Electroencephalogram Signal Processing with Deep Learning

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Contents

Deep learning: the final frontier for signal processing and time series analysis?

Alexandr Honchar

Nov 10, 2018

Sources of Signals

- Natural signal: Temperature, wind speed, …
- Business and finance signals: exchange rate, …
- Bbiosignals: EEG, ECG, EMG
- ...

Classical Approaches

- Time domain analysis: “Looking” how time series evolves over time.
- Frequency domain analysis: Some signals are better represented by what amplitudes they have in it and how they change.
- Nearest neighbors analysis: Compare or measure a distance between two signals.
- (S)AR(I)MA(X) models: Models based on linear self-dependence.
- Decomposition: Decomposing time series into logical parts.
- Nonlinear dynamics: Using differential equations as a tool for modeling dynamical systems.
- Machine learning

Deep Learning Approaches

- RNN: Created for sequences with the ability to maintain its hidden state and learn dependencies over time.
  - However, as it has been shown in this research, RNN is no always efficient.
  - From author’s experience, RNN is good only when deal with short sequences (10-100 steps)
- CNN: Great for vision, also good for even more simple 1D data.

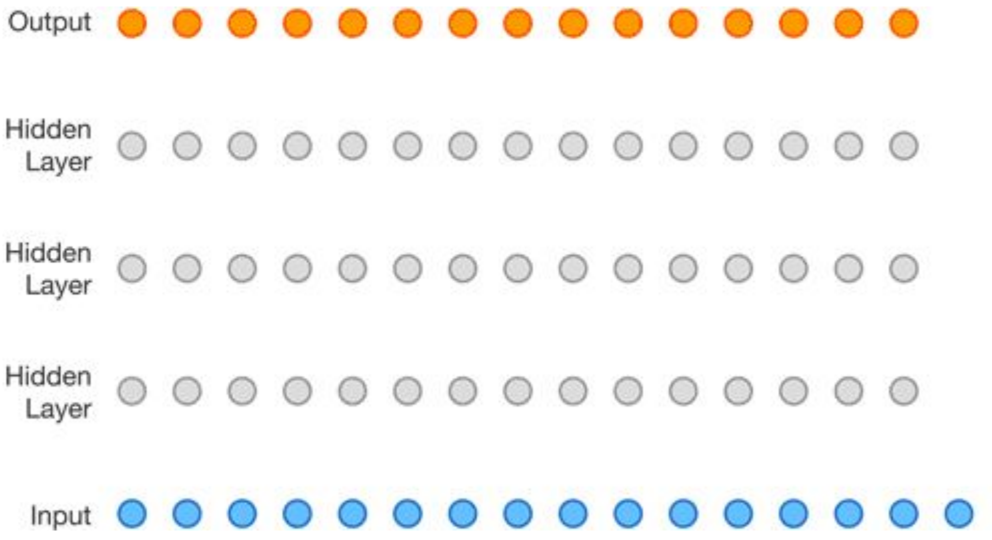
Deep Learning Approaches

- CNN + RNN: Use CNN to obtain local patterns, use RNN to analyse dependencies over time.

```
model= Sequential()
model.add(Embedding(20000,32,input_length=100))
model.add(Conv1D(32,kernel_size=3,padding='same',activation='relu'))
model.add(MaxPooling1D(pool_size=3))
model.add(Conv1D(64,kernel_size=3,padding='same',activation='relu'))
model.add(MaxPooling1D(pool_size=3))
model.add(LSTM(50,return_sequences=True))
model.add(Flatten())
model.add(Dense(128,activation='relu'))
model.add(Dropout(0.45))
model.add(Dense(1,activation='sigmoid'))
model.compile(loss='binary_crossentropy',optimizer='adam',metrics=['accuracy'])
```

