General Artificial Intelligence (1)

Decode Brain Thought and Consciousness

SAIR-Class-2-01: Mental Disease, Brain Signal and Their Transformer

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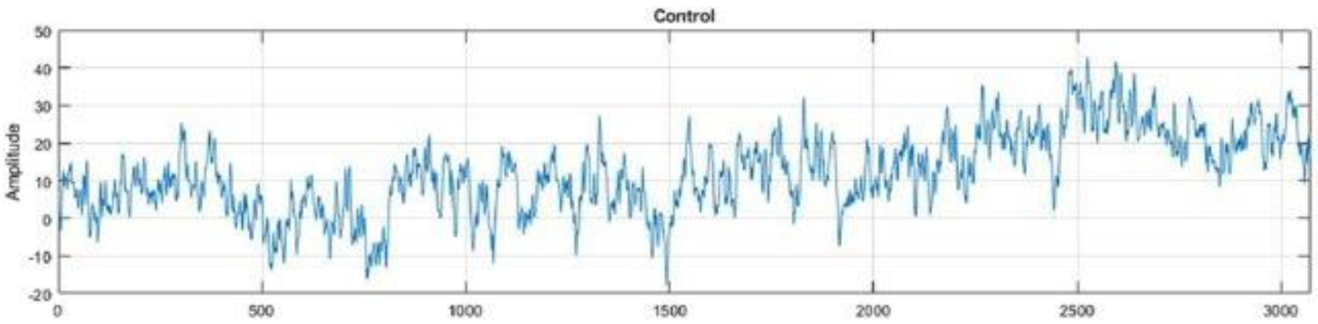
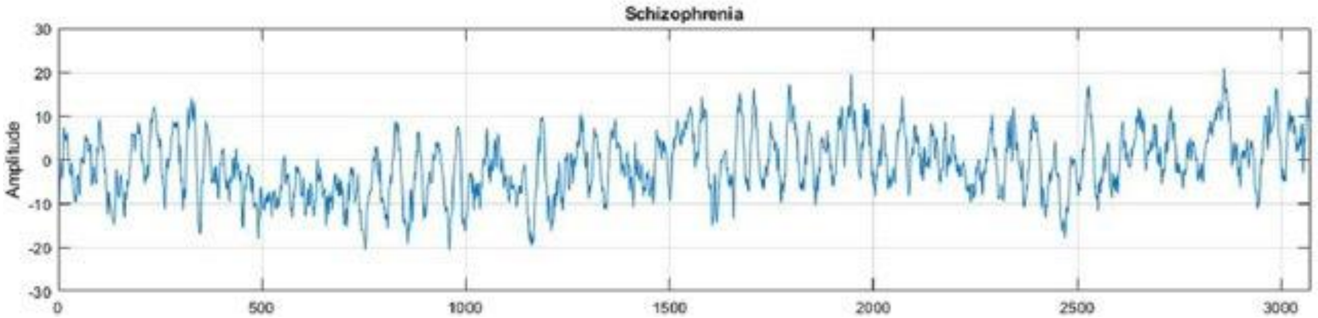
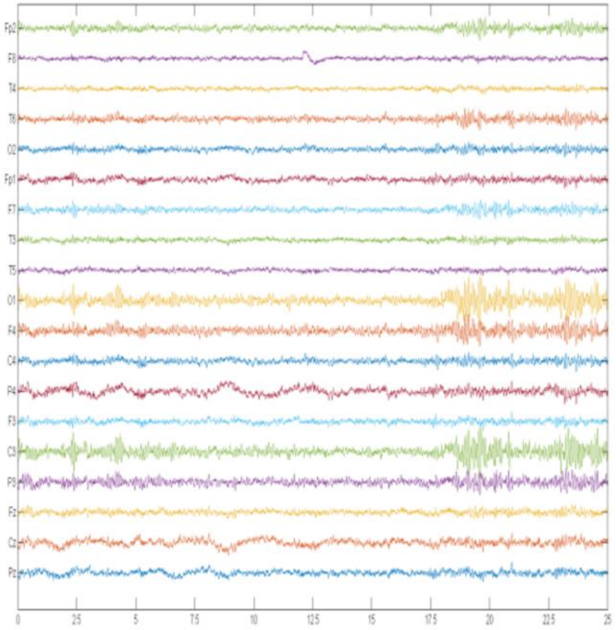
Society of Artificial Intelligence Research

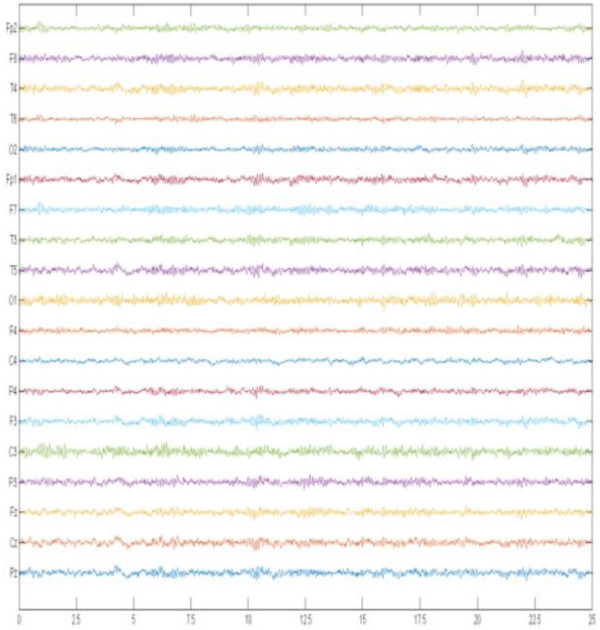
Schizophrenia

Schizophrenia is a mental disorder characterized by continuous or relapsing episodes of psychosis. **Major symptoms include hallucinations, delusions, and disorganized thinking.** Other symptoms include social withdrawal, and flat affect. [Wikipedia](https://en.wikipedia.org/wiki/Schizophrenia)

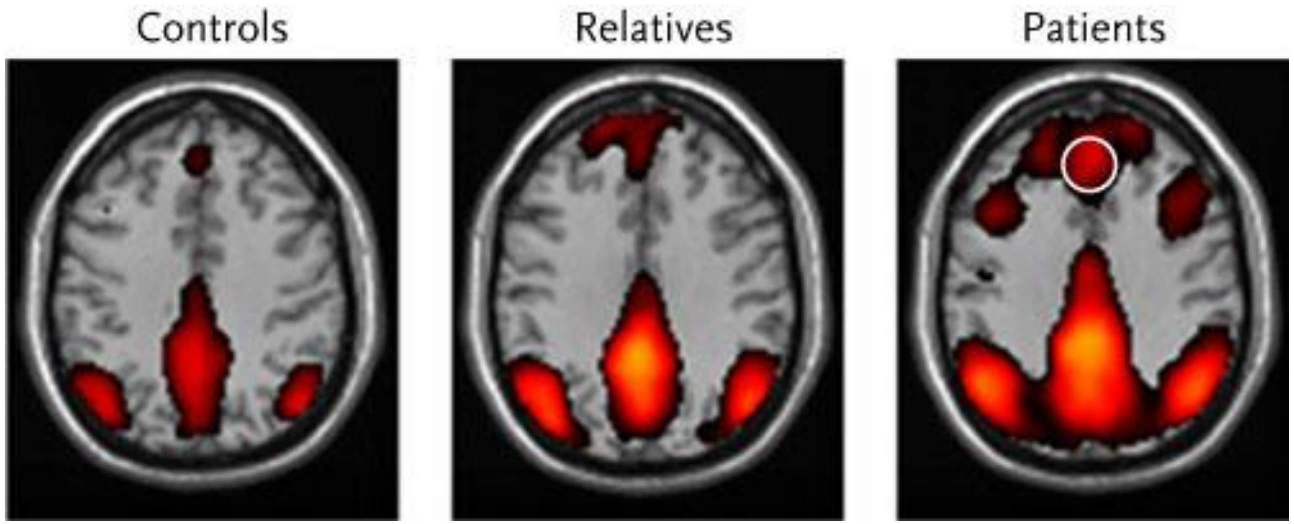








Schizophrenia



Pattern of Brain Activity Signals Danger of Schizophrenia | Harvard Medical School

Bipolar disorder

Bipolar disorder, previously known as manic depression, is **a mental disorder characterized by periods of depression and periods of abnormally elevated mood that each last from days to weeks**. If the elevated mood is severe or associated with psychosis, it is called mania; if it is less severe, it is called hypomania. Wikipedia

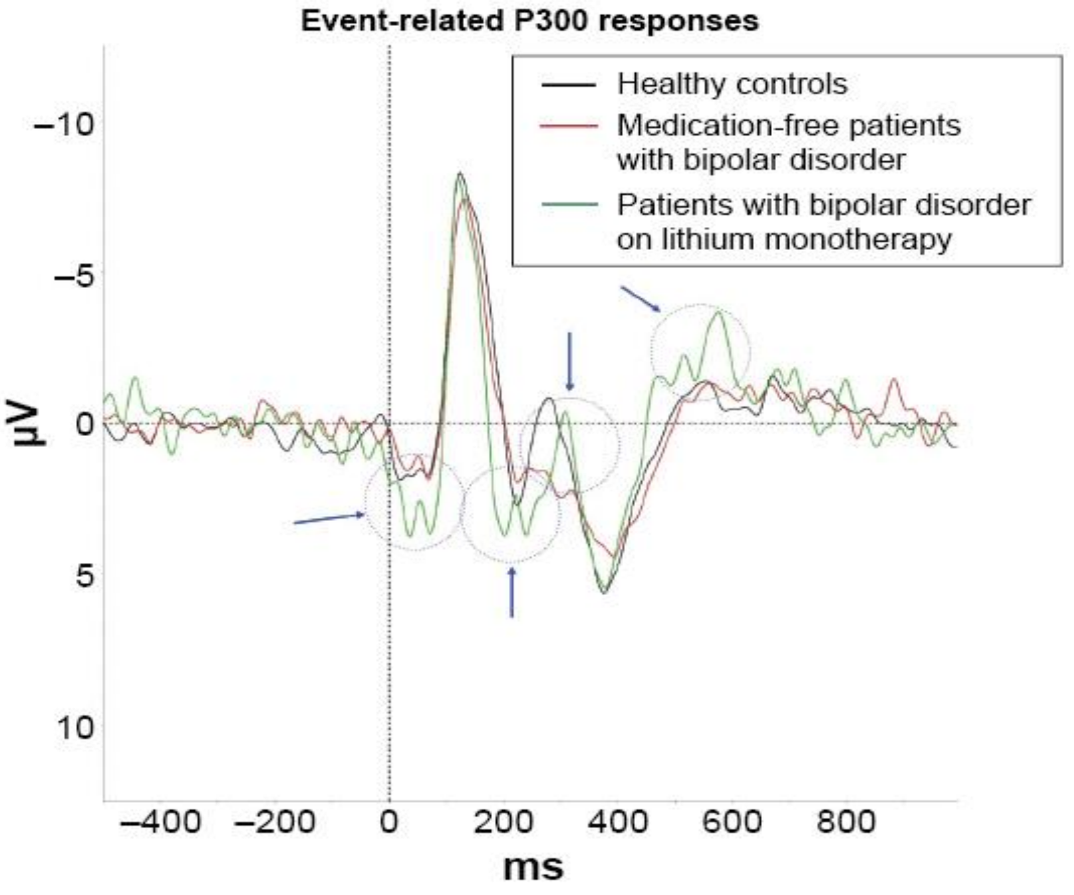
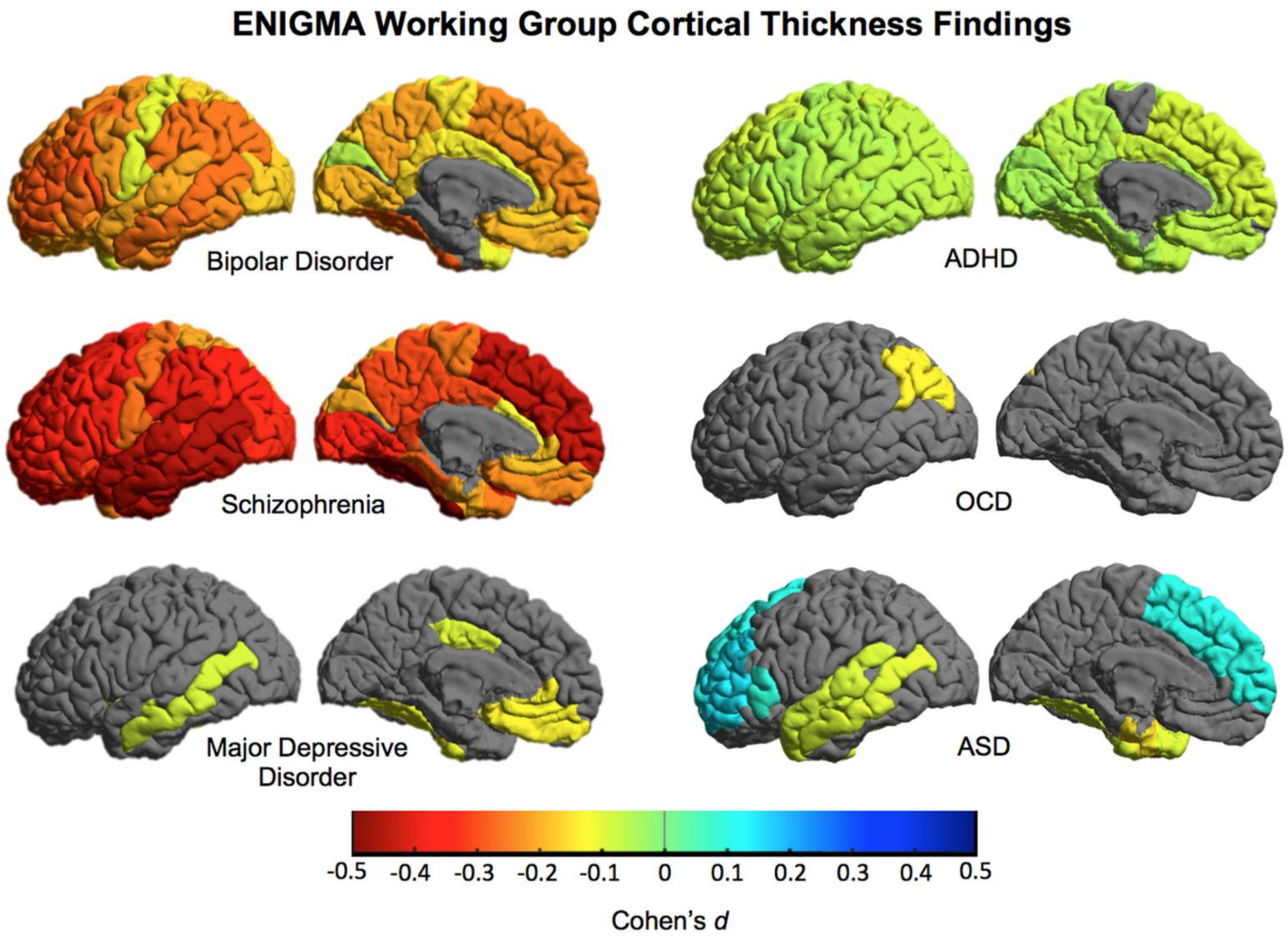


Figure 1 Event-related P300 responses of the patients with bipolar disorder on lithium monotherapy compared with medication-free patients with bipolar disorder and healthy control subjects in auditory oddball experiments.

