Forecasting interictal epileptiform discharges in focal epilepsy with deep learning

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INTRODUCTION

- **Interictal epileptiform discharges (IEDs)** are transient events in hyper-excitable cortex.

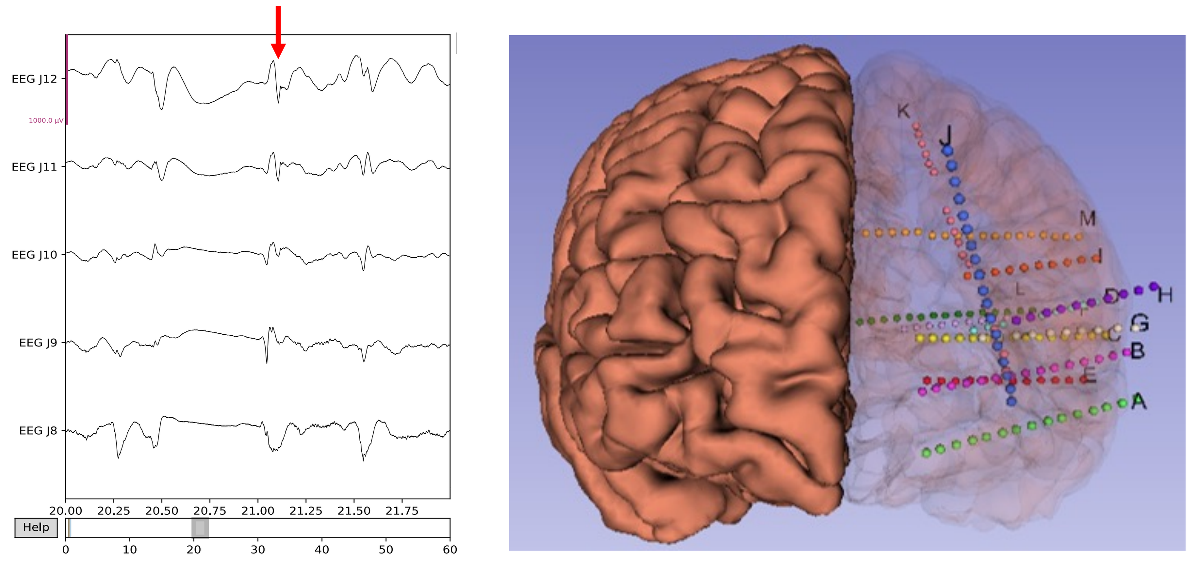


Figure 1: (left) An interictal epileptiform discharge. (right) SEEG depth electrode locations for patient 2.

- Elevated **cortical excitability** is common in uncontrolled epilepsy.
- IEDs serve as passive indicators of this heightened excitability.
- We introduce a novel metric: the forecasted likelihood of IEDs as a continuous measure of cortical excitability.
- This has the potential to guide therapeutic and diagnostic interventions in real-time.

OBJECTIVES

- Develop machine learning models to **forecast the likelihood of upcoming IEDs** using SEEG data.
- Assess model performance on patients not present in the training set.
- Visualise second-by-second changes in IED probability.

PATIENT CHARACTERISTICS

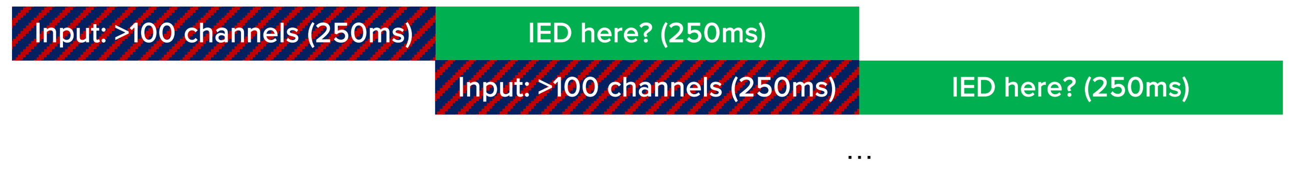
- SEEG recordings were obtained from six patients with drug-resistant epilepsy:

ID	Sex	Age	ASM	Drug reduction	Hypothesis	Seizure onset	Lesion
1	M	12	2	Yes	R Temp	Hippocampus	Yes
2	F	16	2	Yes	L Temp	Hippocampus	Unclear
3	M	5	3	Yes	R Temp	Hippocampus	Yes
4	M	8	1	Yes	R Temp	Hippocampus	No
5	M	14	3	No	L Temp	Hippocampus	No
6	F	17	3	Yes	R Temp	Amygdala	No

- Recordings are 2 hours per patient from >100 channels, resampled at 512 Hz.

DATA PREPARATION

- For each patient, data was segmented into 250ms epochs.
- Bandpass filtering and standardisation was applied to each epoch.
- Epochs were labelled based on the detection of an IED in the subsequent epoch, as determined by a machine learning detector[1]:



VALIDATION STRATEGY

- 3-fold cross-validation was employed.
- Each model was trained on 4 patients.
- AUC scores reported for the 2 unseen patients to assess model generalisability.