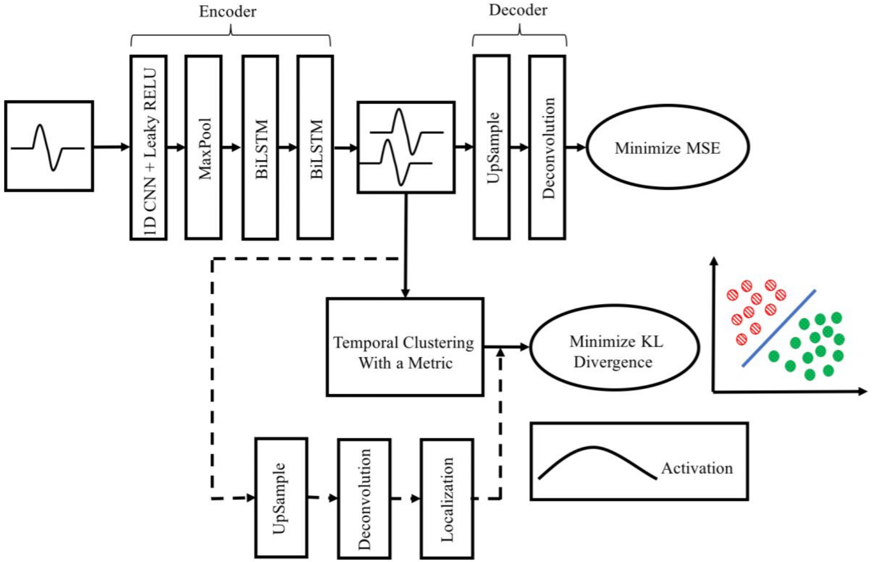
Deep Learning Approaches

- Autoregressive neural nets: Avoid RNN, but still “emulate” dependence from last N time steps and have N quite large.



Deep Learning Approaches

- Clustering using autoencoder.
  - [Deep Temporal Clustering: Fully Unsupervised Learning of Time-Domain Features]
- Anomaly detection.
  - [Efficient GAN-Based Anomaly Detection]
- Hybrid methods.



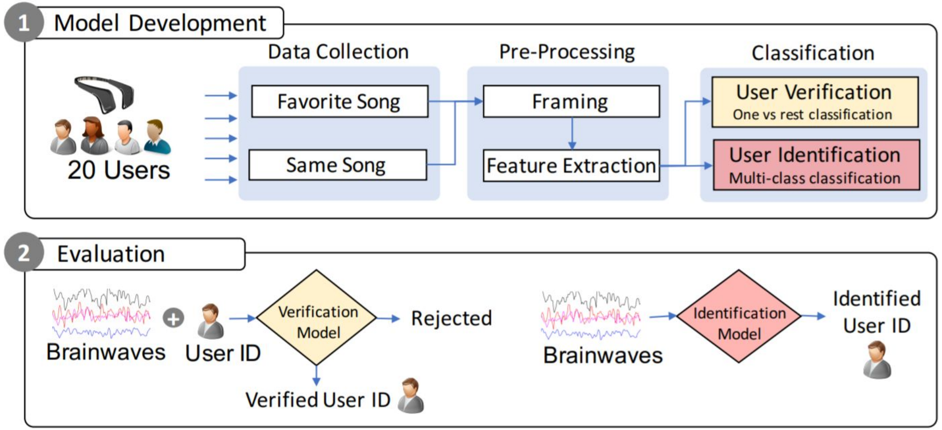
MusicID: A Brainwave-based User Authentication System for Internet of Things

Jinani Sooriyaarachchi, Suranga Seneviratne, Kanchana Thilakarathna, and Albert Y. Zomaya

Data61-CSIRO, Australia
School of Computer Science, The University Sydney, Australia.

