# Optimizing deep learning for Magnetoencephalography (MEG): From sensory perception to sex prediction and brain fingerprinting

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## Abstract

**Artificial Neural Networks (ANN) are becoming the standard machine learning method in a variety of scientific fields. They are currently being increasingly investigated for decoding and modeling brain signals such as electroencephalography (EGG) and functional magnetic resonance imaging (fMRI). However, ANNs are relatively under-exploited for Magnetoencephalography (MEG) data classification and modeling. Here we describe a simple and intuitive convolutional neural network (CNN) architecture for MEG and test its performance on three MEG decoding tasks (n=643 subjects). Our model, specifically built with interpretability and speed in mind, achieved 99% decoding accuracy on the 643 subject identification task, 76.9% on sex prediction and 99.4% for auditory vs visual stimulus classification). In addition to comparison with benchmark models, we showcase tools for latent space visualizations that help uncover the underlying brain mechanisms used by the network. Our work contributes to ongoing efforts within the MEG/EEG community to enhance the usability and interpretability of DL-driven brain decoding.**



**Keywords:** Magnetoencephalography; Convolution; Artificial Neural Networks; Subject identification; Sex identification; Visualization.


## Introduction

Magnetoencephalography (MEG) is a well established electrophysiological brain imaging technique which boasts a high spatio-temporal resolution. The investigation of MEG data with artificial neural networks (ANN) offers exciting opportunities for decoding and modeling brain dynamics in health and disease. The goal of the present study is to investigate the use of convolutional neural networks (CNN) architectures for MEG data classification with an eye on interpretability and computational speed.

## Methods

### MEG data set

We used open access MEG data collected at the Cambridge Centre for Ageing and Neuroscience (Cam-CAN) (Shafto et al., 2014) (resting-state and a passive auditory/visual perception task).The preprocessing steps can be found in (Taylor et al., 2017). The eyes-closed resting-state data consisted of minimum 520-second MEG recordings in each subject. The passive audio-visual task, referred to in the following as "passive task" data consists of 2-min recordings during which subjects were presented with either visual checkerboards or auditory tones (in random order).

The resting-state data was downsampled to 200Hz and epoched into 2-sec trials, resulting in samples with dimensions $3 \times 102 \times 400$, where the first dimension corresponds to the type of sensor (2 gradiometers and a magnetometer), the second to the MEG channel and the last to the time samples. In order to keep the same dimensions for the passive task data, we re-sampled the passive task data to 500Hz from 1000Hz and used the MNE-python (Gramfort et al., 2013) package to split the data in 800ms epochs with stimulus presented 150ms after beginning of the epoch resulting in samples with the same dimension of $3 \times 102 \times 400$.

### MEGNet: Our CNN architecture

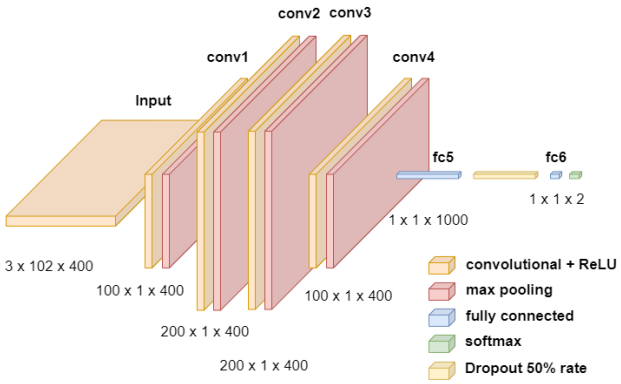



Figure 1: MEGNet network architecture used in this study (v1.0)

We set out to design a general-purpose CNN architecture for MEG classification. To this end we implemented a random grid search algorithm to find the best set of depth, filter size, number of channels and filters etc. Figure 1 shows an illustration of the resulting architecture, coined MEGNet, when optimized for a subset of the data and in a given classification task (e.g. biological sex identification). MEGNet is composed of 4 one-dimensional convolution layers followed by two linear layers. The First convolution layer is spatial, i.e. it aggregates information across channels at each time point. The following convolution layers are temporal (which allows them to also capture spectral information in the data).

We compared performances of our MEGNet architecture to the VGG network (Simonyan & Zisserman, 2014) and an adapted version of EEGNet (Lawhern et al., 2018), two popular CNN architectures previously used for MEG/EEG signal classification (Roy et al., 2019) (In prep: Dehgan, Rish, & Jerbi, 2022). We also included the multi-layer perceptron (MLP) architecture (Pal & Mitra, 1992) as a non convolution-based neural network.

### Classification Tasks

We investigated three classification tasks (n=643): (1) Sex prediction based on resting-state MEG, (2) Subject identification based on resting-state MEG (i.e. 643 classes), (3) Auditory vs visual stimulus classification. The latter also serves as a benchmark task to validate our latent space visualization approach because the spatial, temporal and spectral dynamics of the responses to visual and auditory stimuli are well established (Creel, 2019) (Picton, Hillyard, Krausz, & Galambos, 1974).

