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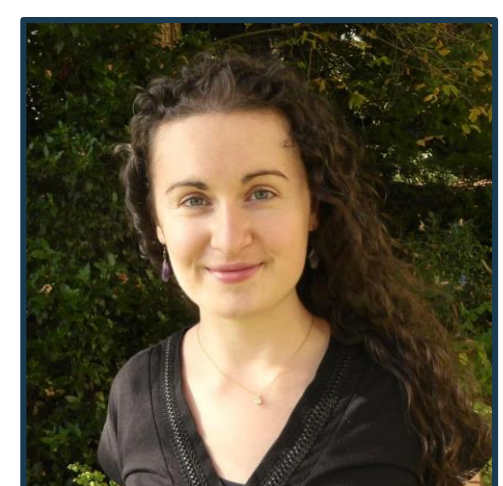
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# Can **neural networks** help improve portability of combined **EEG – fMRI neurofeedback**?

## Improving portability of bimodal neurofeedback: predicting NF-fMRI scores from EEG signals



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### Introduction

- **Neurofeedback** (NF) training is more effective with **simultaneous EEG-fMRI** acquisitions [1].
- However, **the use of MRI is expensive** and draining for the subject.
- So, we need to **reduce its use**.

→ We propose a method based on a one-dimensional **convolutional neural network (1D CNN)**. With this model, we aim to predict fMRI information from EEG recordings.

### Objective

Learning a **neural network model** from simultaneous EEG-fMRI data to **predict NF-fMRI scores from EEG signals alone**.

### Methods

1. **Data:** We acquired **simultaneous EEG-fMRI data** on 15 healthy subjects in a motor imagery context, described in [2]. This includes fMRI and EEG data for three NF runs of five minutes per subject, with their respective NF scores.
2. **Preprocessing:** We compute a **supervised learning dataset**, where a certain number of timesteps from a selection of EEG channels become one sample that has one NF score as target.
3. **Training:** We **train the 1D CNN model**. Since we have 15 subjects with 3 runs each, the training dataset consists of 14 subjects and 2 runs, the validation dataset of the third run from these 14 subjects, and the test dataset of the 3 runs from the 15<sup>th</sup> subject.
4. **Analysis:** After the model is trained, **NF-fMRI scores are predicted**, and compared to the ground truths with the RMSE and Pearson correlation metrics.

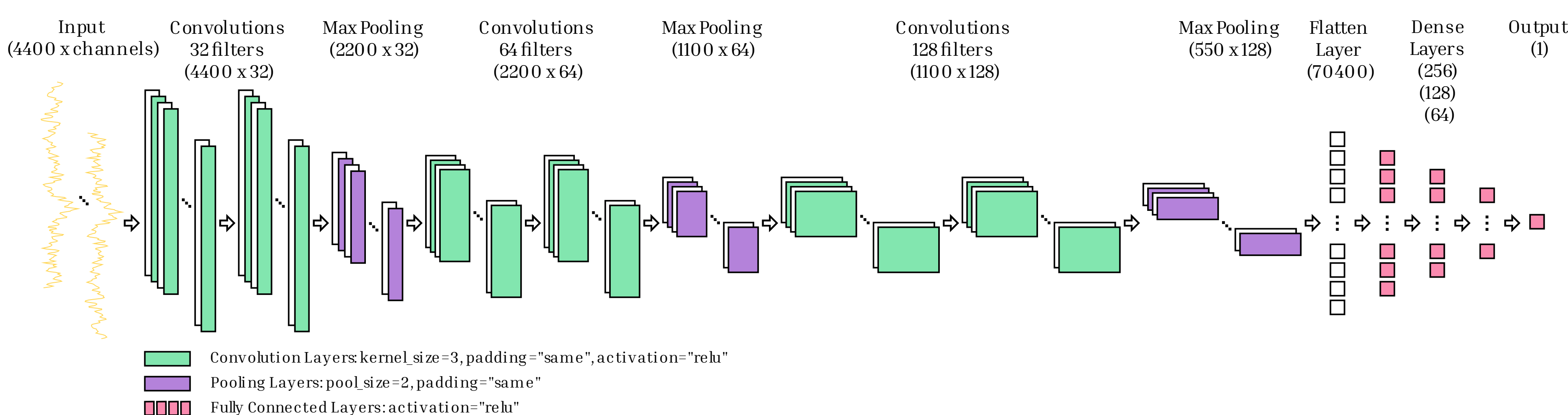
### Discussion

We are currently working on improving the correlations, which are negatively impacted by:

- Sensitivity to the neural network **hyperparameters**
- Noisy nature of the **EEG modality**
- **Lack of diversity in data**

### Conclusion

- The interest of this method compared to the previous modeling [3] is to train a single **deep learning model** for all subjects, which would eventually allow the use of the model to predict these fMRI scores directly online.
- An important aspect of the issue is to **interpret this model**, in order to understand links between EEG and fMRI.