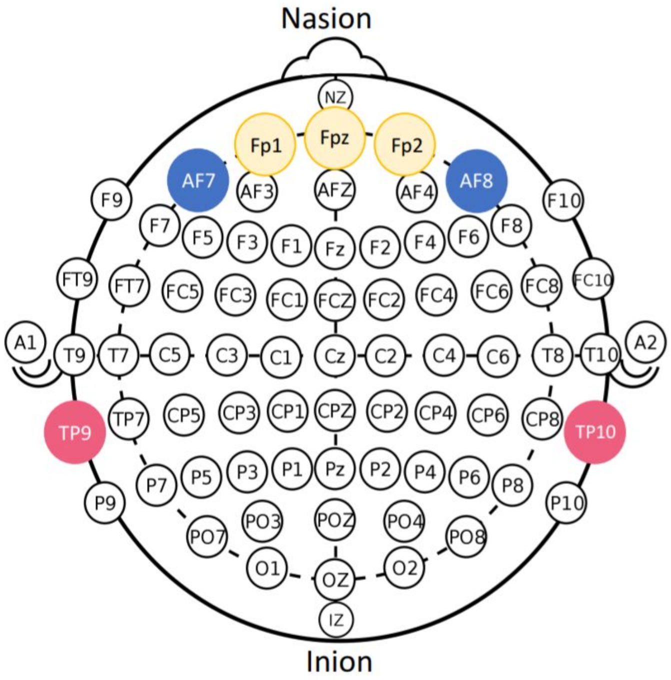
Introduction

- Task: Use music-induced brainwave patterns as a behavioral biometric modality.
- No deep learning methods used, but we are looking at the data collection and preprocessing part.



Data Collection

- 20 volunteers (11 females and 9 males).
- Listen to a popular English song and indifidual’s favorite song.
- Muse brain sensing headset with 4 electrodes in the standard 4-channel configuration (TP9, AF7, AF8, TP10).

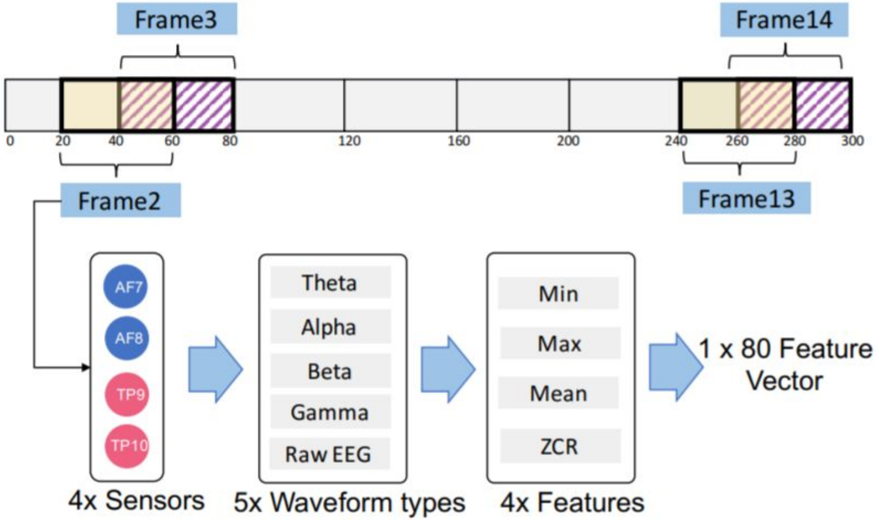


Data Collection

- Listen to the music for 150 seconds, recording interval: 0.5s, thus 300 data sample in total.
- Sampling rate: 220Hz.
- Each data sample included 24 reading:
  - Alpha, Beta, Theta, Delta, Gamma and Raw EEG without separated.
  - Each with 4 channels.

Data Preprocessing

- Remove Delta brainwave, devide 300 samples into 14 frames with 50% override.
- 20 readings each sample.
- Calculate mean, maximux, minimux, zero crossing rate for earh reading.



Classification and Result

- Use random forest classification.
- 98% accuracy for identification.
- 97% accuracy for verification.

EEGNet: A Compact Convolutional Neural Network for EEG-based Brain-Computer Interfaces

Vernon J. Lawhern, Amelia J. Solon, Nicholas R. Waytowich, Stephen M. Gordon, Chou P. Hung, and Brent J. Lance

Human Research and Engineering Directorate, U.S. Army Research Laboratory

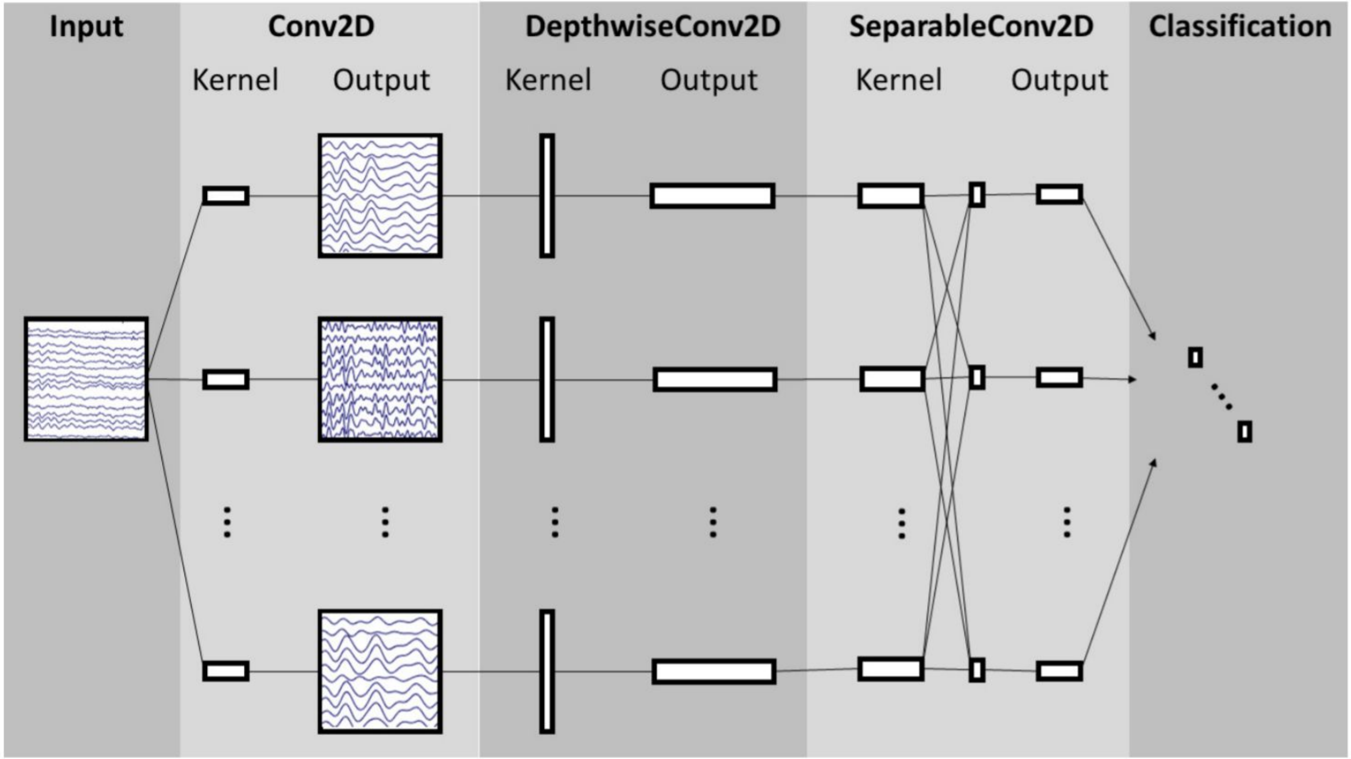
Introduction

- Design a single CNN architecture to accurately classify EEG signals from different BCI paradigms.
- Contribution: EGGNet. The model is robust enough to learn a wide variety of interpretable features over a range of BCI tasks.

Dataset

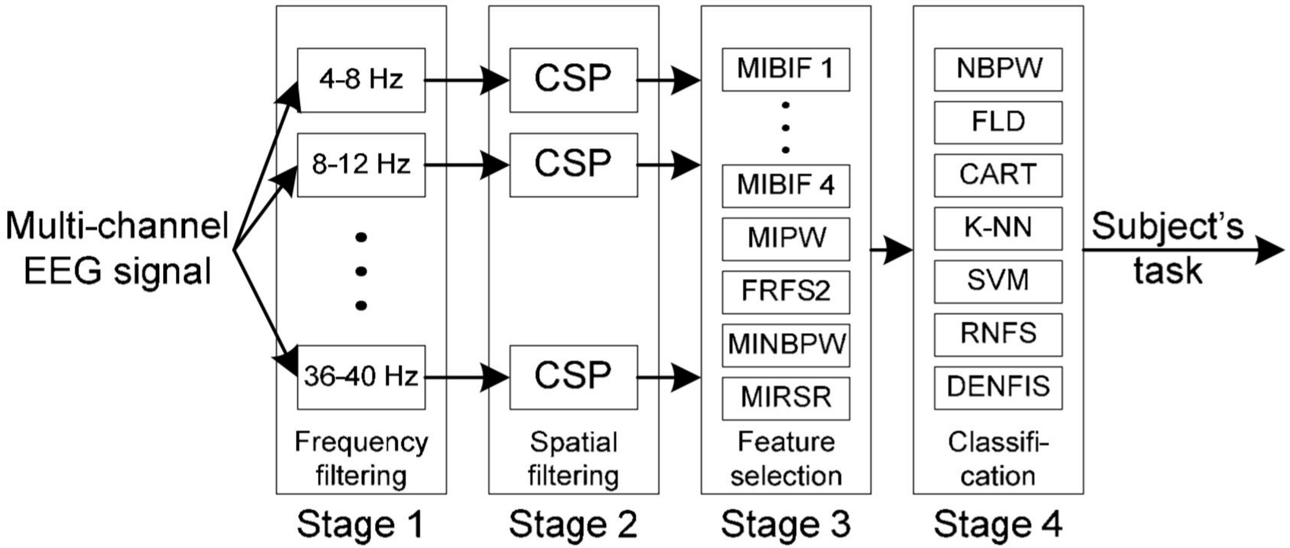
- Two types of BCI depending on the EEG feature of interest:
  - Event-related potential (ERP)
  - Oscillatory
- P300 ERP
- Feedback Error-Related Negativity (ERN)
- Movement-Related Cortical Potential (MRCP)
- Sensory Motor Rhythm (SMR)

EEGNet

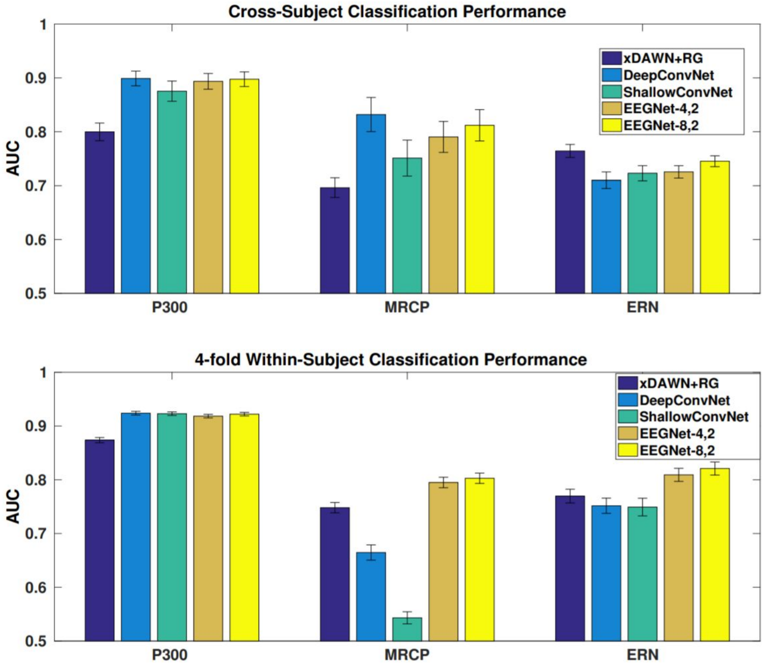

Input
Conv2D
Kernel
Output
DepthwiseConv2D
Kernel
Output
SeparableConv2D
Kernel
Output
Classification

Why do convolution like this?

- First perform convolution on time axis, then compress the feature on frequency axis by another convolution.
- Inspired by [Filter Bank Common Spatial Pattern] algorithm.



Classification Result



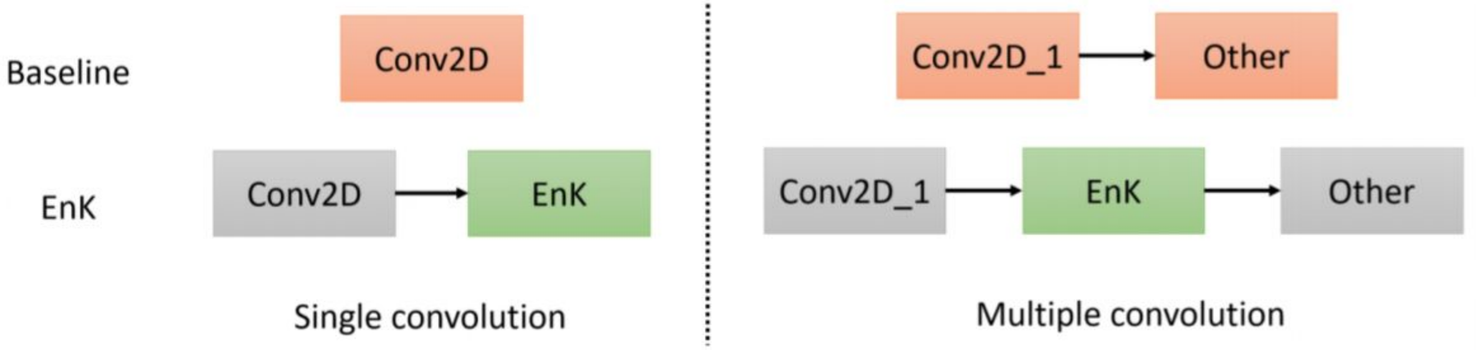
EnK: Encoding Time-Information in Convolution

Avinash K Singh, Chin-Teng Lin

Center for Artificial Intelligence, School of Computer Science University of Technology Sydney

Inspiration

- How to encode denpendency over time?
- Propose EnK (Time Encoding Kernel).



Methods

- Input: Part1=output of the previous conv layer, Part2=input of the previous conv layer.
- Initialize a same conv layer with the previous conv layer, but fixed weight=1.
- Apply the conv layer on Part2.
- Initialize a fixed time encoding vector, value range from 0 to its length. The vector has the same length with Part2 in time axis.
- Expand the time encoding vector to the same size with Part2.
- Multiply Part2 with the time encoding vector and a trainable scaling factor.
- Output: Part1 + Part2.

Result

	EEGNet			ShallowConvNet			DeepConvNet		
Datasets	Org	EnK	Gauss	Org	EnK	Gauss	Org	EnK	Gauss
CC	0.8344	**0.8518**	0.8465	0.8396	**0.8518**	0.8398	0.8468	**0.8518**	0.8218
pHRC	0.8798	**0.8801**	0.8799	0.8782	**0.8799**	0.8791	0.8806	**0.8799**	**0.8799**
P300	**0.9423**	**0.9412**	0.9200	0.8991	**0.9333**	0.9293	0.9200	**0.9333**	0.9320
MRCP	0.4501	**0.5621**	0.4951	0.4816	**0.5804**	0.4885	0.4080	**0.5564**	0.3732

	EEGNet			ShallowConvNet			DeepConvNet		
Datasets	Org	EnK	Gauss	Org	EnK	Gauss	Org	EnK	Gauss
CC	0.7189	**0.7418**	0.7350	0.7263	**0.7418**	0.7253	0.7345	**0.7418**	0.7029
pHRC	0.7856	**0.7862**	0.7856	0.7828	**0.7856**	0.7842	**0.7869**	0.7856	0.7856
P300	**0.9412**	**0.9412**	0.9216	0.8922	**0.9314**	**0.9314**	0.9216	**0.9314**	**0.9314**
MRCP	0.4526	**0.5625**	0.5053	0.4842	**0.6000**	0.4947	0.4421	**0.5579**	0.5053

Deep Learning Human Mind for Automated Visual Classification

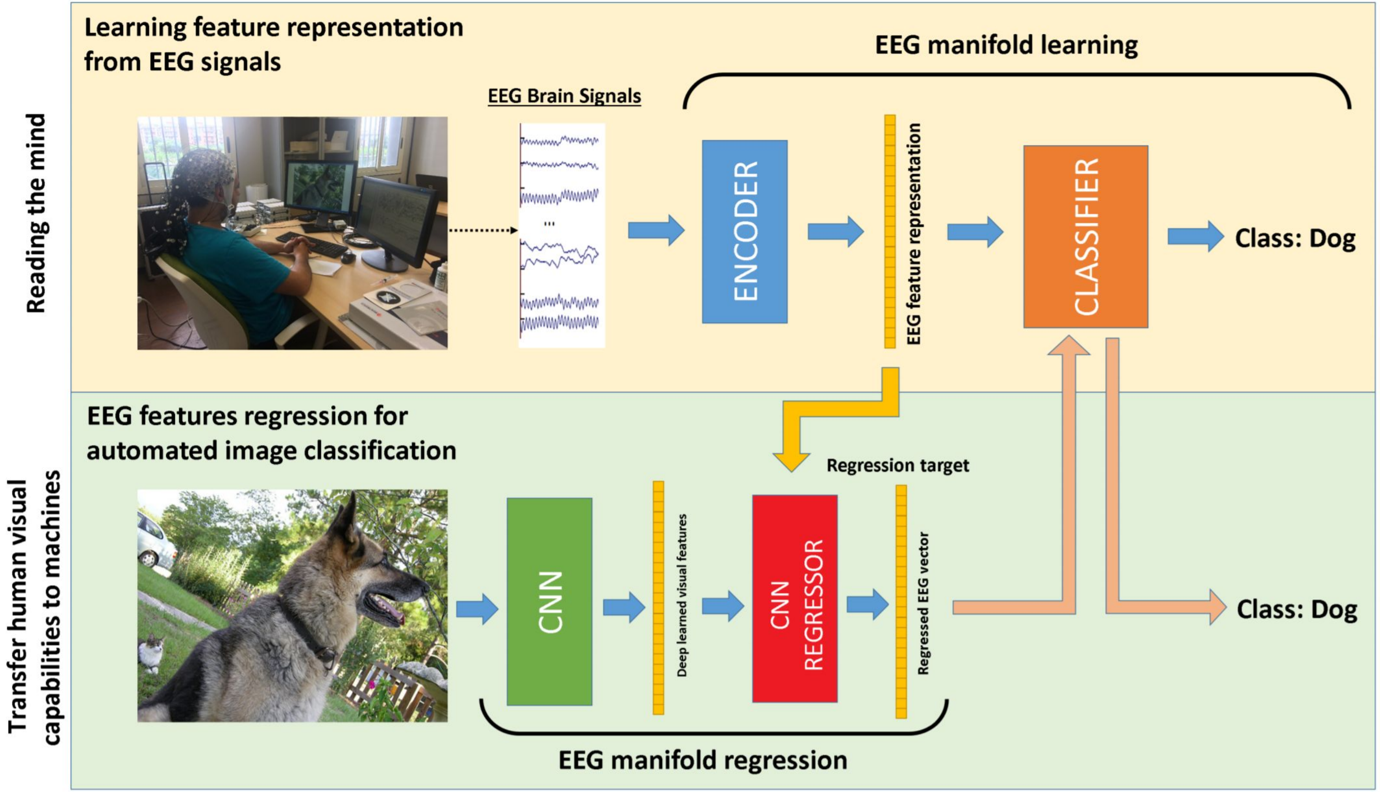
C. Spampinato, S. Palazzo, I. Kavasidis, D. Giordano, N. Souly, M. Shah

Department of Electrical, Electronics and Computer Engineering - PeRCeiVe Lab
Center for Research in Computer Vision – University of Central Florida

Introduction

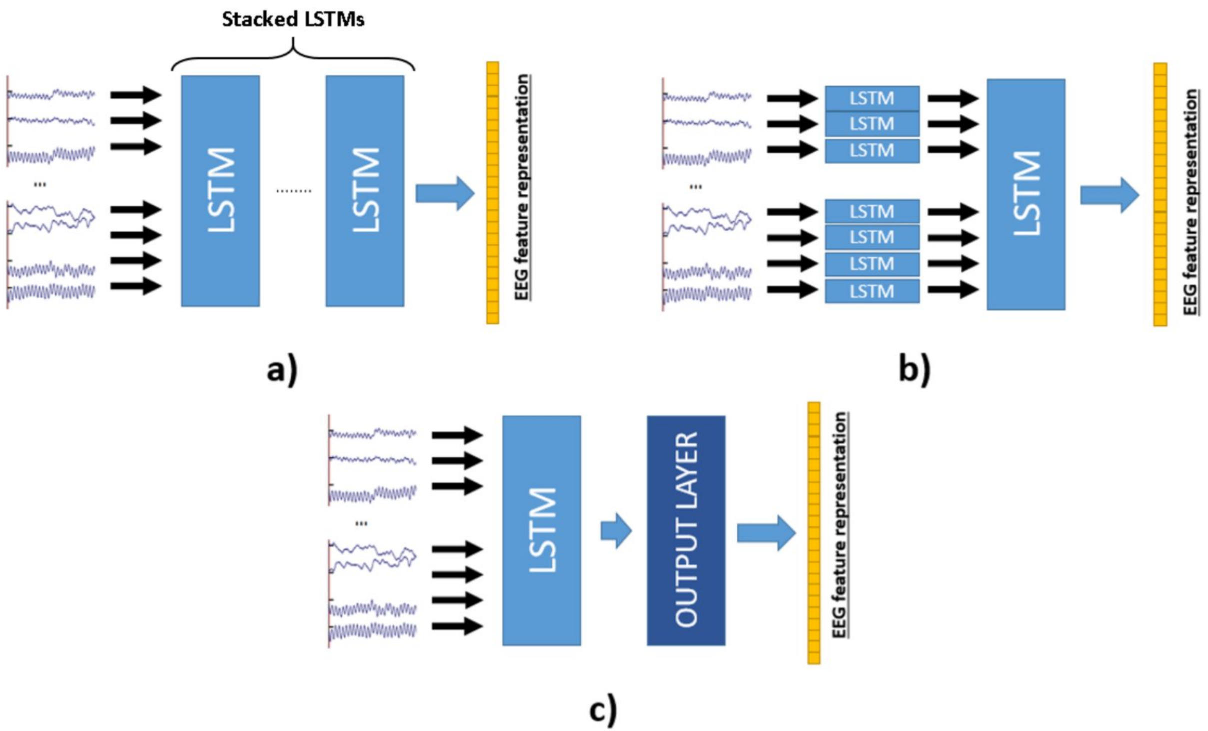
- Task: Read the mind and transfer human visual capabilities to computer vision methods.

Methods



Reading the mind
Learning feature representation from EEG signals
EEG Brain Signals
EEG manifold learning
ENCODER
EEG feature representation
CLASSIFIER
Class: Dog
Transfer human visual capabilities to machines
EEG features regression for automated image classification
CNN
Deep learned visual features
Regression target
CNN REGRESSOR
Regressed EEG vector
Class: Dog
EEG manifold regression

Encoder


Stacked LSTMs
LSTM
LSTM
EEG feature representation
a)
LSTM
LSTM
LSTM
LSTM
LSTM
LSTM
LSTM
LSTM
EEG feature representation
b)
LSTM
OUTPUT LAYER
EEG feature representation
c)

Result

Model	Details	Max VA	TA at max VA
Common	64 common	74.4%	73.9%
	128 common	77.3%	74.1%
	64,64 common	75.9%	72.5%
	128,64 common	79.1%	76.8%
	128,128 common	79.7%	78.0%
Channel + Common	5 channel, 32 common	75.7%	72.9%
	5 channel, 64 common	74.3%	71.2%
Common + output	128 common, 64 output	81.6%	78.7%
	128 common, 128 output	**85.4%**	**82.9%**

Visualization time	Max VA	TA at max VA
40-480 ms	85.4%	82.9%
40-160 ms	81.4%	77.5%
40-320 ms	82.6%	79.7%
320-480 ms	**86.9%**	**84.0%**

Criticism

- Used test dataset to train.
- Signal filtering issues.
- https://arxiv.org/pdf/1812.07697.pdf
- https://www.reddit.com/r/MachineLearning/comments/a8p0l8/p_training_on_the_test_set_an_analysis_of/
- https://www.jiqizhixin.com/articles/2018-12-24-15