### Latent space visualization

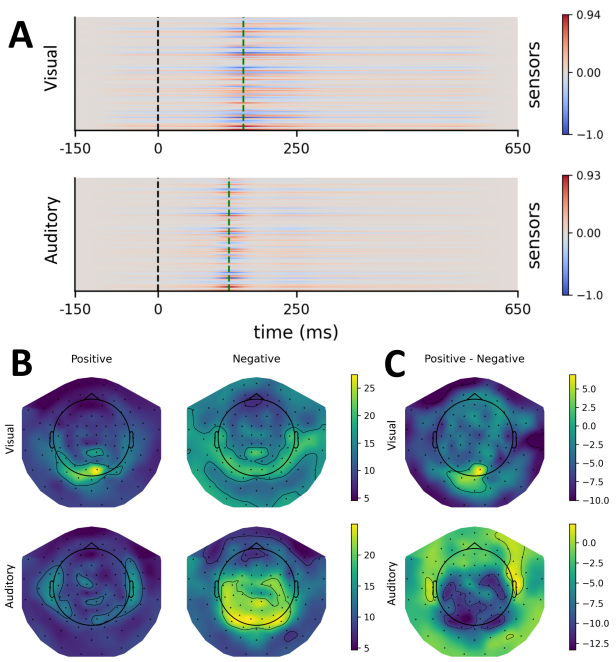



Figure 2: A: saliency maps averaged across all subjects for visual and auditory stimuli for the second array of gradiometers. B: Illustrative GGPSD values in the alpha band from Subject S8 for the auditory stimulus and S13 for the visual stimulus. C: contrast between GGPSD values from positive gradients and GGPSD values from negative gradients.

In order to visualize the latent space of our trained neural network and in the interest of finding how the neural network is able to perform accurate prediction of its target in a designated classification task, we developed a visualization tool adapted to MEG data. We first compute gradients for a specific class using guided back-propagation (Springenberg, Dosovitskiy, Brox, & Riedmiller, 2014) on trials for which our network has a confidence in its prediction that is superior to 95%. The collected saliency maps are then used to acquire information about when and where our networks finds useful information for a successful prediction. We defined useful information in the MEG signal as spots where saliency is superior to twice the standard deviation above the mean saliencies in a given trial. The useful spots in the signal are used to find salient 300ms window on which we compute power spectral density using the multi-taper method. We call the resulting PSD values gradient-guided PSD (GGPSD).

## Results

Table 1 lists the performance of the 4 networks tested on the classification tasks (the decoding accuracy scores are mean validation scores after 5-Fold cross-validation). Our network achieved the highest decoding in the auditory vs visual stimulus classification task (98.35%) and on the biological sex classification task (76.88%). However on the subject identification task, both EEGNet and VGG16 reached higher accuracies (99.81% and 99.58% respectively) while our network reaches 99.04%. The same table shows that our network has the lowest compute time across all 3 classification problems.

Table 1: Performances and compute time for MEGNet compared to benchmarks.

| Decoding Accuracy (%) | VGG16 | MLP | EEGNet | MEGNet |
|---|---|---|---|---|
| Auditory vs Visual | 94.39 | 94.52 | 96.34 | **98.35** |
| Sex Identification | 76.30 | 62.72 | 57.07 | **76.88** |
| Subject Identification | 99.58 | 89.70 | **99.81** | 99.04 |
| Compute Time (hours) | VGG16 | MLP | EEGNet | MEGNet |
| Auditory vs Visual | 2.8 | 13.6 | 6.7 | **0.5** |
| Sex Identification | 3.8 | 17.8 | 2.0 | **1.6** |
| Subject Identification | 18.2 | 6.5 | 13.0 | **3.6** |

The temporal evolution of saliency depicted in figure 2A, suggests the peak time for correctly classifying an auditory MEG trial is at 127 ms after stimulus onset, while it is at 153 ms for a visual stimulus. The gradient guided power spectral densities (GGPSD) topographies shown in the first row of 2B indicate that alpha activity in the occipital cortex contributes positively towards successful prediction of the visual stimulus whereas alpha -range activity in the auditory cortices contribute negatively to prediction of the visual stimulus. The second row of panel B, shows the opposite efffect for the prediction of auditory stimulus. Panel C shows the contrast between both maps highlighting the role of alpha power in occipital and bilateral temporal cortices in auditory vs visual stimulus encoding.

## Discussion

Our network reaches state-of-the-art accuracies in terms of subject identification and does so on the largest MEG subject identification study to date. Our network performances are not the highest but there is still room for optimization. Our aim when building the new architecture was to reach good accuracies on the multiple MEG tasks while still being lightweight, fast and easily interpretable. Future work includes comparisons with other networks used with EEG, such as LF-CNN and VAR-CNN from (Zubarev, Zetter, Halme, & Parkkonen, 2019) and the network used in (Van Putten, Olbrich, & Arns, 2018). It would also be of interest to compare our performance with shallow approaches based on commonly-used hand-crafted MEG/EEG features and see how well classical machine learning approaches perform on these tasks.

We used the auditory vs visual classification task as a benchmark for our visualization tool and the information gathered through our results are in line with the literature on alpha (visual) and tau (auditory) oscillations in the brain in response to auditory and visual stimuli (Creel, 2019), (Picton et al., 1974). The temporal saliency and GGPSD tools used here for visualization allow for an interesting view at what our network finds important for successful prediction in the temporal and spatial dimension.

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