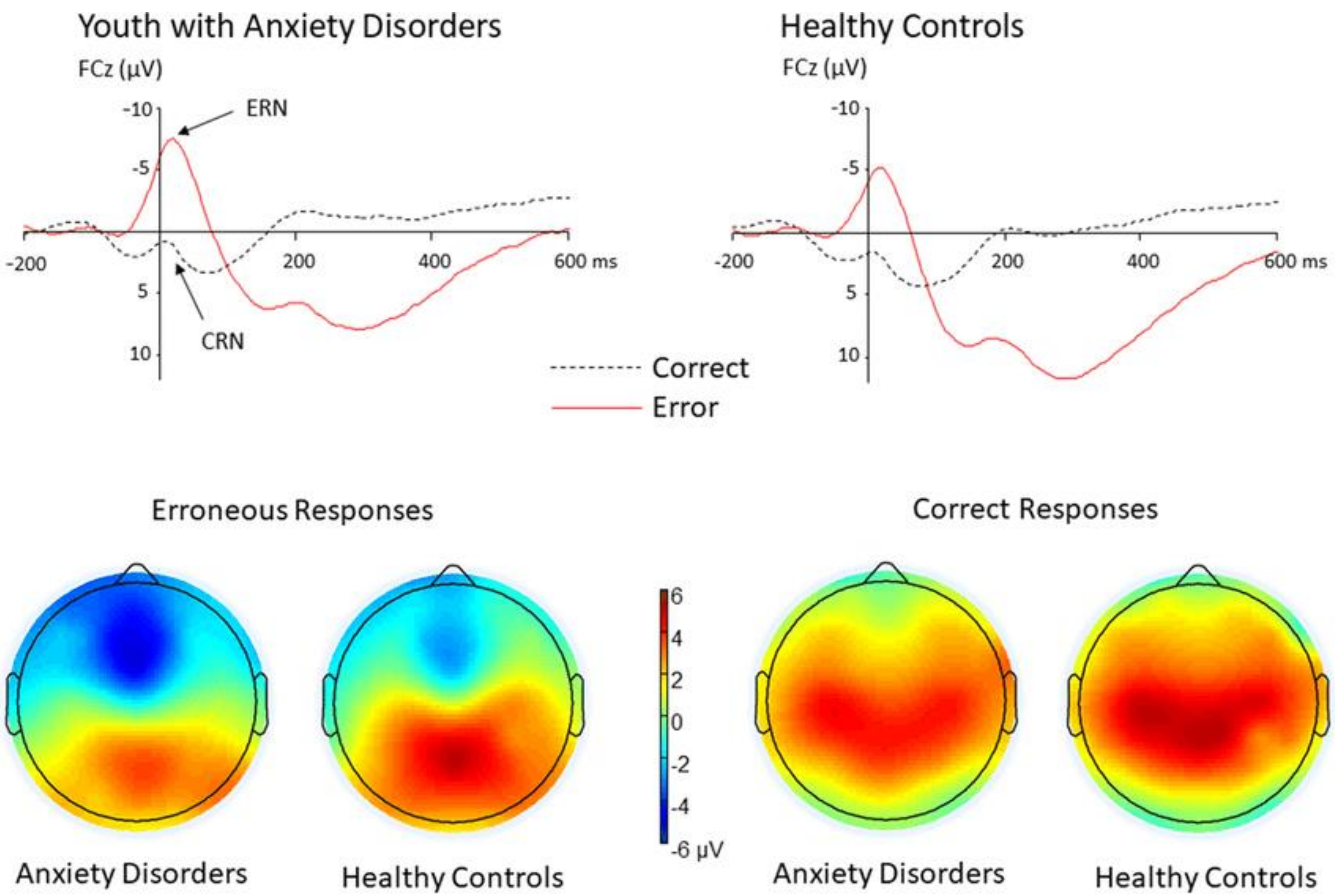
Notes: The lithium group showed abnormally higher peaks (arrows). Copyright © 2015. Adapted from Atagün et al. Lithium excessively enhances event related beta oscillations in patients with bipolar disorder. *J Affect Disord*. 2015;170:59–65.[51] with permission from the publisher.

Bipolar disorder



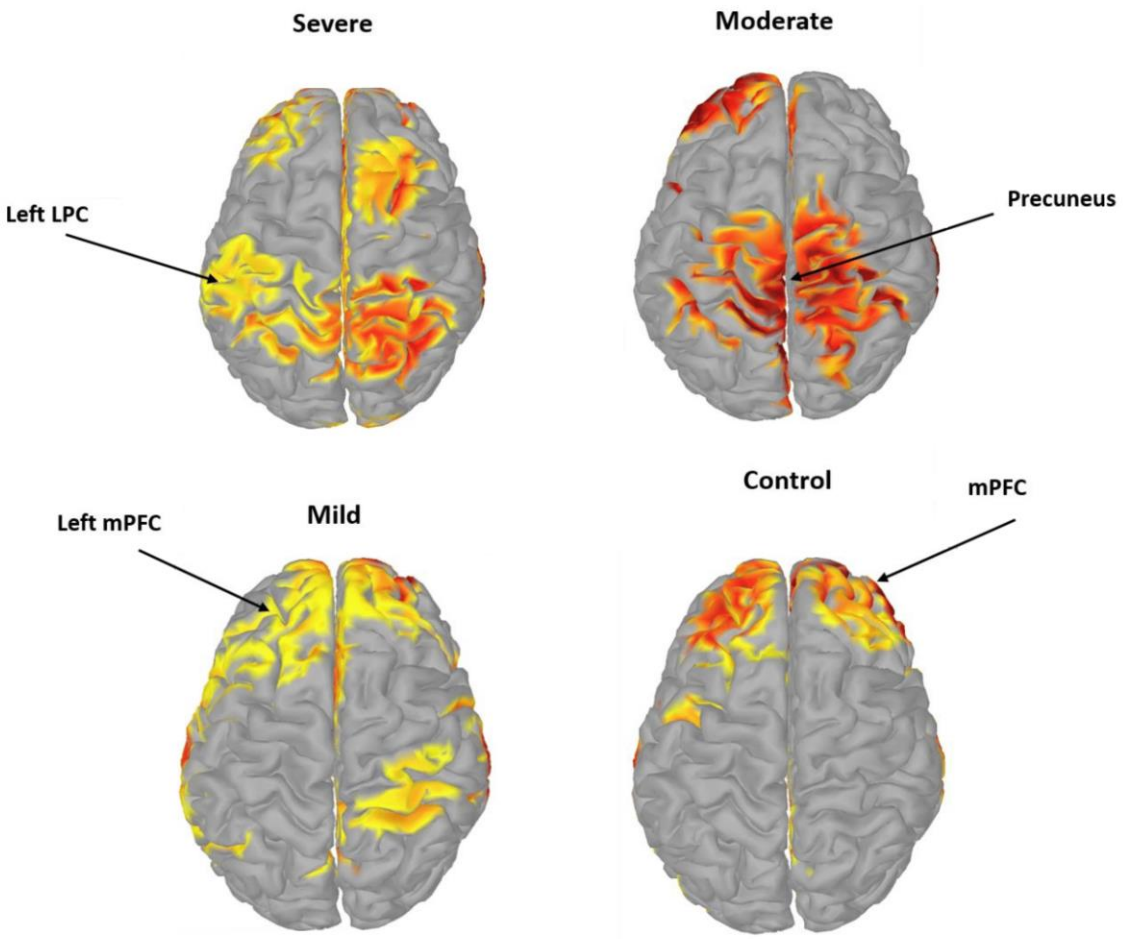
Anxiety disorders

Anxiety disorders are a cluster of mental disorders characterized **by significant and uncontrollable feelings of anxiety and fear such that a person's social, occupational, and personal function are significantly impaired**. Wikipedia



Grand averages of electroencephalogram (EEG) recordings in 96 patients

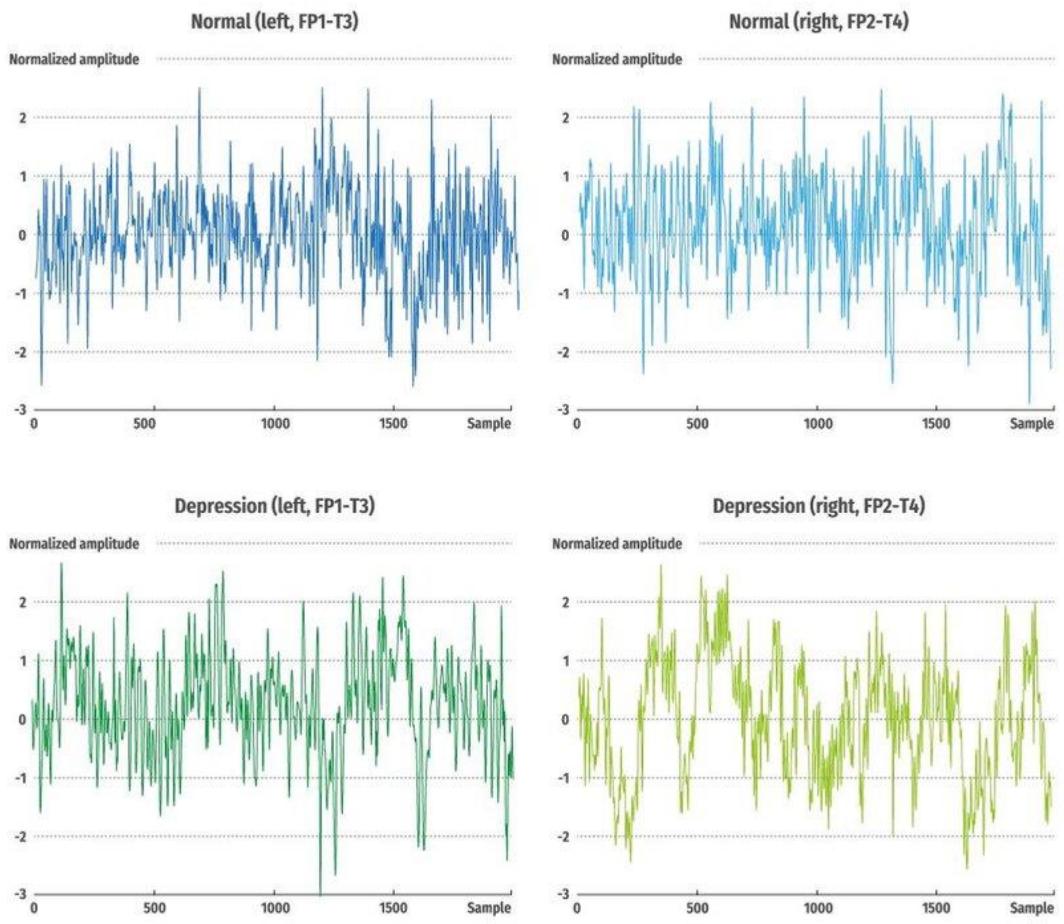
Anxiety disorders



Abdulhakim Al-Ezzi et al. 2021. Analysis of Default Mode Network in Social Anxiety Disorder

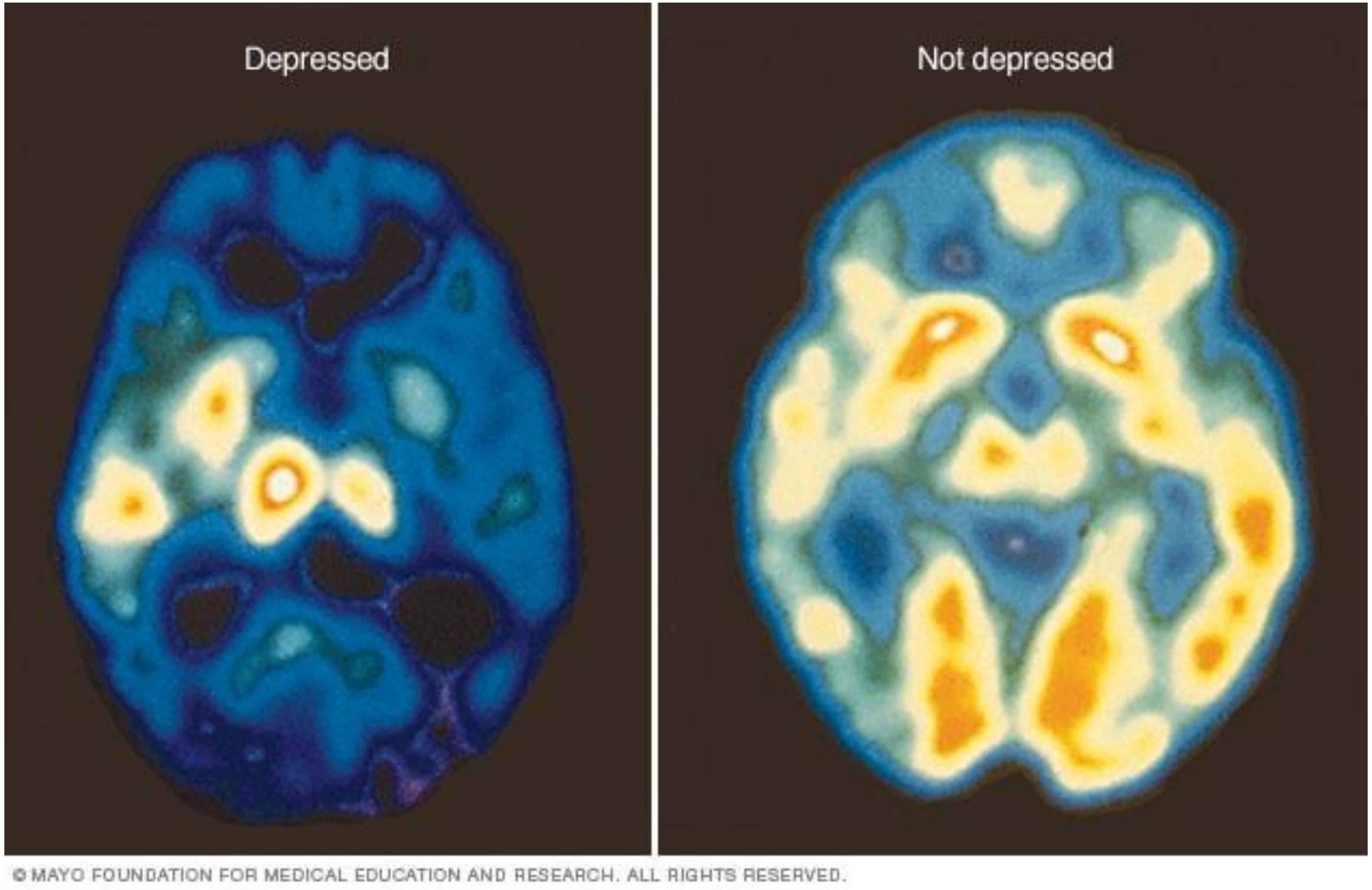
Depression

Depression is a mental state of **low mood and aversion to activity**. It affects more than 280 million people of all ages. Depression affects a person's thoughts, behavior, feelings, and sense of well-being. Wikipedia