MODEL

- SEEG channels vary between patients, both in number and placement.
- An **attention-based remapping module**[2] was used to enable cross-patient models.
- Remapped SEEG epochs were then processed by ResNet-18, a **Convolutional Neural Network (CNN).**

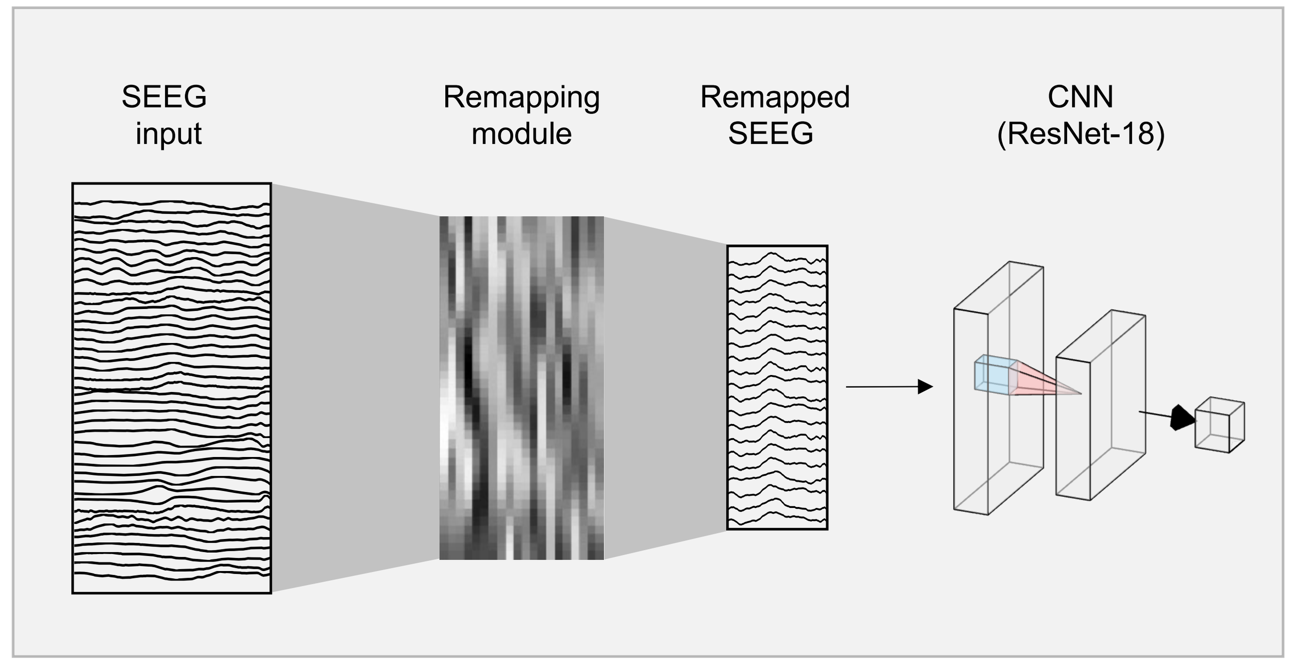


Figure 2: The model architecture. Inputs are remapped and then processed by ResNet-18.

RESULTS

- An **average AUC of 0.61** was achieved:

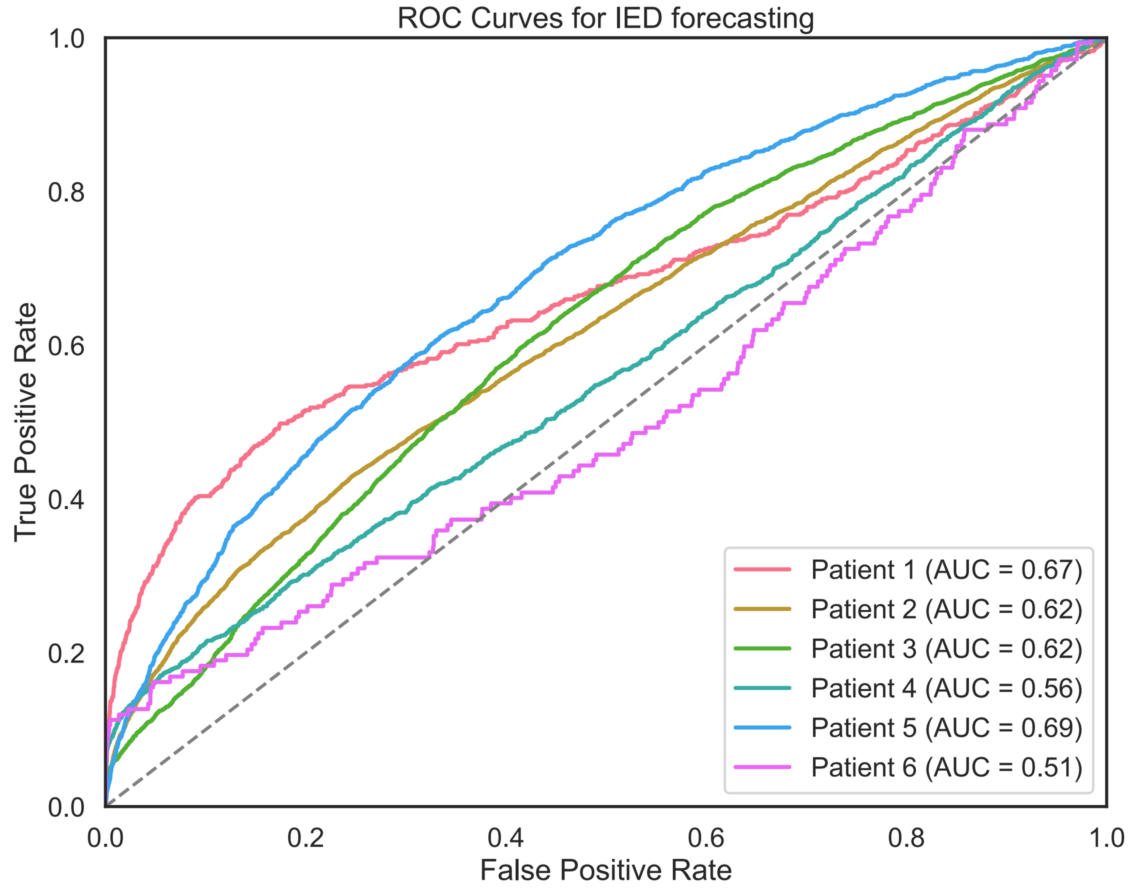


Figure 3: Model performance for each patient. The average AUC was 0.61.

DISCUSSION

- A significantly better performance than by chance was achieved for 5/6 patients, despite not having been trained on their data.
- For these patients, forecasted IED probability correlates with detected IEDs:

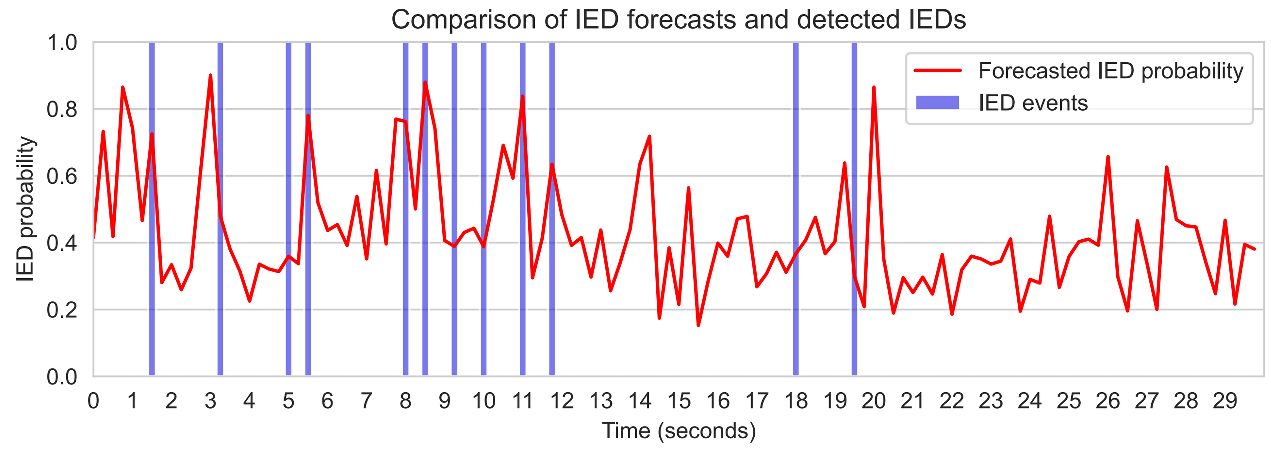


Figure 4: Forecasted IED probability alongside detected IEDs for a 30 second segment.

- At 0.61 AUC, the algorithm's performance is **suboptimal**, particularly compared to patient-specific models.
- Preliminary analysis suggests that the **remapping module is the bottleneck**; a larger cohort may address this issue.

NEXT STEPS

- Train/test models on a **larger cohort**.
- Investigate the relationship between model outputs and evoked responses to stimulation.

REFERENCES

[1] Baud, Maxime O., et al. "*Multi-day rhythms modulate seizure risk in epilepsy.*" Nature communications 9.1 (2018): 1-10.

[2] Saeed, Aaqib, et al. "*Learning from heterogeneous eeg signals with differentiable channel reordering.*" ICASSP 2021-2021 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP).