

### UNIVERSITY | TECHMED OF TWENTE. | CENTRE

### LEARNING TO WRITE MEDICAL REPORTS FROM EEG DATA

Automatic report generation

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### What is Epilepsy?

Neurological disorder

Over 70 Million people Worldwide

Increased likelihood of unprovoked seizures

# Time consuming EEG analysis and **EEG** recording

#### Motivation

Diagnosis is difficult/complex

report writing

Subjectivity

CLINICAL HISTORY: S8 year old right-handed gentleman with a history of epilepse, hepatitis C, prior right temporal hemorrhage, admitted following a cluster of seizures. Multiple injuries over the course or his life.

MEDICATIONS: Depakote, Keppra.

INTRODUCTION: Digital video EEG was performed in lab using standard 10-20 system of electrode placement with 1 channel of ENG. Photic stimulation is performed. The patient is

DESCRIPTION OF THE RECORD: The initial sections of the EEG demonstrate prominent, rhythmic slowing from the right temporal region, particularly the posterior temporal region. Ingular shape, periodic complexes, are noted at 16, 00, primarily at 16. As the recording confinence, additional shape wares are noted with a phase of reversal that is more med to anterior temporal 27-14. Focal showing accompanies these shape waves and there are bursts of local slowing mid to posterior temporal region and sometimes involving C4. Features of drousshess include an increase in background showing. Photic stimulation is performed while the patient is transitioning into stage 2 sleep and does not activate the record JHS: 96 bym.

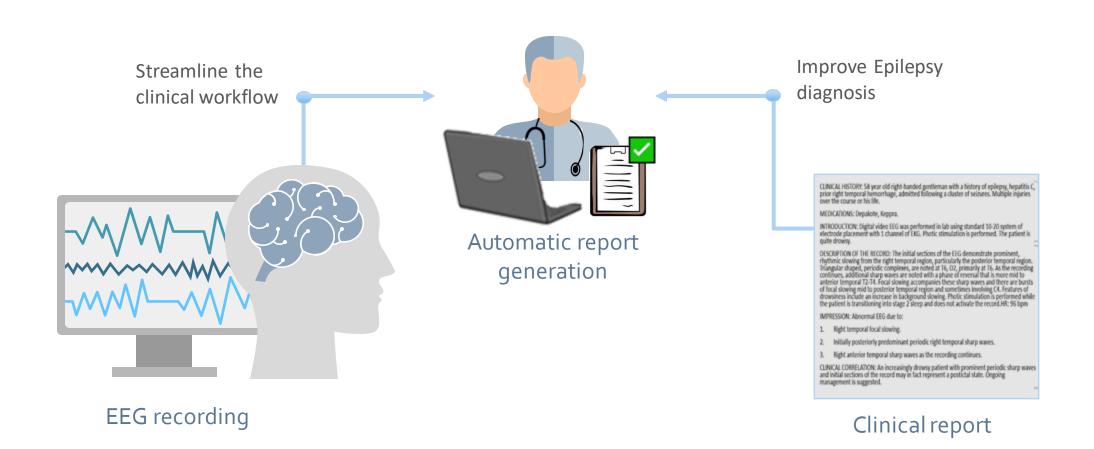
#### IMPRESSION: Abnormal EEG due to:

- Right temporal focal slowing.
- 2. Initially posteriorly predominant periodic right temporal sharp waves.
- 3. Right anterior temporal sharp waves as the recording continues.

CLINICAL CORRELATION: An increasingly drowsy patient with prominent periodic sharp waves and initial sections of the record may in fact represent a posticial state. Ongoing management is suggested.

Clinical report

## What if we could "translate" what the brain is saying?



## What if we could "translate" what the brain is saying?





CLINICAL HISTORY: 58 year old right-handed gentleman with a history of epilepsy, hepatitis C, prior right temporal hemorrhage, admitted following a cluster of seitures. Multiple injuries over the course or his life.

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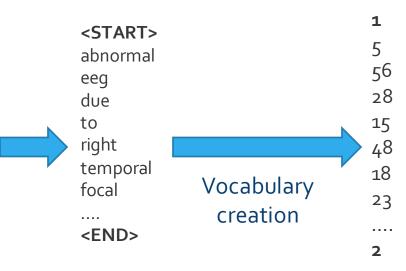
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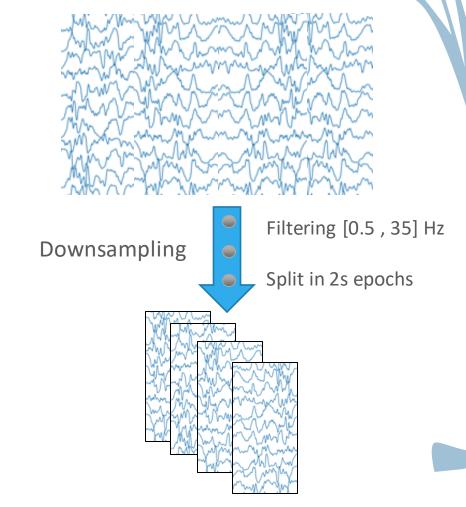


abnormal eeg due to right temporal focal slowing and predominance of sharp waves, initially in the right posterior temporal region and continuing in the right anterior temporal region.

#### Clean and normalize text

**Data Preparation** 





Tokenization

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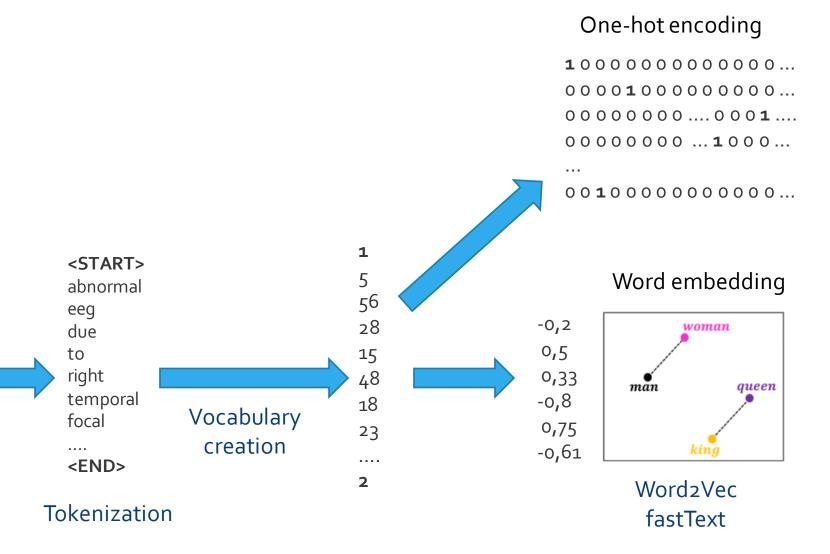
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#### Clean and normalize text

### **Data Preparation**



#### Dataset

Clinical EEG database of Temple University Hospital (TUH EEG Corpus)

• Patient gender:

51% Female 49% Male Patient age :

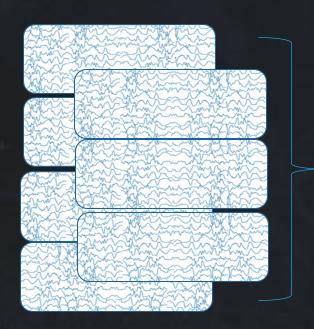
1 - 90 years old average 51.6 years

Table 1. TUH EEG Seizure Corpus

Set	Total AR Sessions	Sessions with Impression section	Patients	Epochs (2s)	Times (hours)
Train	687	641	304	904640	251
Test	182	167	36	263307	146
Total	869	808	340	1167947	398

### Challenges & Limitations

EEG signals are extremely variable and affected by noise.



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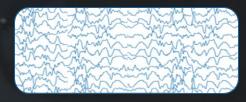
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CLINICAL CORRELATION: An increasingly drowsy patient with prominent periodic sharp waves and initial sections of the record may in fact represent a posticial state. Ongoing management is suggested. The content, the **detail** of the report and the **style of writing** are very characteristic of each doctor

EEG signals are time series with different lengths

### Challenges & Limitations

Deep learning models need a lot of data to learn efficiently



I have no idea what this is...

How can I write ...?

Train: 641 reports (80%)
Test: 167 reports (20%)

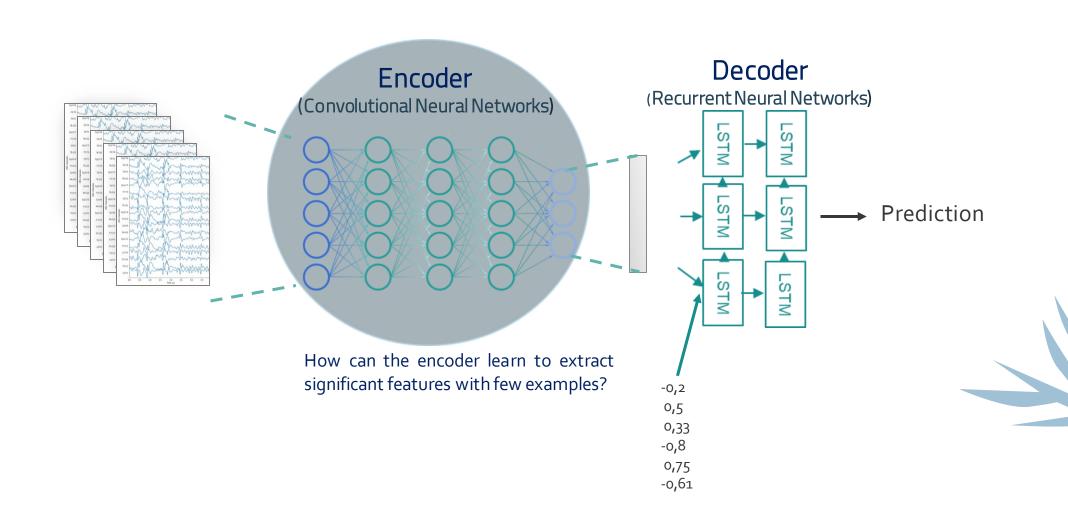
Lack of annotations of TUH EEG dataset and data imbalance

TUH EEG Seizure Corpus (epileptic/no-epileptic)

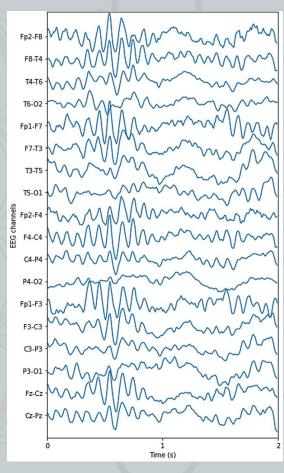
#### Phenotypes:

- normality
- generalized slowing
- focal slowing
- epileptiform discharges
- seizures
- abnormal delta waves
- sharp waves
- .

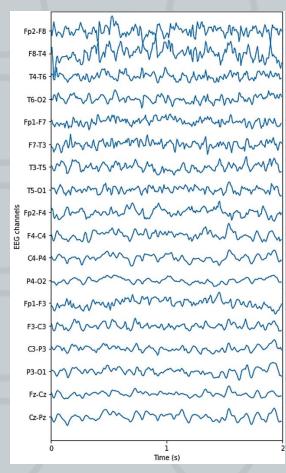
### Encoder-Decoder architecture



### Pre-training Encoder

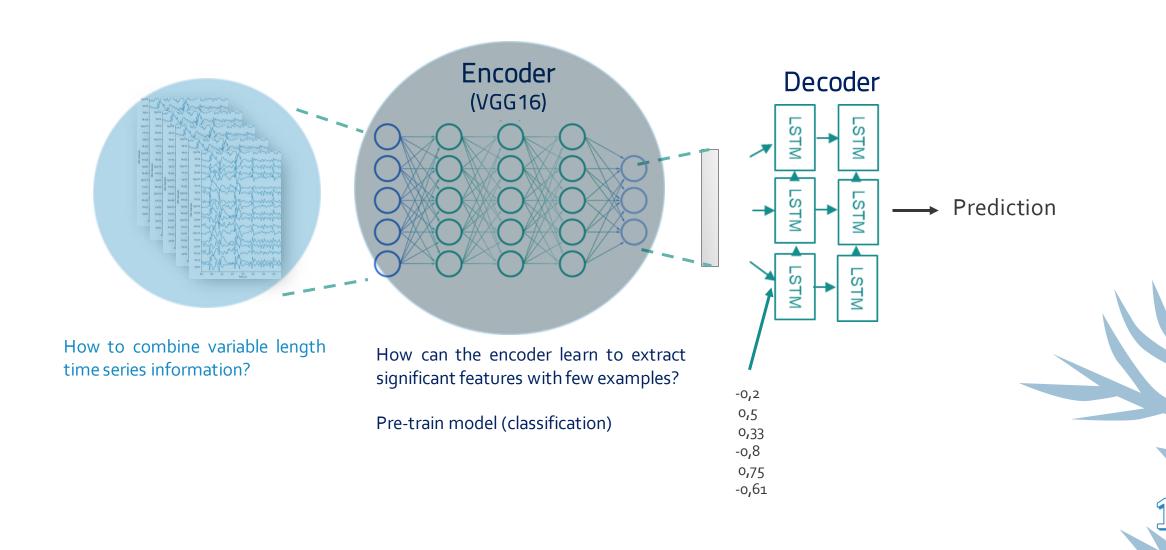


Epileptic event (Spikes and/or Sharp Waves: SPSW)

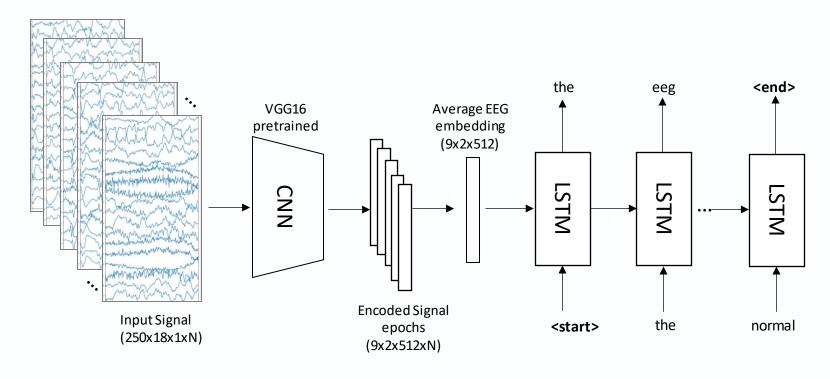


No-Epileptic event (Background: BCKG)