Acharya AU et al. 2018. Automated EEG-based Screening of Depression Using Deep Convolutional Neural Network

Depression

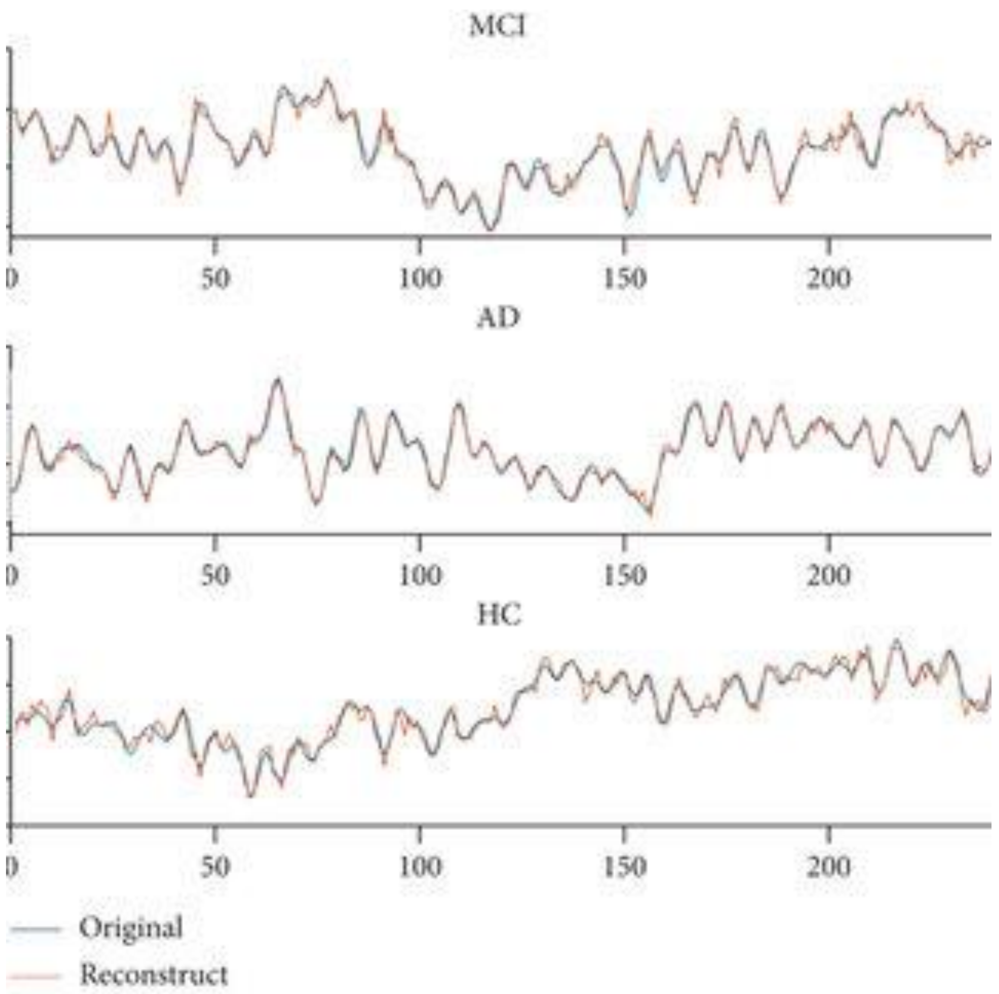


PET scan of the brain for depression - Mayo Clinic

Alzheimer's disease

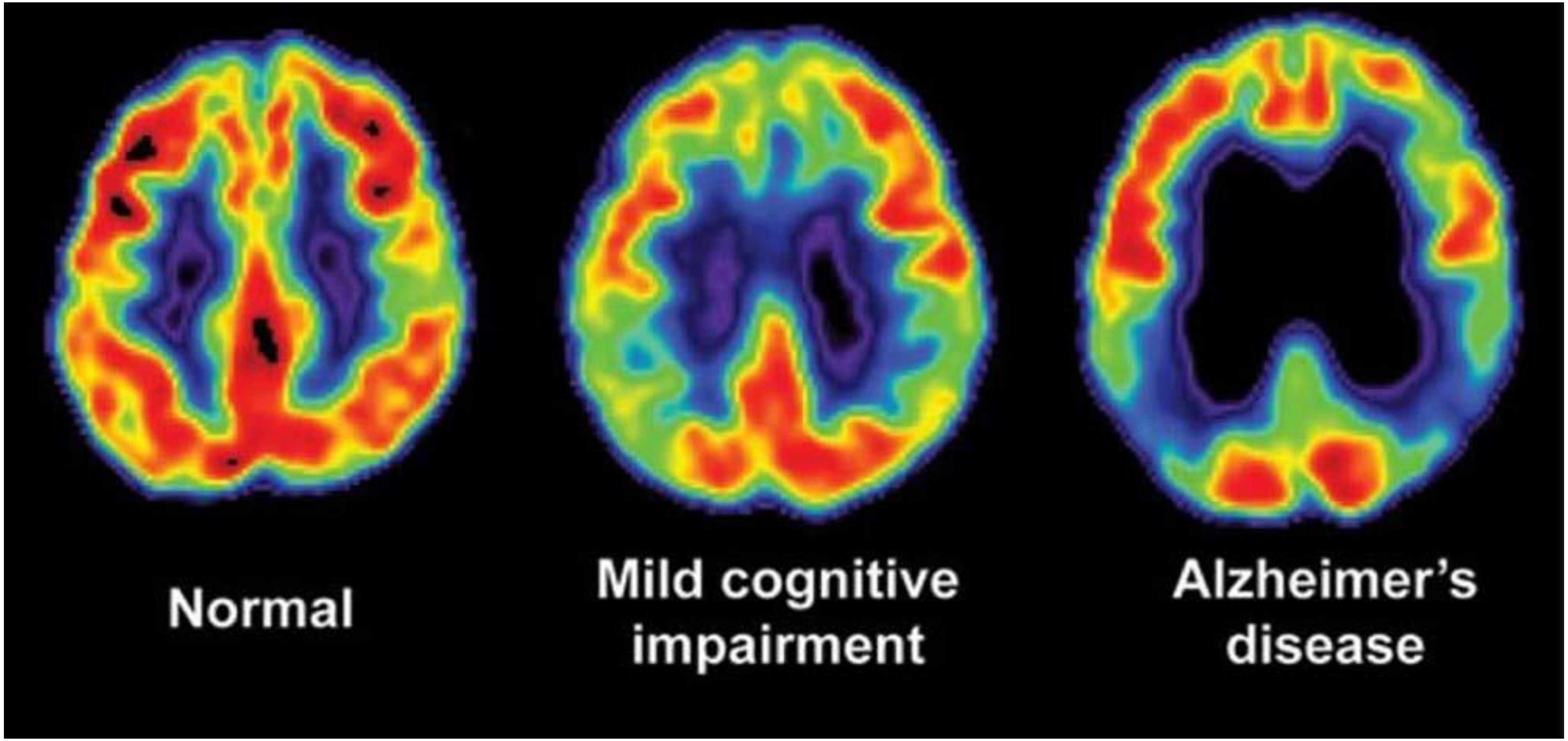
Alzheimer's disease is a brain disorder that gets worse over time. **It's characterized by changes in the brain that lead to deposits of certain proteins**. Alzheimer's disease causes the brain to shrink and brain cells to eventually die. Alzheimer's disease is the most common cause of dementia — a gradual decline in memory, thinking, behavior and social skills. These changes affect a person's ability to function.

About 6.5 million people in the United States age 65 and older live with Alzheimer's disease. Among them, more than 70% are 75 years old and older. Of the about 55 million people worldwide with dementia, 60% to 70% are estimated to have Alzheimer's disease.



Amini M et al. Diagnosis of Alzheimer's Disease by Time-Dependent Power Spectrum Descriptors and Convolut2021. ional Neural Network Using EEG Signal

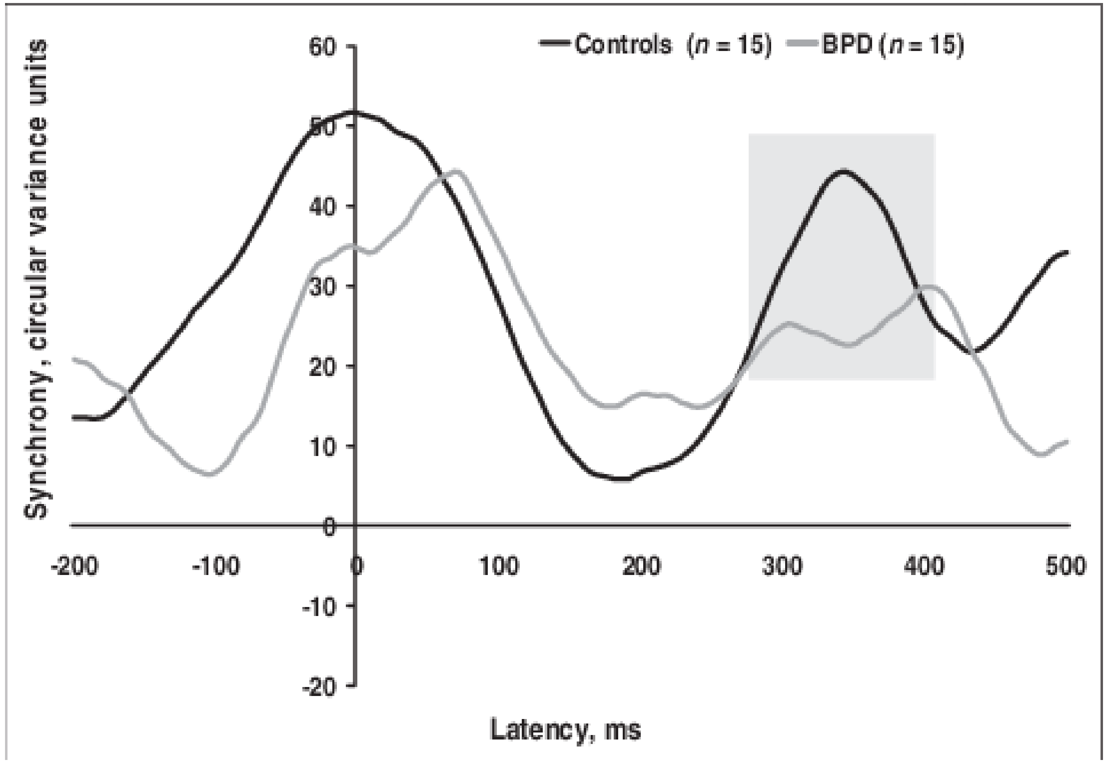
Alzheimer's disease



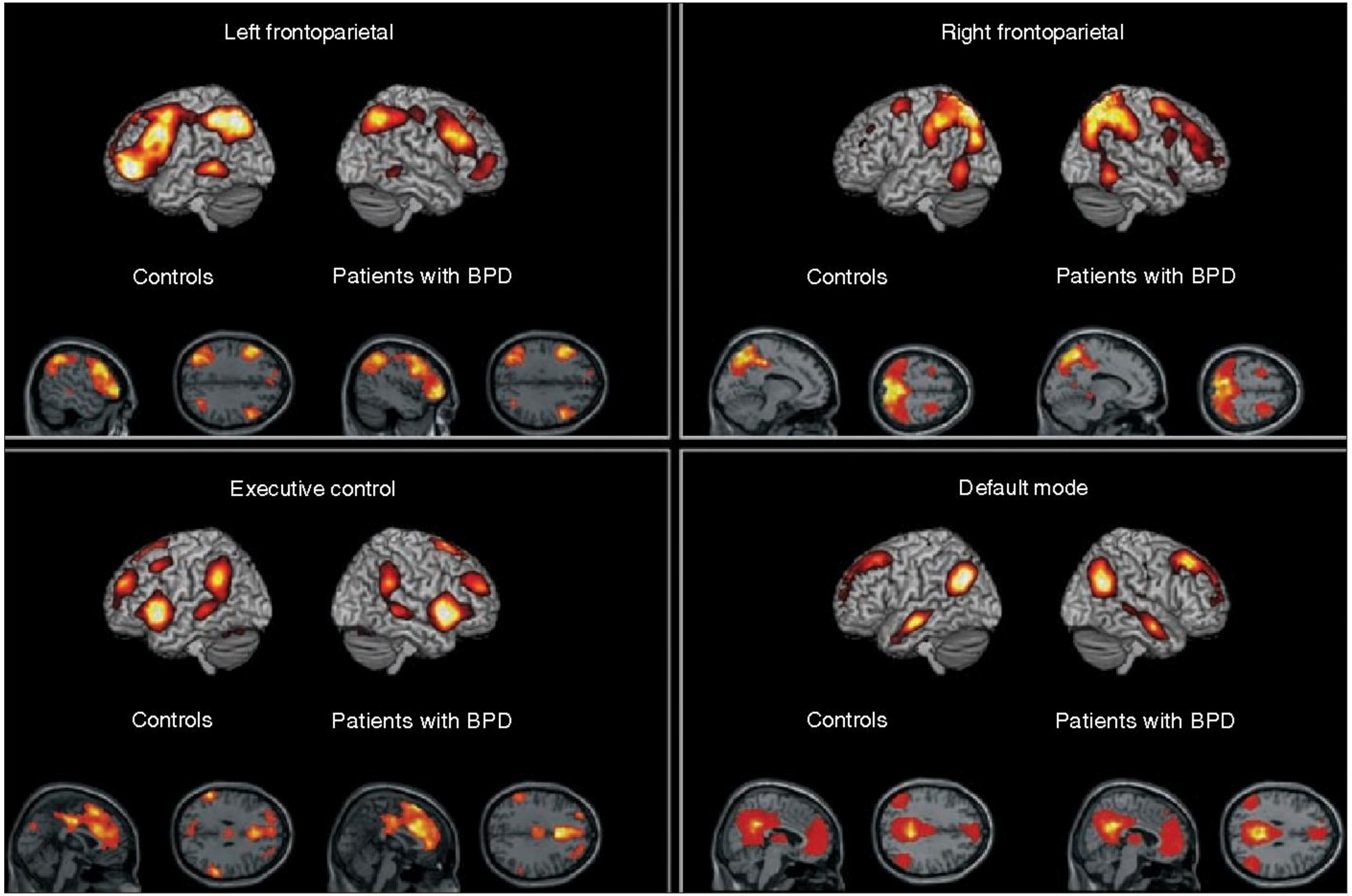
Brain Imaging for Alzheimer's & Dementia | Pacific Brain Health Center

Personality disorder

Personality disorder
Panic disorder
Panic disorder is a mental and behavioral disorder, specifically an anxiety disorder **characterized by reoccurring unexpected panic attacks.** Wikipedia



