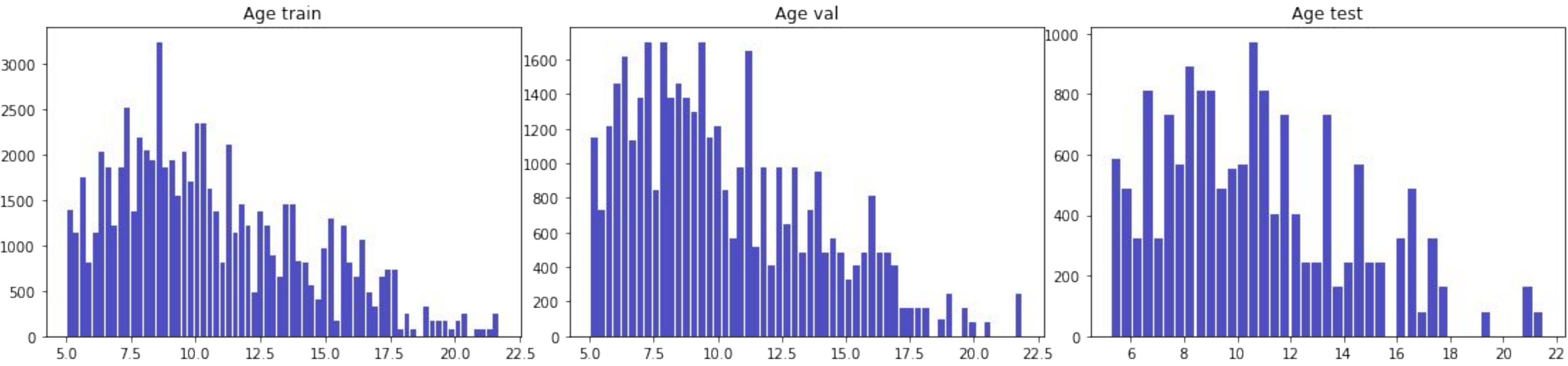
Data preprocessing

- Pre-processing following (Putten et al., 2018) using EEGLAB toolbox (Delorme & Makeig, 2014):
    - Remove baseline
    - Filter 0.25-25Hz
    - Resample 128Hz
    - Re-reference to average mastoids
    - Epoching: eye-closed, 3 40-second blocks. Ignored first and last 3 seconds of each block
    - clean_rawdata – ASR (Mullen et al. 2015)
    - Sub-select 24 channels
        - Fp1, Fp2, F7, F3, Fz, F4, F8, FC3, FCz, FC4, T3, C3, C4, T4, CP3, CPz, CP4, T5, P3, Pz, P4, T6, O1, Cz
    - Segment 2-second non-overlapping windows
        - ~ 81 samples per subject
- **No feature extraction was done**



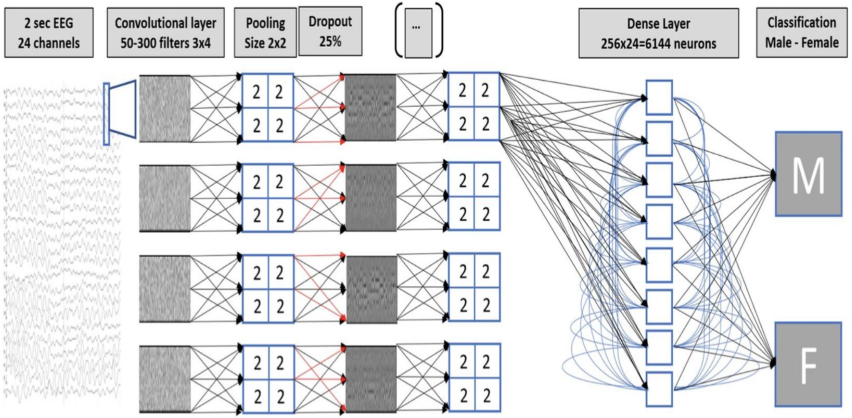
Data selection

- 10-30-60 split
  - 885 subjects for training -> 71,381 samples
  - 492 subjects for validation -> 39,868 samples
  - 197 subjects for testing -> 15,925 samples



Deep Learning models

Original model



van Putten et al. (2018)