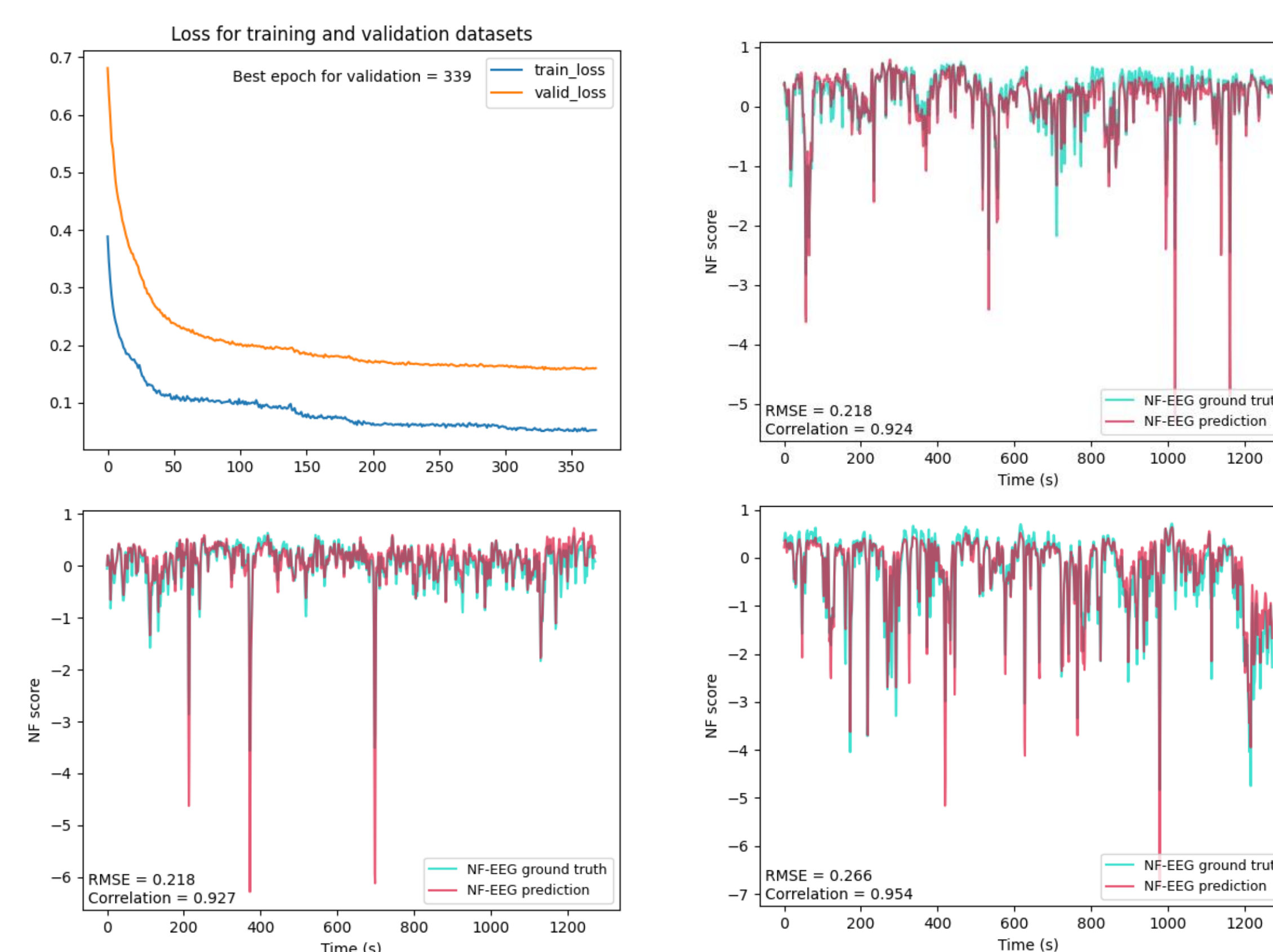


**Fig. 1:** Architecture of the 1D CNN used to predict NF-EEG and NF-fMRI scores from raw EEG signals. The input sample consists of 4400 timesteps from every EEG channels selected. When predicting NF-EEG scores, we select 9 channels corresponding to the laplacian of the C3 channel, and when predicting NF-fMRI scores, we select 25 channels above the motor area.