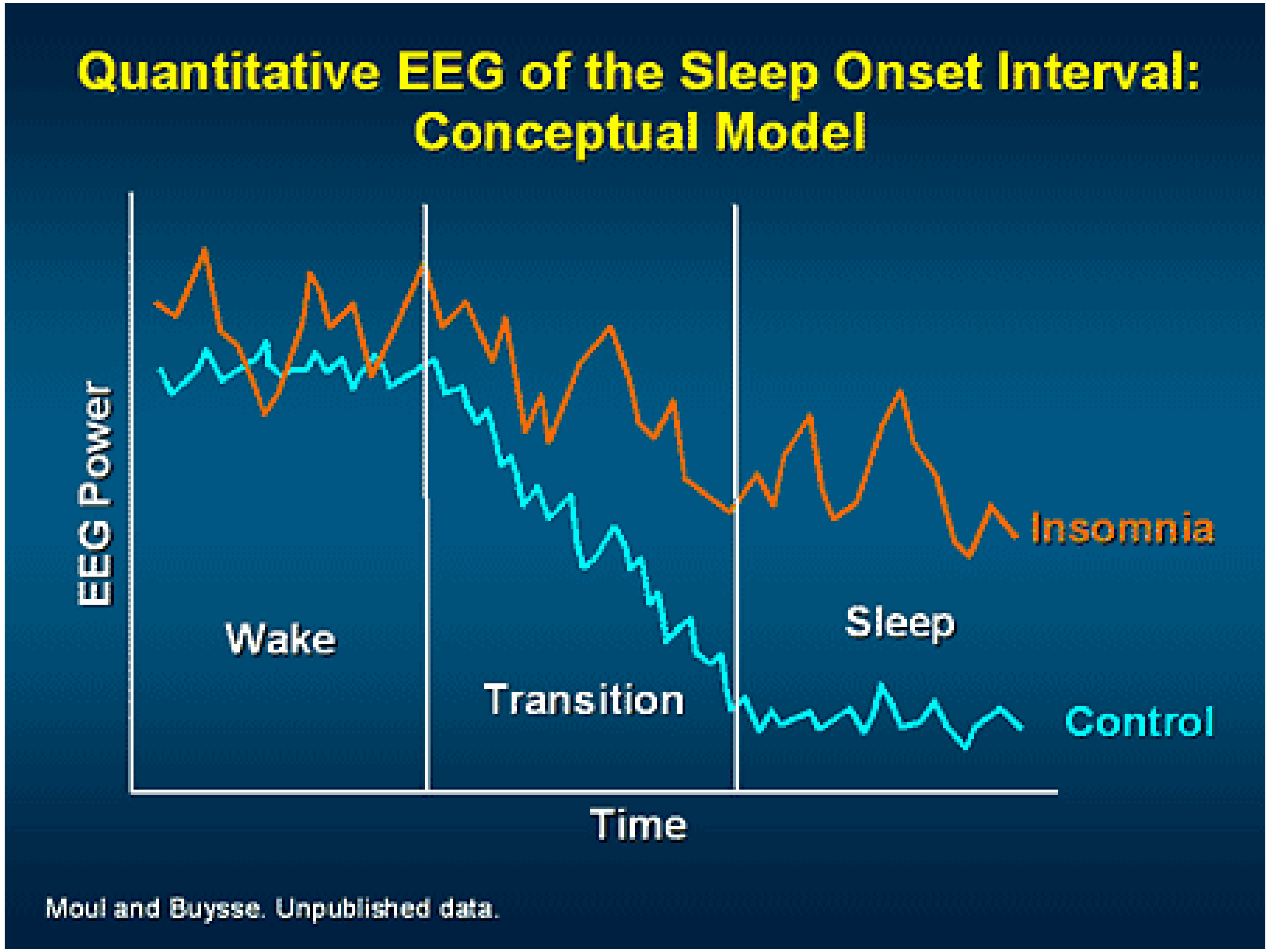
Williams LM et al. 2006. “Missing links” in borderline personality disorder: Loss of neural synchrony relates to lack of emotion regulation and impulse control



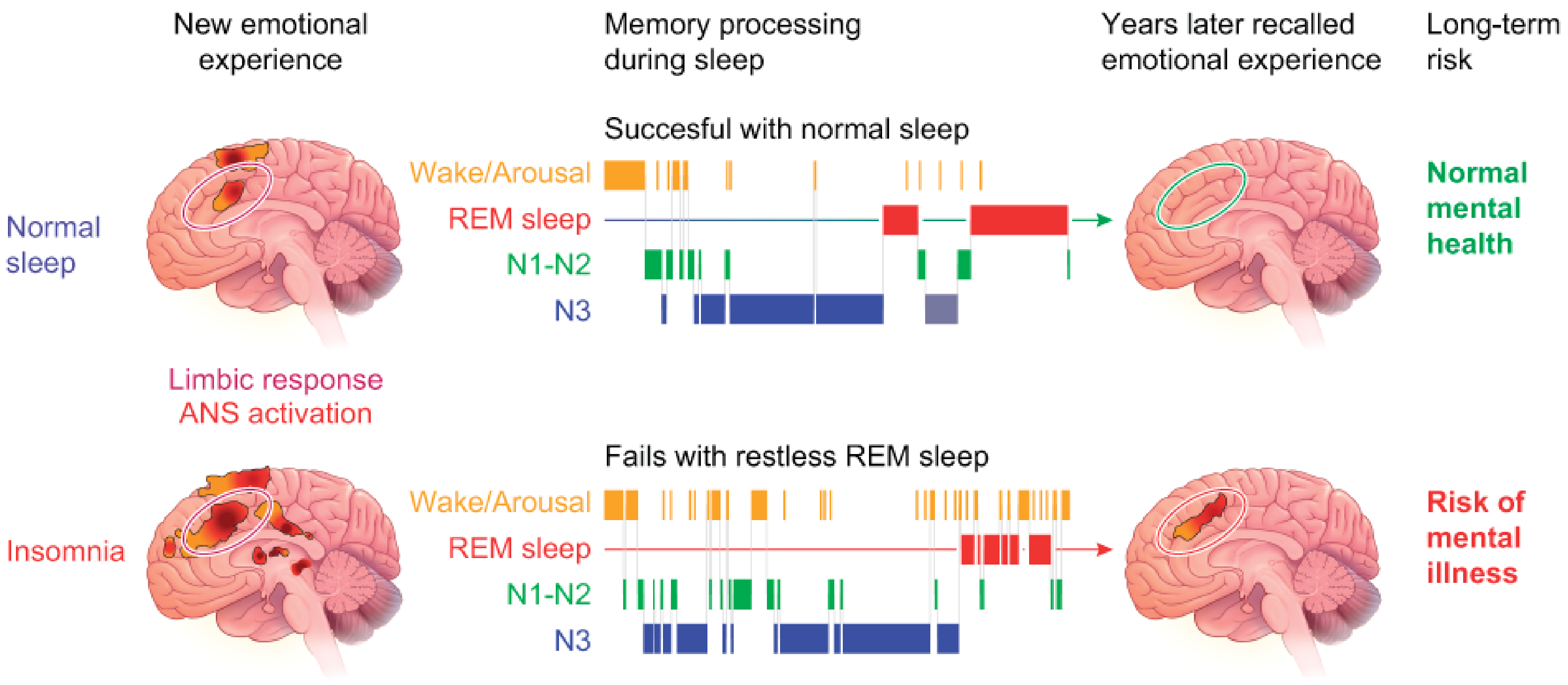
Wolf R. et al. 2011. Aberrant connectivity of resting-state networks in borderline personality disorder.

insomnia

There are several different types of sleep-wake disorders, of which insomnia is the most common. Other sleep-wake disorders include obstructive sleep apnea, parasomnias, narcolepsy, and restless leg syndrome. Sleep difficulties are linked to both physical and emotional problems.



Walsh JK et al. New Visions for Insomnia: Evolving Insights and Emerging Directions



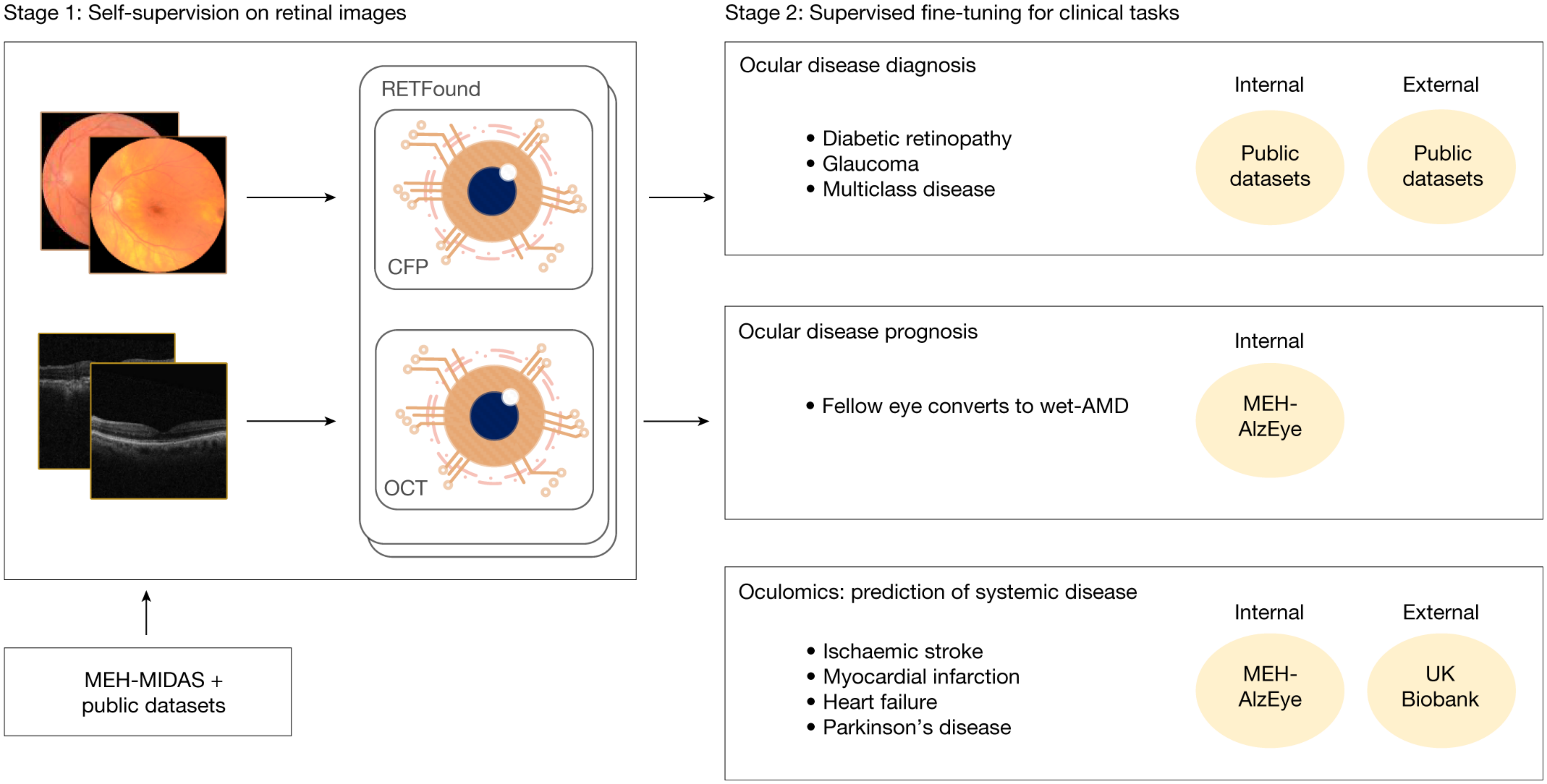
rapid eye movement (REM)

New Framework for Diagnosis of Disease in Medical AI

- data are abundant and healthcare tasks are diverse but labels are scarce
- A foundation model is defined as a large AI model trained on a vast quantity of unlabelled data at scale resulting in a model that can be adapted to a wide range of downstream tasks
- Specifically, we develop two separate RETFound models, one using CFP and the other using OCT, by means of an advanced SSL technique (masked autoencoder) successively on natural images (ImageNet-1k) followed by retinal images mfrom the Moorfields diabetic image dataset (MEH-MIDAS) and public data (totalling 904,170 CFPs and 736,442 OCTs).
- We adapt RETFound to a series of challenging detection and prediction tasks by fine-tuning RETFound with specific task labels, and then validate its performance.

A foundation model for generalizable disease detection from retinal images

Zhou et al. Nature September 2023

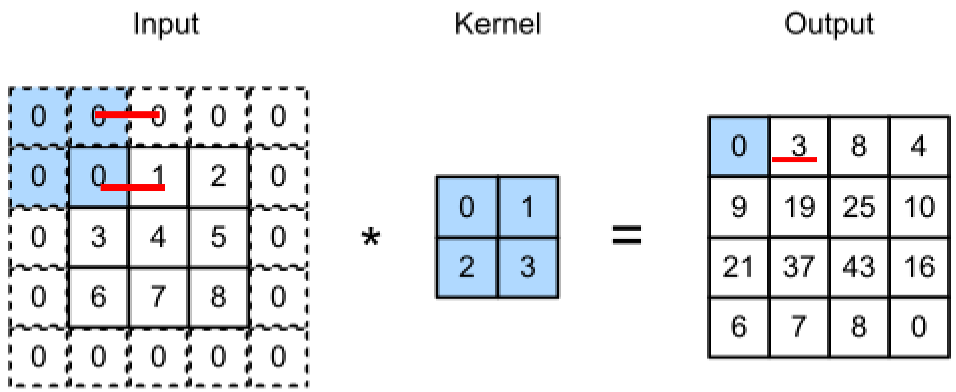


Stage 1: Self-supervision on retinal images
RETFound
CFP
OCT
MEH-MIDAS + public datasets
Stage 2: Supervised fine-tuning for clinical tasks
Ocular disease diagnosis
• Diabetic retinopathy
• Glaucoma
• Multiclass disease
Internal
Public datasets
External
Public datasets
Ocular disease prognosis
• Fellow eye converts to wet-AMD
Internal
MEH-AlzEye
Oculomics: prediction of systemic disease
• Ischaemic stroke
• Myocardial infarction
• Heart failure
• Parkinson's disease
Internal
MEH-AlzEye
External
UK Biobank