Layer (type)	Input Shape	Param #	Tr. Param #
Conv2d-1	[1, 1, 24, 256]	1,000	1,000
ReLU-2	[1, 100, 22, 254]	0	0
MaxPool2d-3	[1, 100, 22, 254]	0	0
Dropout-4	[1, 100, 11, 127]	0	0
Conv2d-5	[1, 100, 11, 127]	90,100	90,100
ReLU-6	[1, 100, 9, 125]	0	0
MaxPool2d-7	[1, 100, 9, 125]	0	0
Dropout-8	[1, 100, 4, 62]	0	0
Conv2d-9	[1, 100, 4, 62]	180,300	180,300
ReLU-10	[1, 300, 3, 60]	0	0
MaxPool2d-11	[1, 300, 3, 60]	0	0
Dropout-12	[1, 300, 1, 30]	0	0
Conv2d-13	[1, 300, 1, 30]	630,300	630,300
ReLU-14	[1, 300, 1, 24]	0	0
MaxPool2d-15	[1, 300, 1, 24]	0	0
Dropout-16	[1, 300, 1, 23]	0	0
Conv2d-17	[1, 300, 1, 23]	90,100	90,100
Conv2d-18	[1, 100, 1, 21]	30,100	30,100
Flatten-19	[1, 100, 1, 19]	0	0
Linear-20	[1, 1900]	11,679,744	11,679,744
Linear-21	[1, 6144]	12,290	12,290

Total params: 12,713,934
Trainable params: 12,713,934
Non-trainable params: 0

Deep Learning models

1D Convolution

Layer (type)	Output Shape	Param #	Tr. Param #
Conv1d-1	[1, 64, 254]	4,672	4,672
ReLU-2	[1, 64, 254]	0	0
Conv1d-3	[1, 64, 252]	12,352	12,352
ReLU-4	[1, 64, 252]	0	0
Dropout-5	[1, 64, 252]	0	0
MaxPool1d-6	[1, 64, 126]	0	0
Flatten-7	[1, 8064]	0	0
Linear-8	[1, 100]	806,500	806,500
ReLU-9	[1, 100]	0	0
Linear-10	[1, 2]	202	202

Total params: 823,726
Trainable params: 823,726
Non-trainable params: 0

https://machinelearningmastery.com/cnn-models-for-human-activity-recognition-time-series-classification/

EEGNet

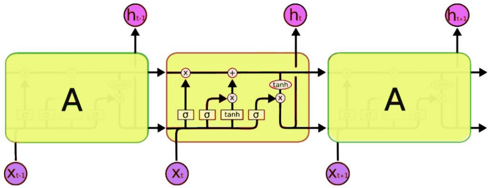
Layer (type)	Output Shape	Param #	Tr. Param #
Conv2d-1	[1, 4, 28, 197]	260	260
BatchNorm2d-2	[1, 4, 28, 197]	8	8
Conv2d-3	[1, 8, 5, 197]	192	192
BatchNorm2d-4	[1, 8, 5, 197]	16	16
ELU-5	[1, 8, 5, 197]	0	0
AvgPool2d-6	[1, 8, 2, 50]	0	0
Dropout-7	[1, 8, 2, 50]	0	0
SeparableConv2d-8	[1, 8, 4, 37]	192	192
BatchNorm2d-9	[1, 8, 4, 37]	16	16
ELU-10	[1, 8, 4, 37]	0	0
AvgPool2d-11	[1, 8, 1, 5]	0	0
Dropout-12	[1, 8, 1, 5]	0	0
Flatten-13	[1, 40]	0	0
Linear-14	[1, 2]	82	82

Total params: 766
Trainable params: 766
Non-trainable params: 0

Vernon J Lawhern et al. (2018)

Deep Learning models

LSTM and ConvLSTM



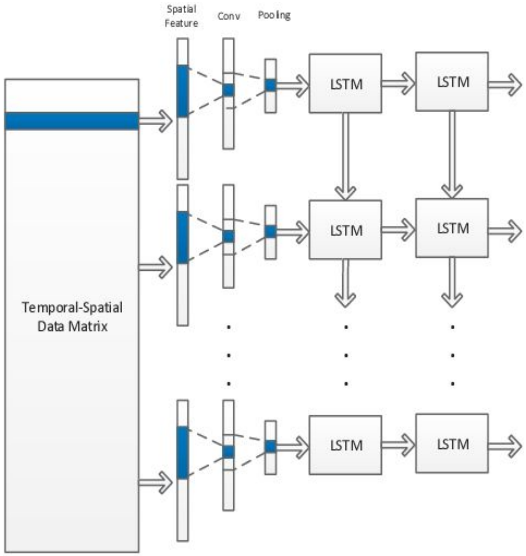


Fig. 3. The Conv-LSTM Structure

Traditional Machine Learning

(as baseline):