### Results

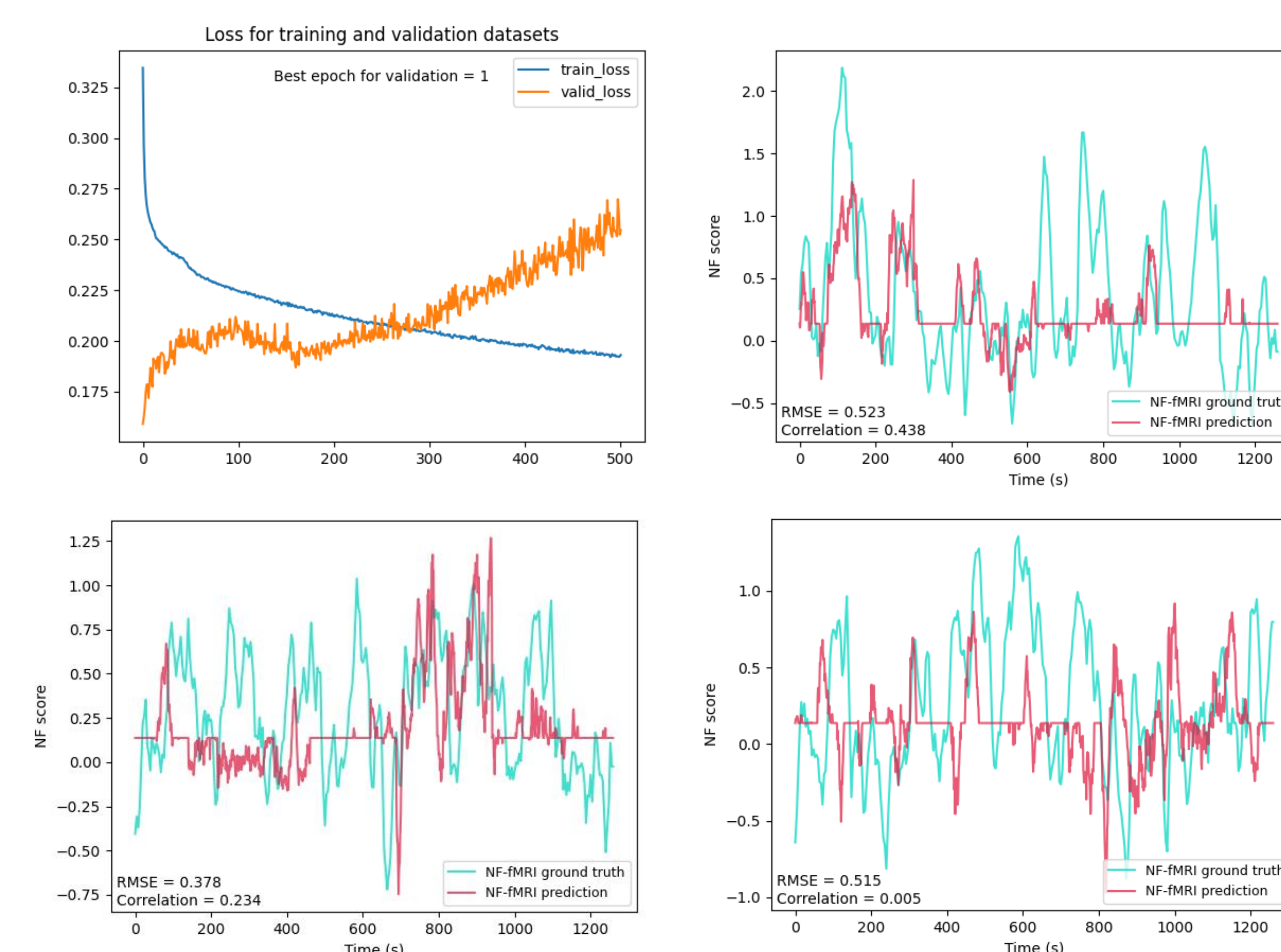
	Predicting NF-EEG scores	Predicting NF-fMRI scores
Mean RMSE	0.23	0.47
Mean correlation	<b>0.94</b>	<b>0.23</b>
Min-max correlation	(0.92 → 0.95)	(0.00 → 0.44)

### Predicting NF-EEG scores to validate our approach:



**Fig. 2:** Prediction of NF-EEG scores: train and valid loss curves (top left) and comparison between NF-EEG ground truth and NF-EEG prediction for the 1<sup>st</sup> run (top right), the 2<sup>nd</sup> run (bottom left) and the 3<sup>rd</sup> run (bottom right) from the test subject.

### Predicting NF-fMRI scores to achieve our goal:



**Fig. 3:** Prediction of NF-fMRI scores: train and valid loss curves (top left) and comparison between NF-fMRI ground truth and NF-fMRI prediction for the 1<sup>st</sup> run (top right), the 2<sup>nd</sup> run (bottom left) and the 3<sup>rd</sup> run (bottom right) from the test subject.



1. Perronnet et al. "Unimodal versus bimodal EEG-fMRI neurofeedback of a motor imagery task." (2017)
2. Lioi et al. "Simultaneous EEG-fMRI during a neurofeedback task, a brain imaging dataset for multimodal data integration." (2020)
3. Cury et al. "A sparse EEG-informed fMRI model for hybrid EEG-fMRI neurofeedback prediction." (2020)



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