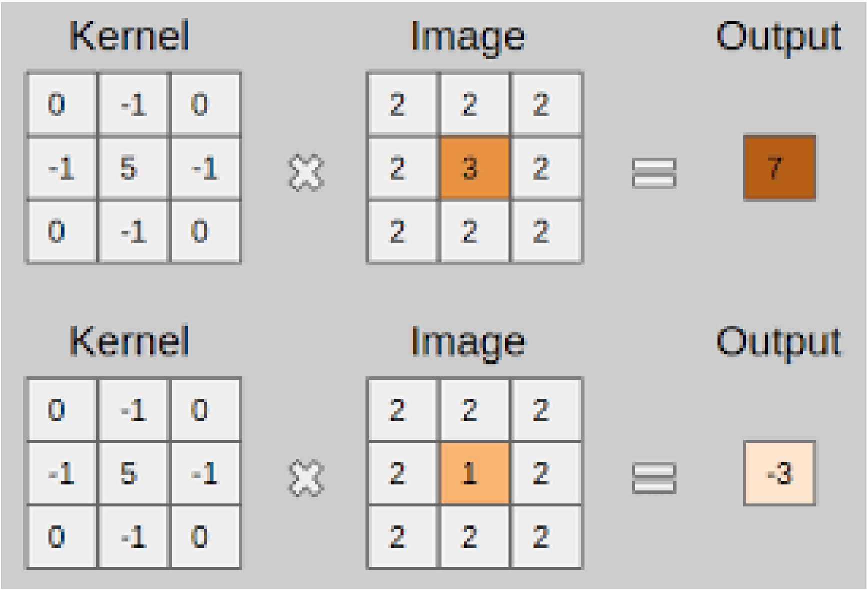
Motivation

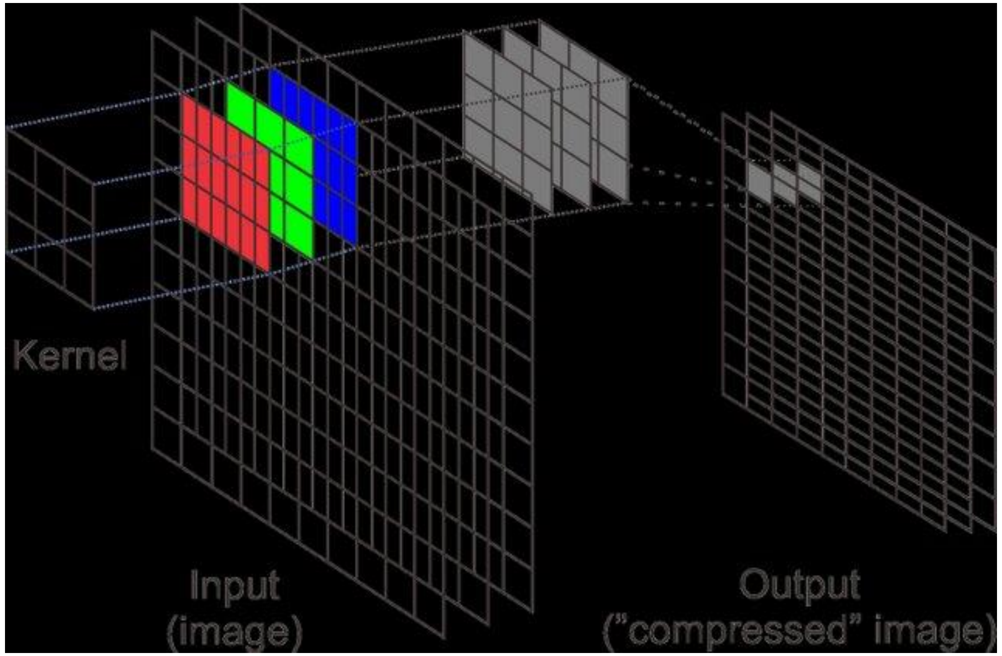
- EEG regression and classification tasks, fundamental to neuroscience research and applications like Brain-Computer Interfaces(BCIs).
- Have traditionally relied on Convolutional Neural Networks (CNNs) . While CNNs have proven their use for extracting localized features from time-series EEG data, they struggle with capturing the long-term dependencies, subject-independent and session-independent patterns inherent in EEG data. This limitation motivates the exploration of other model architectures that can replace or support CNNs.
- EEG is characterized as the fluctuation of postsynaptic membrane potential of neurons, recorded from the surface of the head.

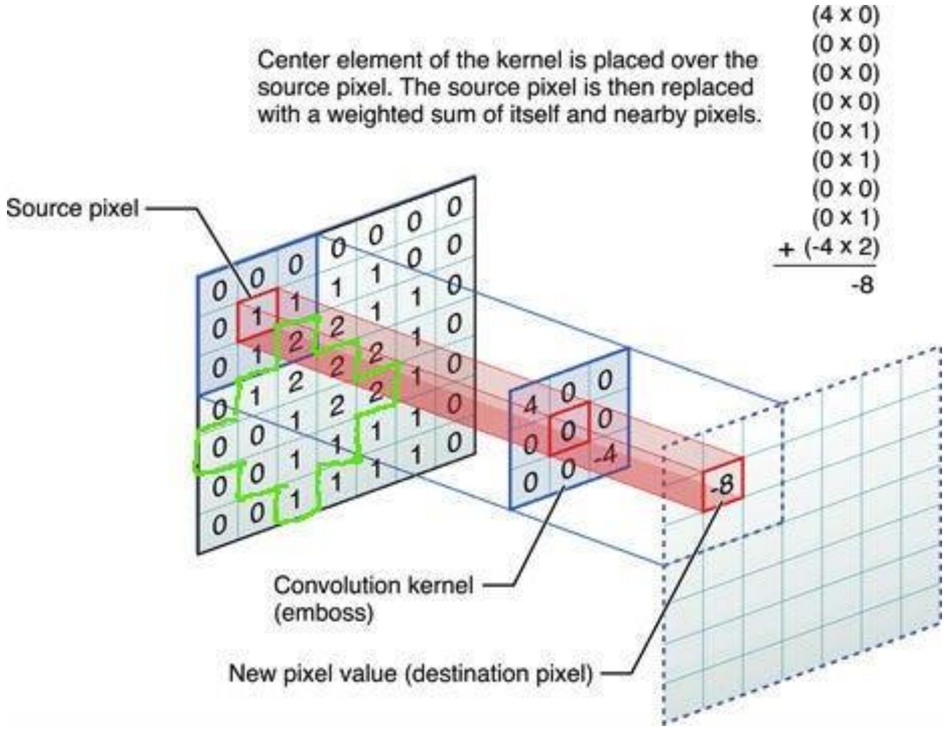
EEGNet: A Compact Convolutional Neural Network for EEG-based Brain-Computer Interfaces



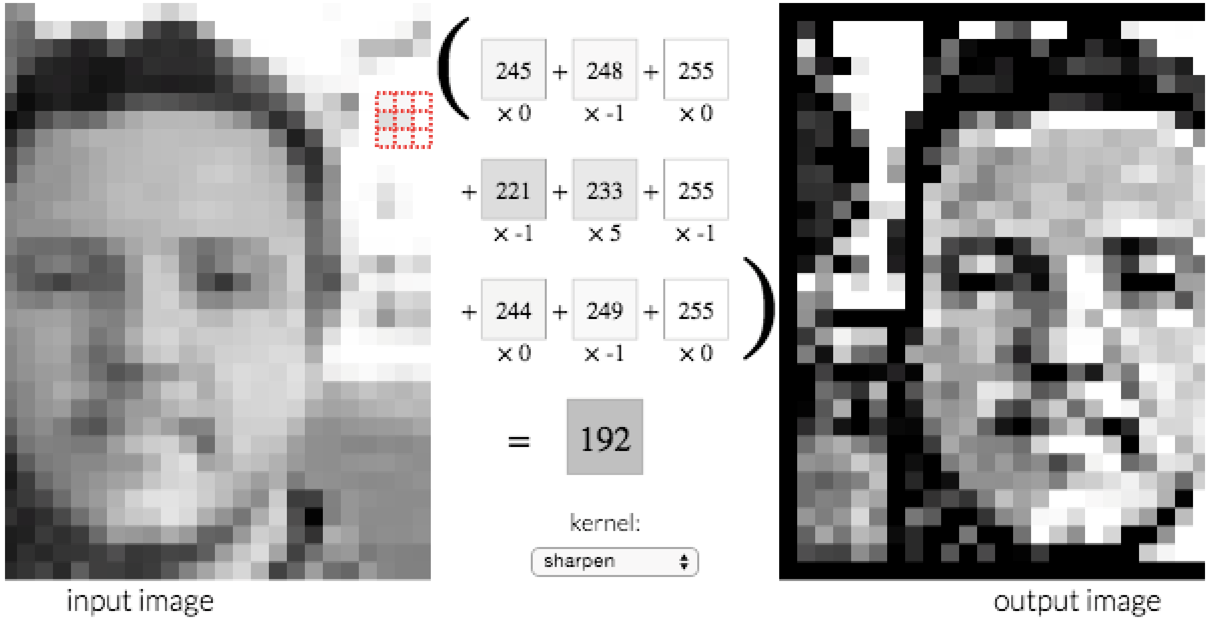
$$\begin{bmatrix}0 & 0\\0 & 1\end{bmatrix} * \begin{bmatrix}0 & 1\\2 & 3\end{bmatrix} = \begin{bmatrix}0 * 0 = 0 & 0 * 1 = 0\\0 * 2 = 0 & 1 * 3 = 3\end{bmatrix}$$



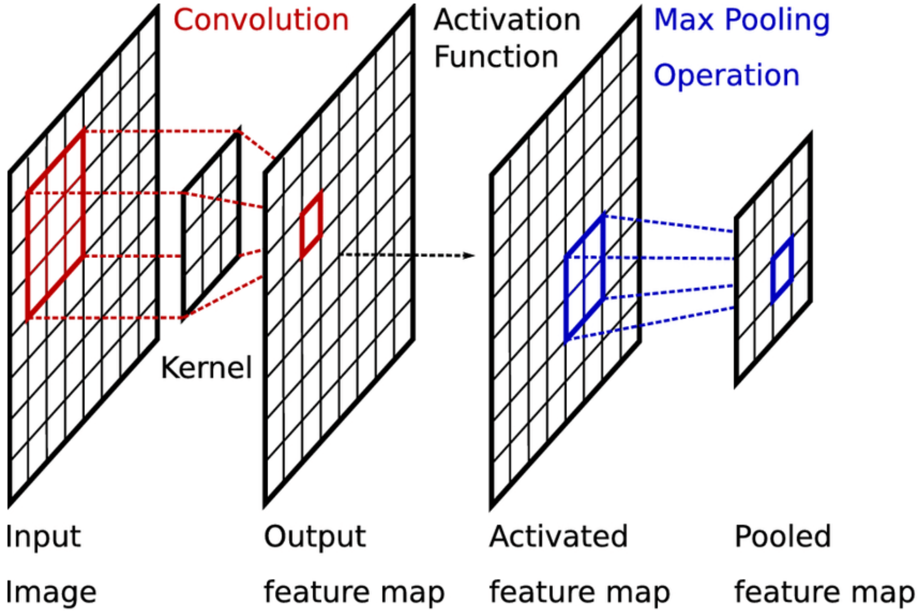




Types of Convolution Kernels : Simplified



$$\begin{pmatrix} 0 & -1 & 0 \\ -1 & 5 & -1 \\ 0 & -1 & 0 \end{pmatrix}$$

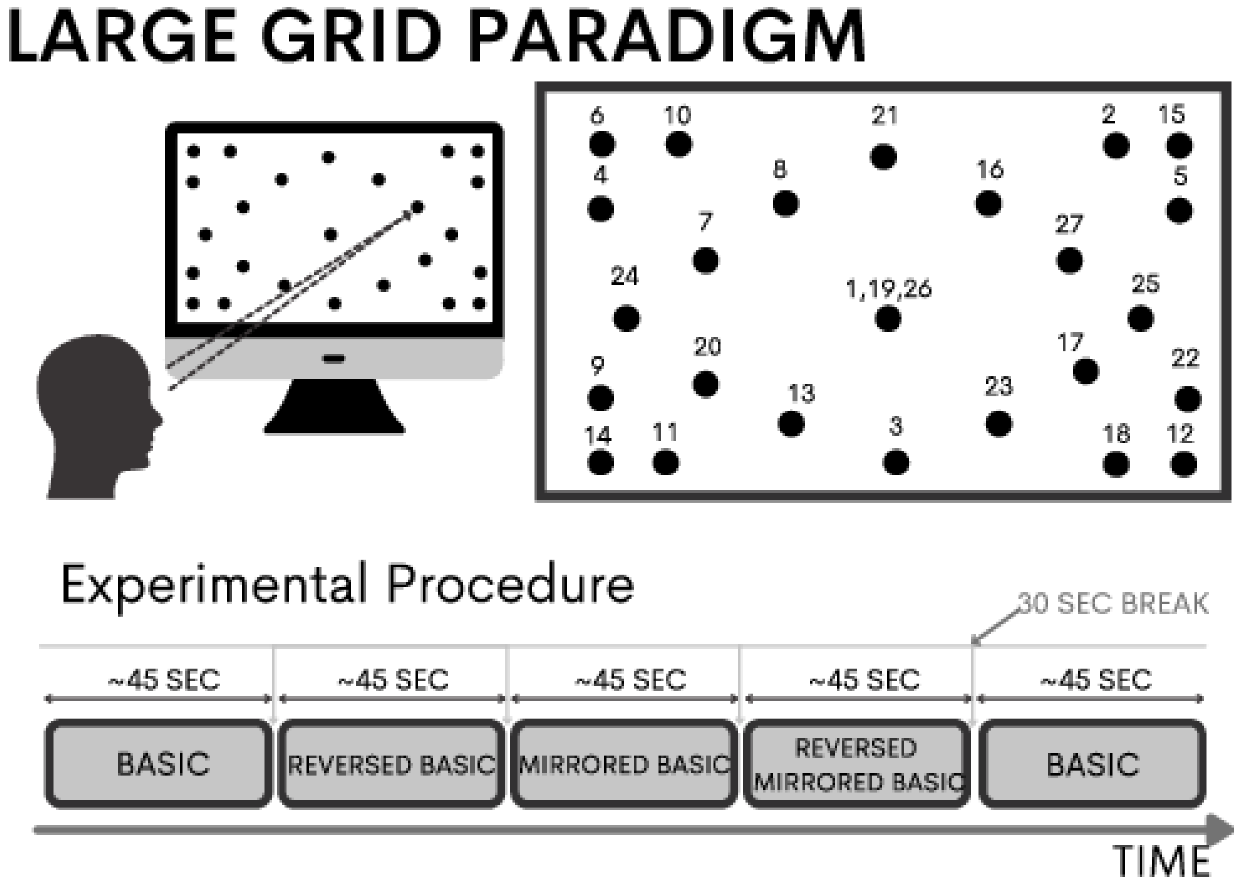


Basic CNN block. A single layer is shown which applies a kernel on an...