- Decision Tree
- AdaBoost

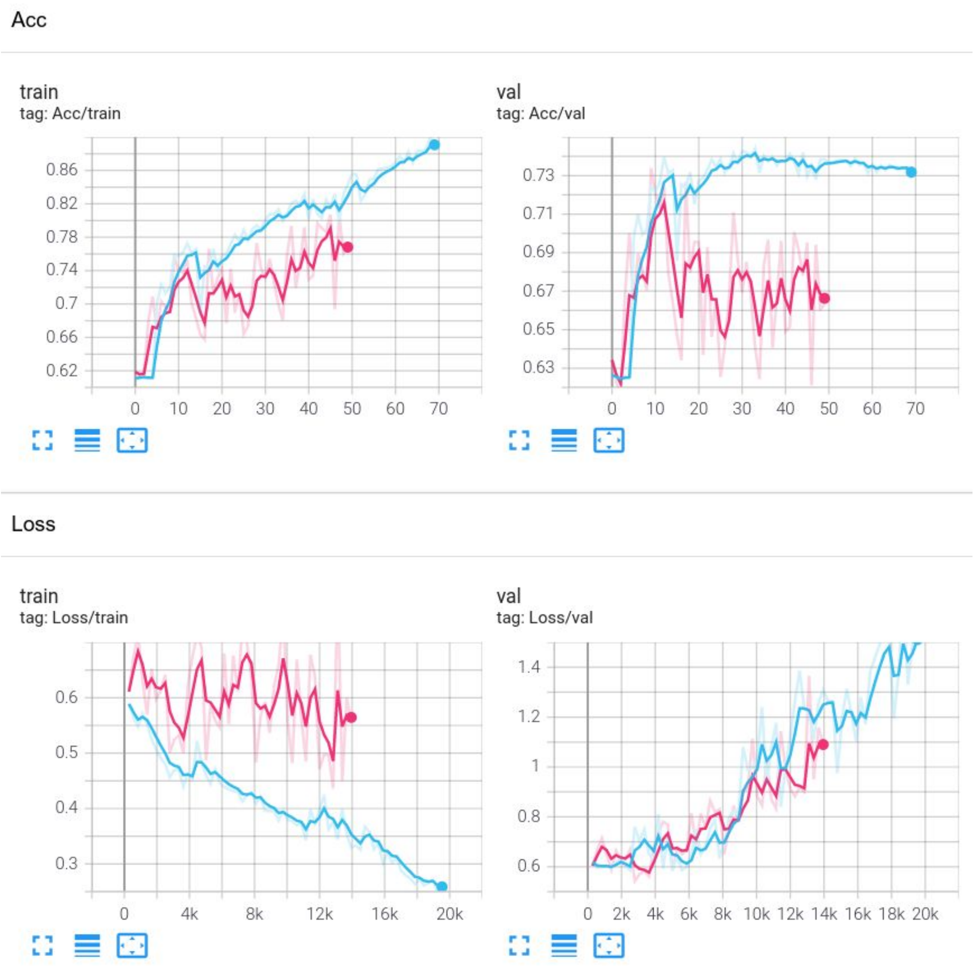
Experiment

- Python 3.7.10, PyTorch 1.3.1, Tensorflow 1.4.1 & Keras, Scikit
- Single NVIDIA V100 SMX2 GPU (32 GB)
- During training, the validation data were used to assess models' performance and to inform stopping rules
- Adamax optimizer with default hyperparameters (learning rate = 0.002, $\beta 1$ = 0.9, $\beta 2$ = 0.999, ϵ = 1e-08)
- Batch size was set at 256
- 50+ training epochs

Results

Classifiers	Test Accuracy
Putten et al.	**74.37%**
Conv1D	71.45%
EEGNet	55.24%*
(Conv)LSTM	55.24%*
AdaBoost	61.41%
Decision Tree	60.88%
Majority voting⁺ (Putten)	**80.71%**

* Models predicted all 0s
⁺ Majority voting: use 40 segments per subject to predict subject age group



Loss and accuracy vs. training epoch for training and validation set for Putten et al. (pink) and Conv1D (blue)

Next steps

- Expand the problem to a regression task
- Add Random Forest and/or Relevant Vector Machine models to compare with (Vandenbosch et al., 2019)‘s result
- If time allowed, we would also like to apply visualization technique used in Putten et al. (2018) to investigate discriminative features between two age groups learned by the model
    - This would demonstrate the benefit of training Deep Learning on raw EEG data for scientific hypothesis generation

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THANK YOU!