ViT2EEG: Leveraging Hybrid Pretrained Vision Transformers for EEG Data

Code is available at:
https://github.com/ruiqiRichard/EEGEyeNet-vit

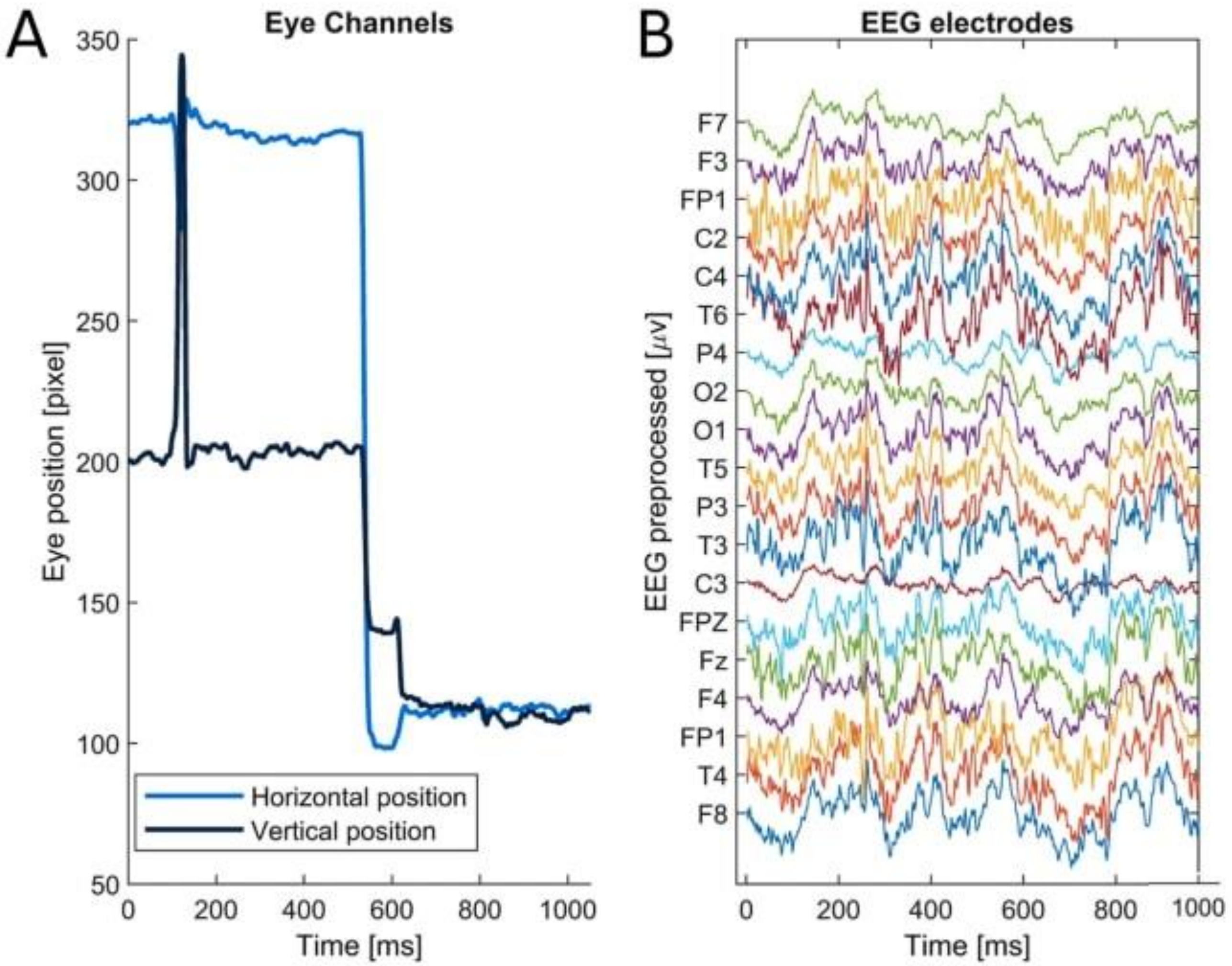
EEGEyeNet



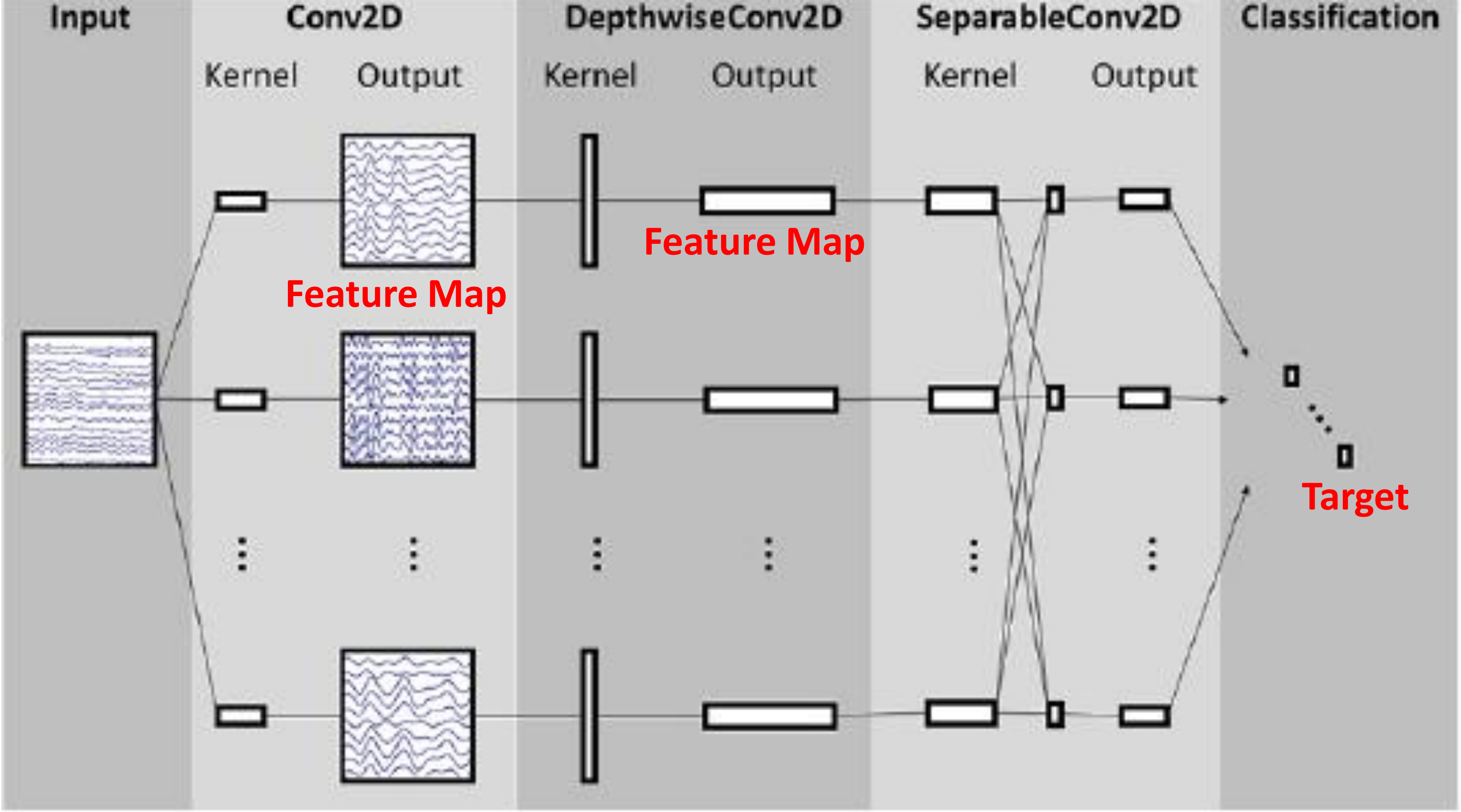
Participants of this paradigm are instructed to fixate on a sequence of 25 dots appearing at distinct screen positions, for 1.5 to 1.8 seconds each

Kastrati A. et al. 2021. EEGEyeNet: a Simultaneous Electroencephalography and Eye-tracking Dataset and Benchmark for Eye Movement Prediction

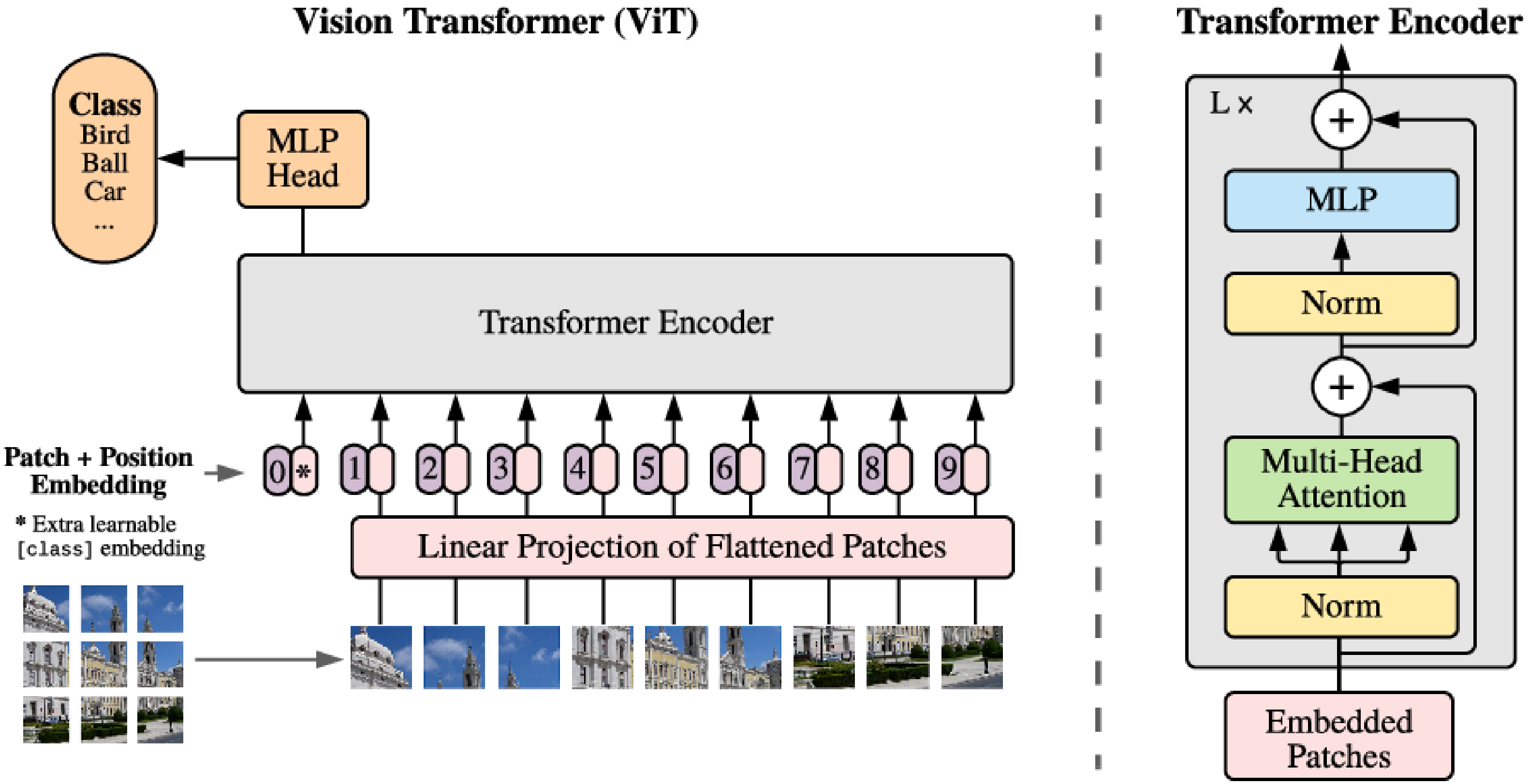
EEGEyeNet



https://paperswithcode.com/dataset/eegeyenet



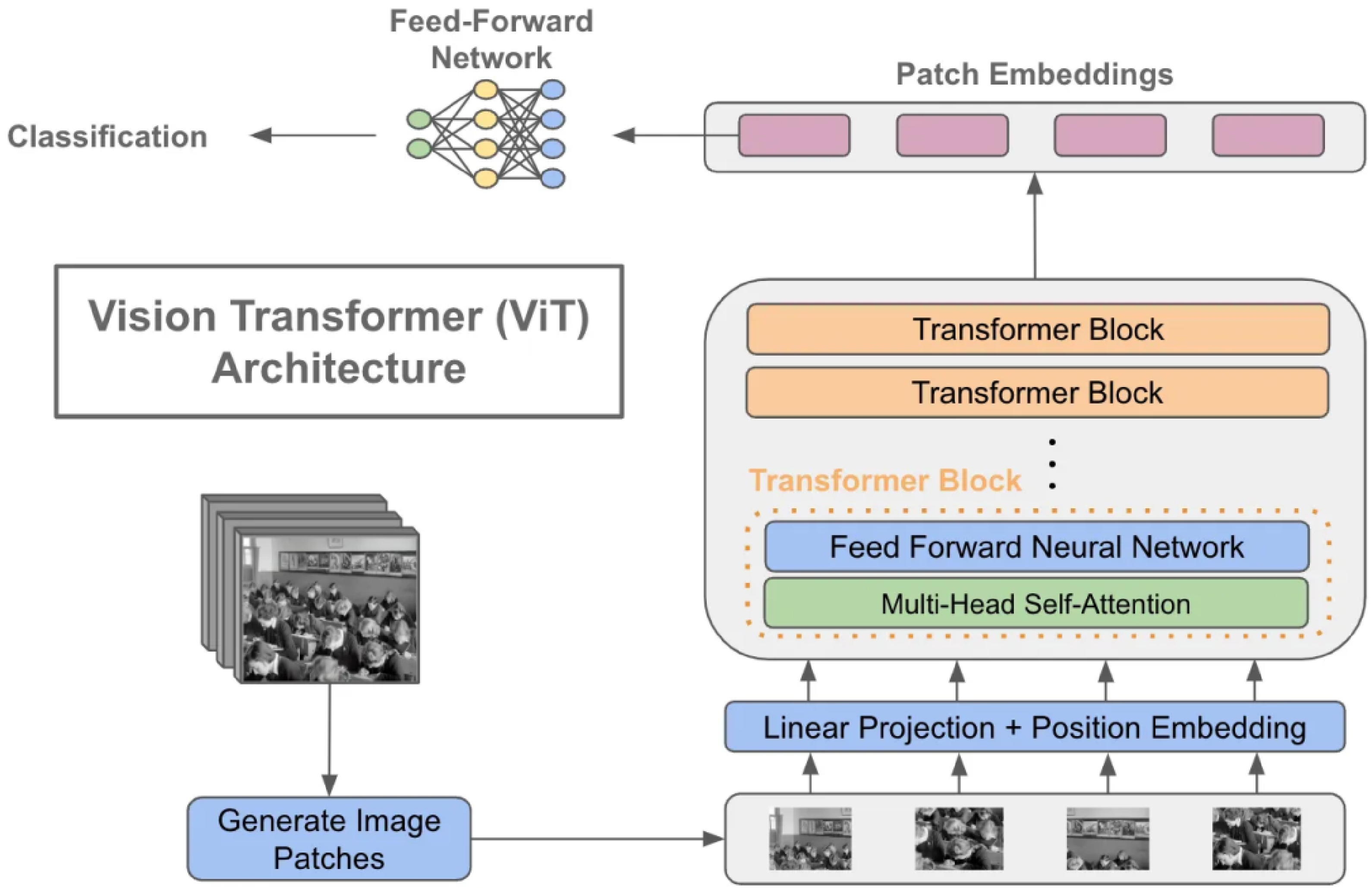
Overall visualization of the **EEGNet** architecture. Lines denote the convolutional kernel connectivity between inputs and outputs (called feature maps) . The network starts with a temporal convolution (second column) to learn frequency filters, then uses a depthwise convolution (middle column), connected to each feature map individually, to learn frequency-specic spatial filters. The separable convolution (fourth column) is a combination of a depthwise convolution, which learns a temporal summary for each feature map individually, followed by a pointwise convolution, which learns how to optimally mix the feature maps together.



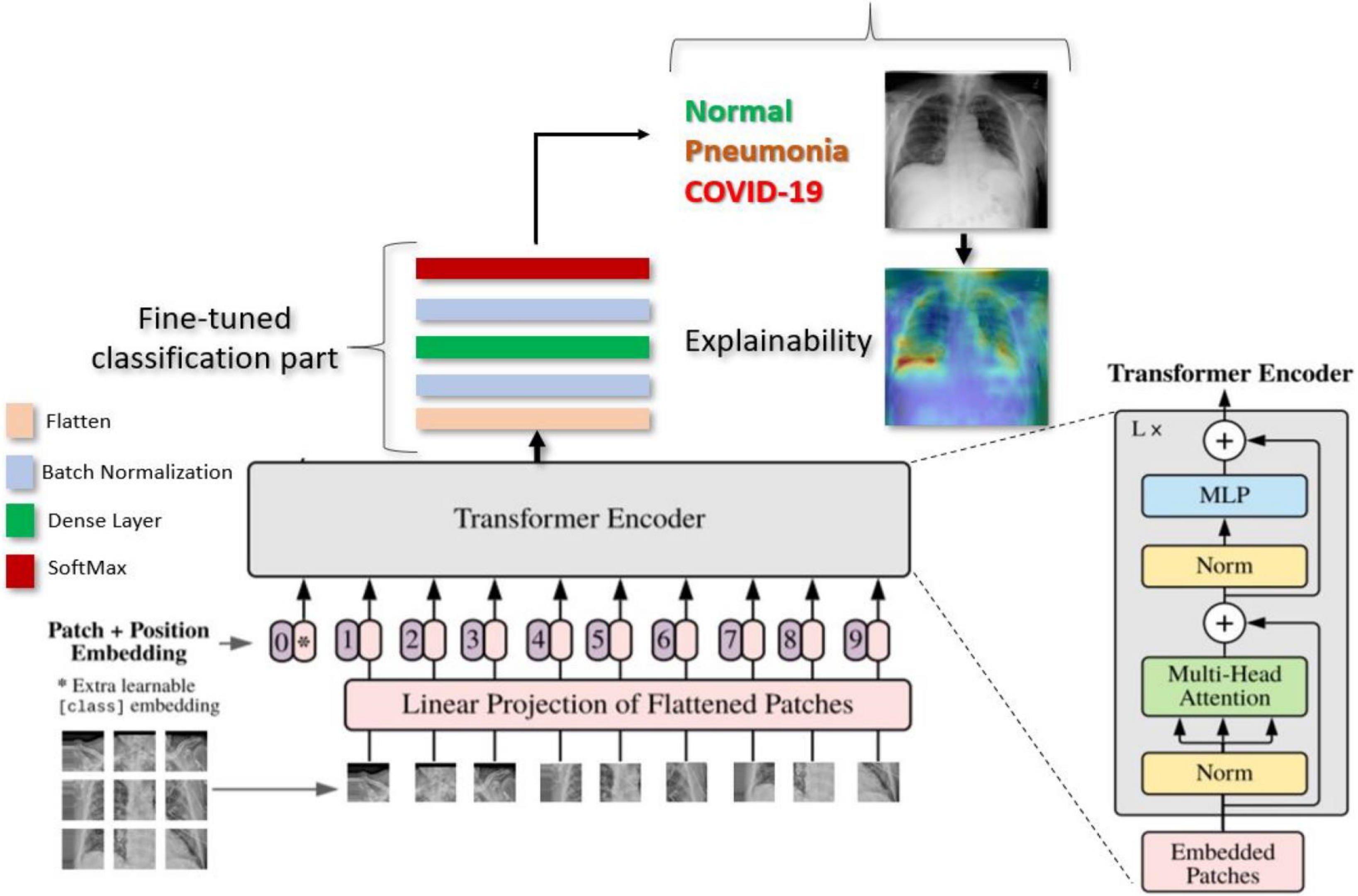
1. Split the image into 16*16 patches.
2. Flatten the image and concatenate it with the position embedding.
3. Pass the training parameters into the transformer.
4. The output is sent to a MLP Head which works as a classifier.

Positional embeddings are added to retain positional information, the authors tried 2D position embeddings but no significant improvements.

An image is worth 16x16 words: Transformers for image recognition at scale. arXiv preprint arXiv:2010.11929 (2020).



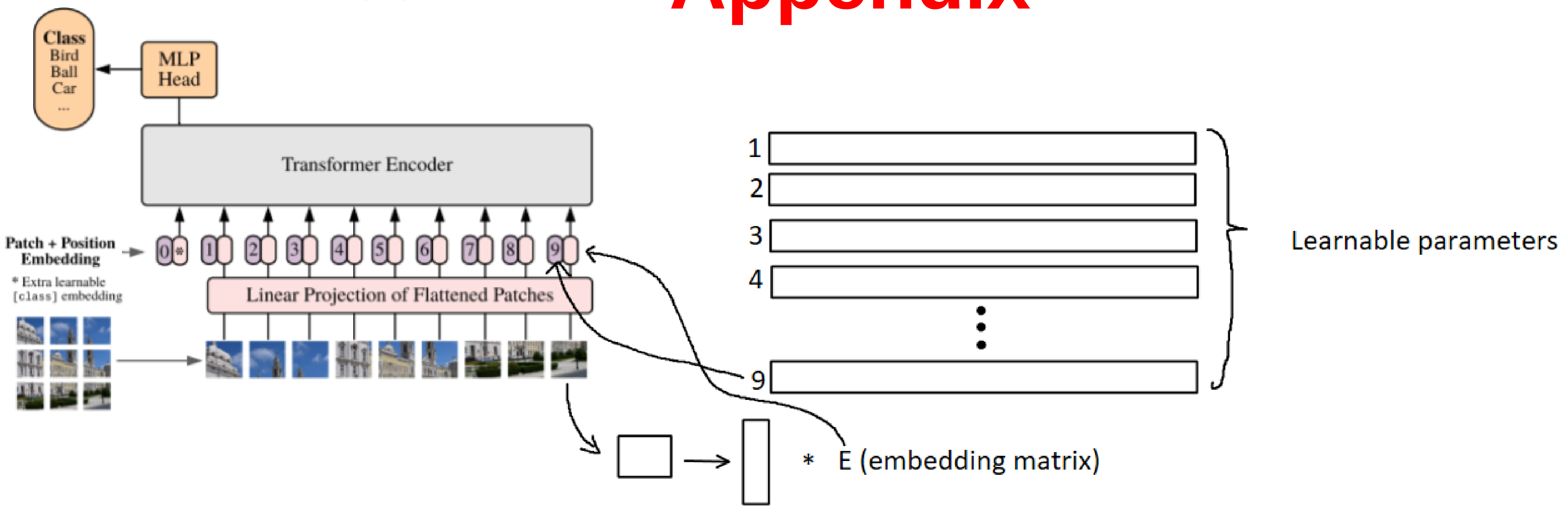
Demystifying Vision Transformers (ViT): A Revolution in Computer Vision



JCM | Free Full-Text | Explainable Vision Transformers and Radiomics for COVID-

Appendix

Vision Transformer (ViT)



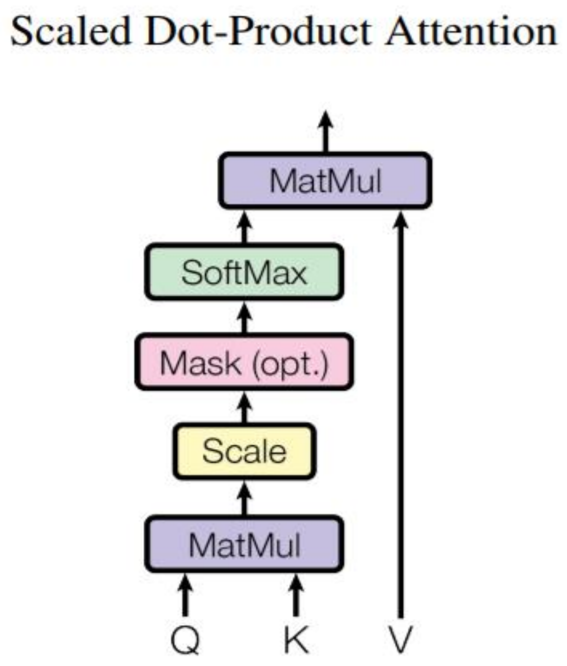
$$X_p \in R^{N\times(P\times P\times C)}.\ N = \frac{HW}{P^2}, (P,P){:}\ patch\ size, D{:}\ dimension\ of\ embedding\ of\ a\ Patch$$

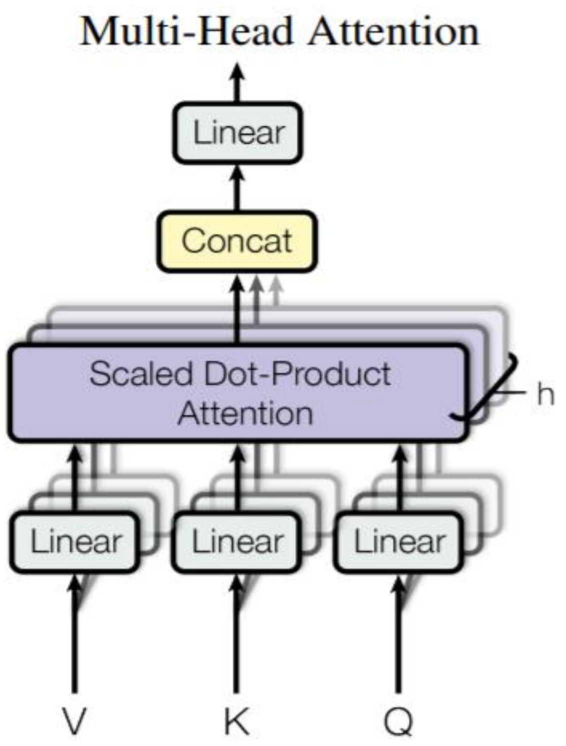
Patch 1 , X_p^1	Patch 2 , X_p^2	…	Patch N , X_p^N

$X_p^i \in R^{P\times P\times C}$

$$Z_0 = \left[X_{class};\ X_p^1E; \ldots, X_p^N E\right] + E_{pos} \qquad E \in R^{(P^2.C)\times D}, E_{pos} \in R^{(N+1)\times D}$$

Transformer Encoder





The embedded patches will be pass through a normalization layer, then pass through a multi-head attention layer.

Layer normalization (LN)

$$Y = LN(Z_{l-1}) = \begin{bmatrix} LN(Z_{l-1}^{0}) \\ \vdots \\ LN(Z_{l-1}^{N}) \end{bmatrix}, \mathrm{LN}\left(Z_{l-1}^{i}\right) = \begin{bmatrix} LN(Z_{l-1}^{i,1}) \\ \vdots \\ LN(Z_{l-1}^{i,D}) \end{bmatrix}$$

Layer normalization (LN)

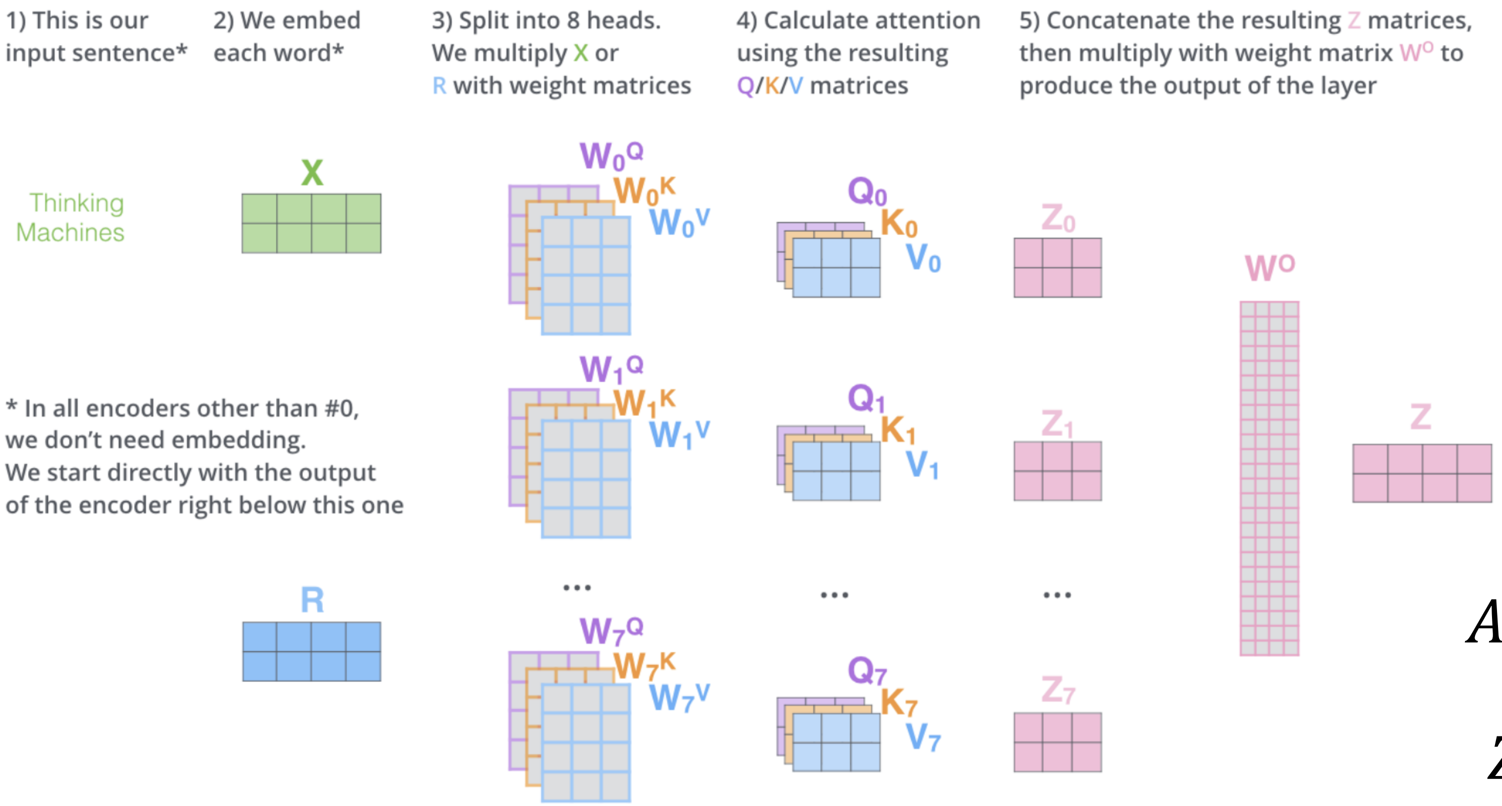
$$\mu_i = \frac{1}{D}\sum_{k=1}^{D} Z_{l-1}^{i,k}, \sigma_i^2 = \frac{1}{D}\sum_{k=1}^{D}\left(z_{l-1}^{i,k} - \mu_i\right)^2$$

$$\hat{z}_{l-1}^{i,k} = \frac{z_{l-1}^{i,k} - \mu_i}{\sqrt{\sigma_i^2 + \varepsilon}}$$

$$Z_{l-1}^{i} = \begin{bmatrix} z_{l-1}^{i,1} \\ \vdots \\ z_{l1}^{i,D} \end{bmatrix}, \mathrm{Y} = \begin{bmatrix} y^0 \\ \vdots \\ y^N \end{bmatrix}$$

$$\boldsymbol{Y = LN(Z_{l-1}) = \begin{bmatrix} LN(z_{l-1}^{0}) \\ \vdots \\ LN(z_{l-1}^{N}) \end{bmatrix}}$$

$$y_i = LN_{\gamma,\beta}\left(Z_{l-1}^{i}\right) = \gamma \hat{Z}_{l-1}^{i} + \beta, i = 0, 1, \dots, N$$



$$Q_i = XW_i^Q$$
$$K_i = XW_i^K$$
$$V_i = XW_i^V$$
$$A_i = softmax\left(\frac{Q_i K_i^T}{\sqrt{D_h}}\right)$$
$$Z_i = (SA)_i(X) = A_i V_i$$

$$Z = MSA(X) = [Z_1 \quad \cdots \quad Z_h]W^0, Q_i, K_i, V_i \in R^{N\times D_h}, A_i \in R^{N\times N}$$

$$X \in R^{N\times D}, W_i^Q \in R^{D\times D_h}, W_i^K \in R^{D\times D_h}, W_i^V \in R^{D\times D_h}, W^0 \in R^{hD_h\times D}, Z_i \in R^{N\times D_h},$$

- **Let MLP be two layers with a GELU non-linearity. In Summary**

$$Z_0 = \left[X_{class};\ X_p^1 E; \dots, X_p^N E\right] + E_{pos}$$

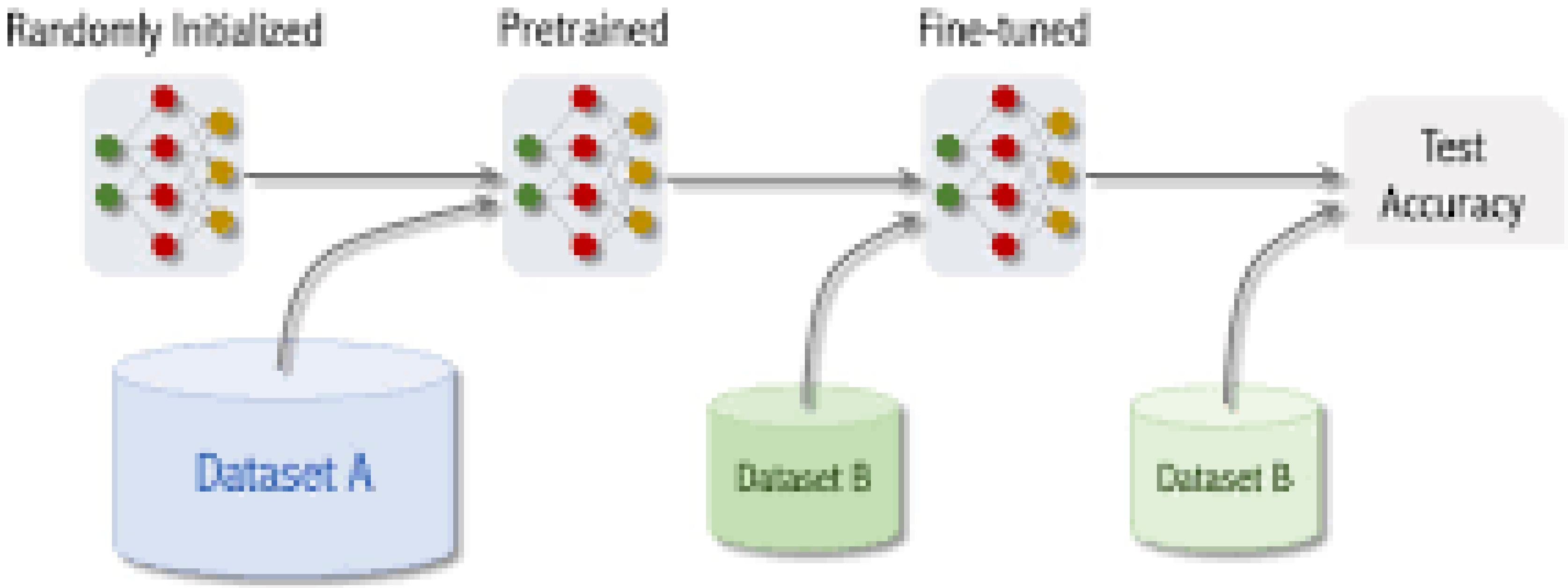
$$Z_l' = MSA\left(LN(Z_{l-1})\right) + Z_{l-1}$$

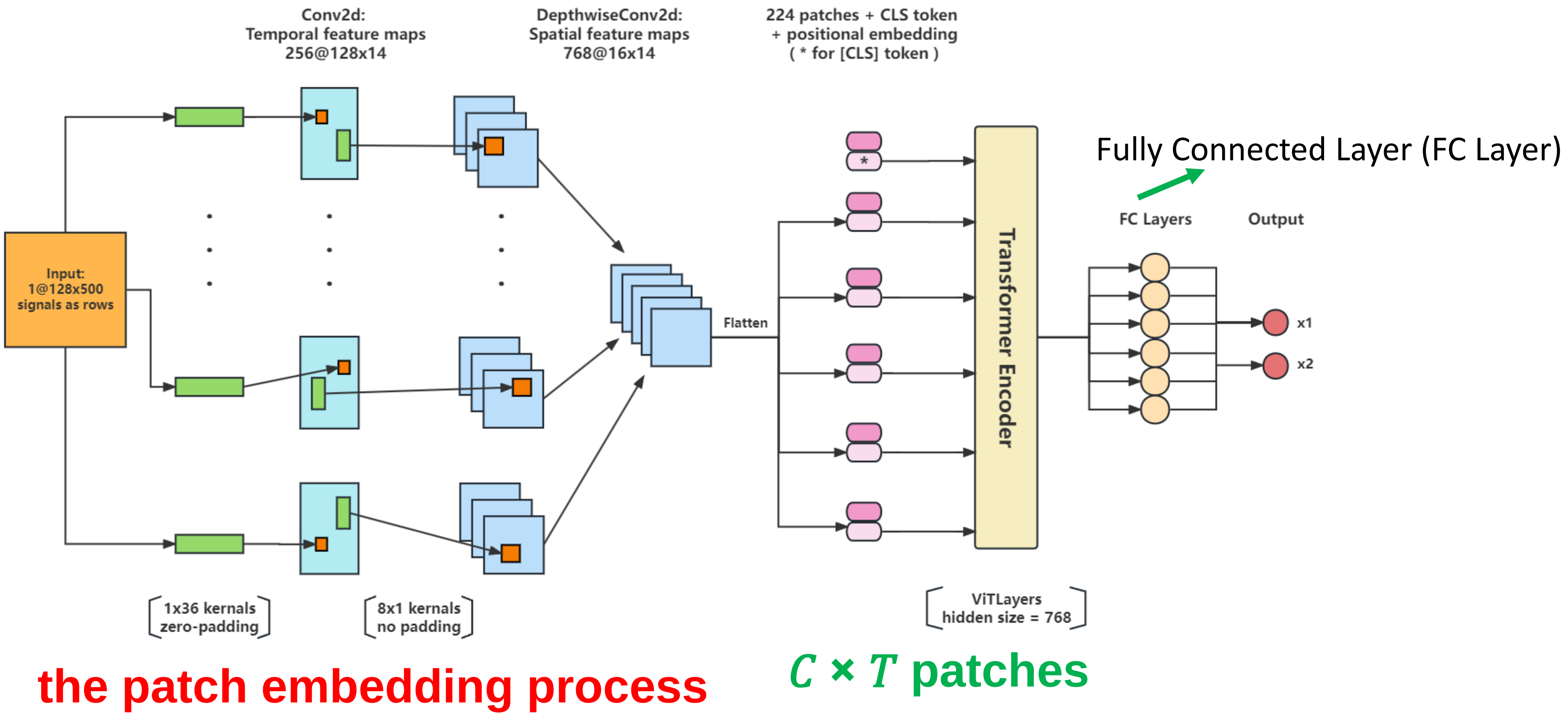
$$Z_l = MLP\left(LN\left(Z_l'\right)\right) + Z_l', l = 1, \dots, L$$

$$y = LN(Z_L^0)$$

Appendix

Vision Transformer





Proposed EEGViT, a hybrid ViT (Vision Transformer) architecture designed specifically for EEG raw signal as input. A two-step convolution operation is applied to generate patch embeddings. Then we add positional embeddings and pass the resulting sequence into ViT layers.

EEGViT Training

- **Mean Squared Error (MSE) loss function**

minimize the prediction error of continuous output values

Although we employed MSE for training, we decided to use **Root Mean Square Error (RMSE)** to measure our results.

- **Train two different model architectures.**

(1) ViTBase Model

Unmodified, non-pretrained ViTBase model: 8×36 Kernel

Pretrained version of the ViT-Base model:

trained on the ImageNet dataset, using the weights from **https://github.com/huggingface/transformers**

(2) EEGViT model by adding the Two-Step Convolution Block

Randoml initialized weights

Relying on the weights of ViT-Base obtained on the ImageNet dataset

BASELINE METHODS

- **Naive Guessing**

  adopt the Naive Guessing baseline from EEGEyeNet, where the mean position from the training set is used as the constant prediction for every test data point.
- **Machine Learning Methods**
- **Deep Learning Methods**

  Convolutional Neural Network (CNN)

  Pyramidal CNN

  EEGNet, an EEG-specific CNN architecture that employs depthwise and separable convolutions

RESULTS

Model	Absolute Position RMSE (mm)
Naive Guessing	123.3
KNN	119.7
RBF SVR	123
Linear Regression	118.3
Ridge Regression	118.2
Lasso Regression	118
Random Forest	116.7
CNN	70.4
Pyramidal CNN	73.9
EEGNet	81.3
ViT Base	61.5
ViT-base Pretrained	58.1
EEGViT	61.7
EEGViT Pretrained	55.4

RESULTS

- EEGViT model significantly outperforms conventional regression models, Convolutional Neural Networks (CNNs), and the baseline ViT-Base, establishing the utility of transfer learning and the enhancement potential of image data for EEG analysis.

ViT2EEG: Leveraging Hybrid Pretrained Vision Transformers for EEG Data

Code is available at: https://github.com/ruiqiRichard/EEGEyeNet-vit

EEGformer: A transformer–based brain activity classification method using EEG signal

Transformer-based ensemble deep learning model for EEG-based emotion recognition

A novel method for diagnosing Alzheimer’s disease using deep pyramid CNN based on EEG signals

Data will be made available on request.

EEG-based clinical decision support system for Alzheimer's disorders diagnosis using EMD and deep learning techniques

The original contributions presented in the study are included in the article/Supplementary material, further inquiries can be directed to the corresponding author.

Method for Classifying Schizophrenia Patients Based on Machine Learning

The datasets used and/or analyzed during the present study are available from the corresponding author on reasonable request.

Computational methods of EEG signals analysis for Alzheimer’s disease classification

All data used in this study are publicly available at Ref[42]

Data from: Computational methods of EEG signals analysis for Alzheimer’s disease classification. https://osf.io/2v5md/, (2023)

The database was designed jointly by Dr. Dennis Duke and other researchers at Florida State University and it was recorded from the 19 scalp loci of the international 10-20 system using a Biologic Systems Brain Atlas III Plus workstation. The dataset consists of 24 healthy elderly, all being negative for any neurological or psychiatric disorder, and 160 probable AD patients diagnosed through the N…

This dataset contains the EEG resting state-closed eyes recordings from 88 subjects in total. Participants: 36 of them were diagnosed with Alzheimer's disease (AD group), 23 were diagnosed with Frontotemporal Dementia (FTD group) and 29 were healthy subjects (CN group).

https://openneuro.org/datasets/ds004504/versions/1.0.6

EEG Records Databases

EEG of healthy adolescents and adolescents with symptoms of schizophrenia

EEG Database Description

There are two EEG data archives for two groups of subjects. The subjects were adolescents who had been screened by psychiatrist and devided into two groups: healthy (n = 39) and with symptoms of schizophrenia (n = 45).

Each file contains an EEG record for one subject. Each TXT file contains a column with EEG samples from 16 EEG channels (electrode positions). Each number in the column is an EEG amplitude (mkV) at distinct sample. First 7680 samples represent 1st channel, then 7680 - 2nd channel, ets. The sampling rate is 128 Hz, thus 7680 samples refer to 1 minute of EEG record.

Download Database:

- **Health adolescents -- [ZIP]**
- **Adolescents with symptoms of schizophrenia -- [ZIP]**

http://brain.bio.msu.ru/eeg_schizophrenia.htm

Detection of Parkinson's disease from EEG signals using discrete wavelet transform, different entropy measures, and machine learning techniques

Datasets used are online available: SanDiego dataset: https://openneuro.org/datasets/ds002778/versions/1.0.2. UNM dataset (d002): http://predict.cs.unm.edu/downloads.php

EEG Psychiatric Disorders Dataset

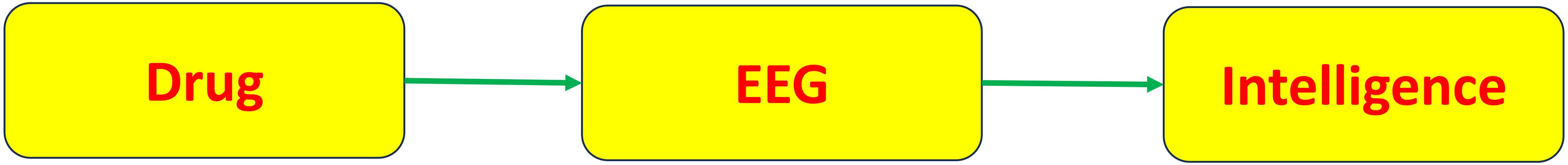
A psychiatric disorder is a mental illness diagnosed by a mental health professional that greatly disturbs your thinking, moods, and/or behavior and seriously increases your risk of disability, pain, death, or loss of freedom. In addition, your symptoms must be more severe than expected in response to an upsetting event, such as normal grief after the loss of a loved one.

A large number of psychiatric disorders have been identified. Chances are that, whether or not you or someone close to you has been diagnosed with a psychiatric disorder, you know something about one or more of the following examples:

Depression
Personality disorders
Anxiety disorders
Schizophrenia
Eating disorders
Addictive behaviors
Content
EEG Dataset with approx 1k attributes for identifying psychiatric disorders.

https://www.kaggle.com/datasets/shashwatwork/eeg-psychiatric-disorders-dataset

Project



Find the papers and Datasets?

Homework 1

1. Calculate the convolution:

$$\begin{pmatrix} 0 & 0 & 0 \\ 0 & 0 & 1 \\ 0 & 3 & 4 \end{pmatrix} * \begin{pmatrix} 0 & -1 & 0 \\ -1 & 5 & -1 \\ 0 & -1 & 0 \end{pmatrix}$$

2. What are the merits and limitation of Hybrid Pretrained Vision Transformers for EEG Data ?