### Encoder-Decoder architecture

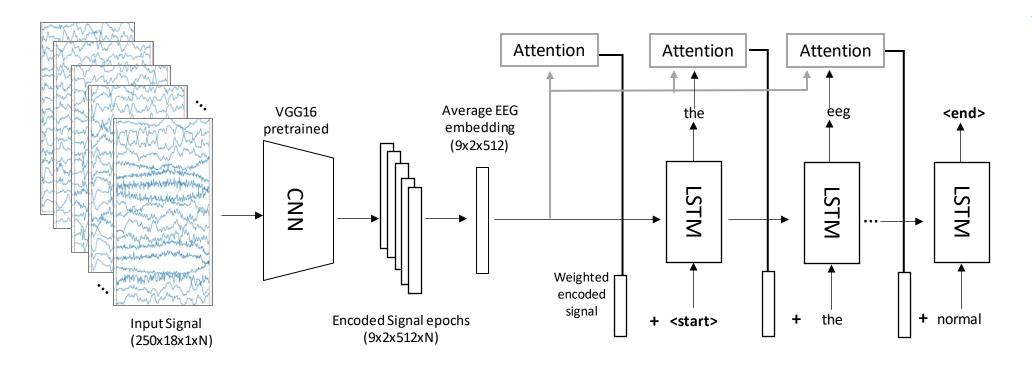


## Average EEG Embedding (CNN-LSTM)

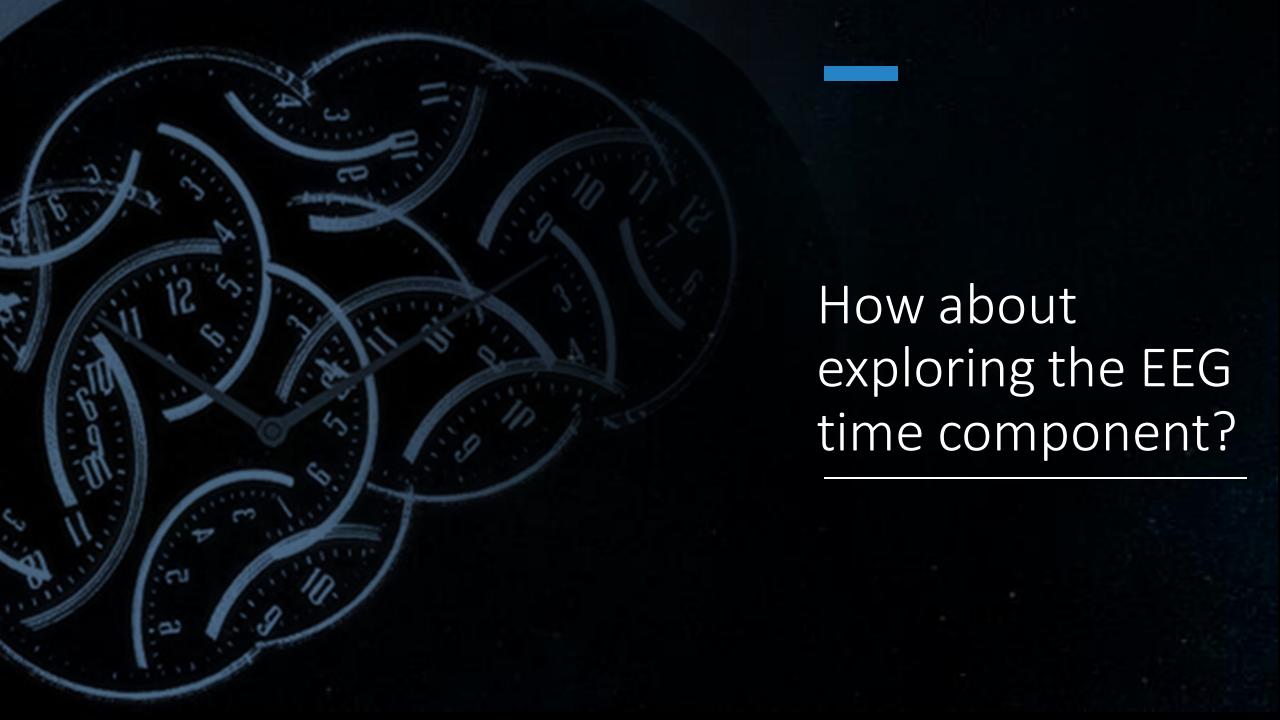




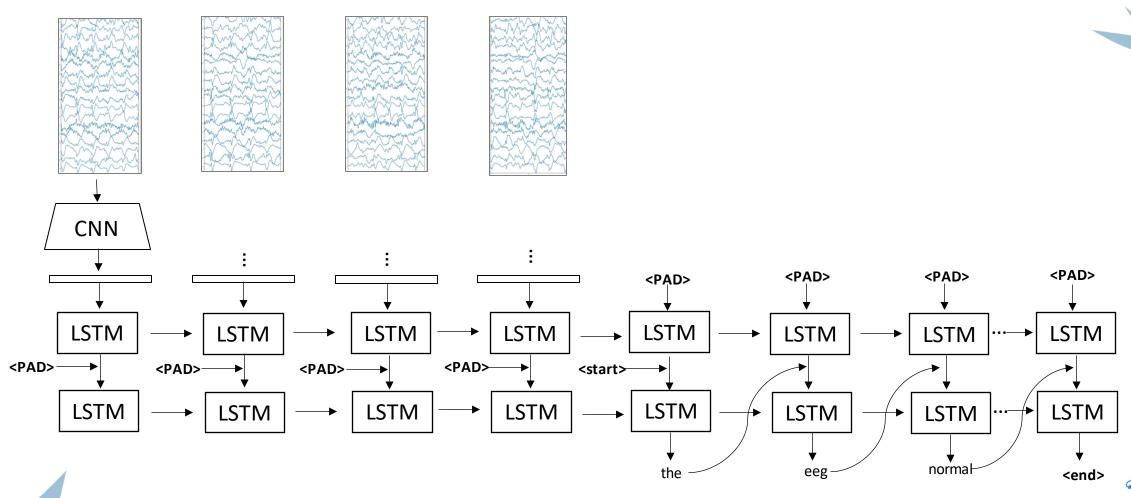
## Average EEG Embedding (CNN-Att-LSTM)



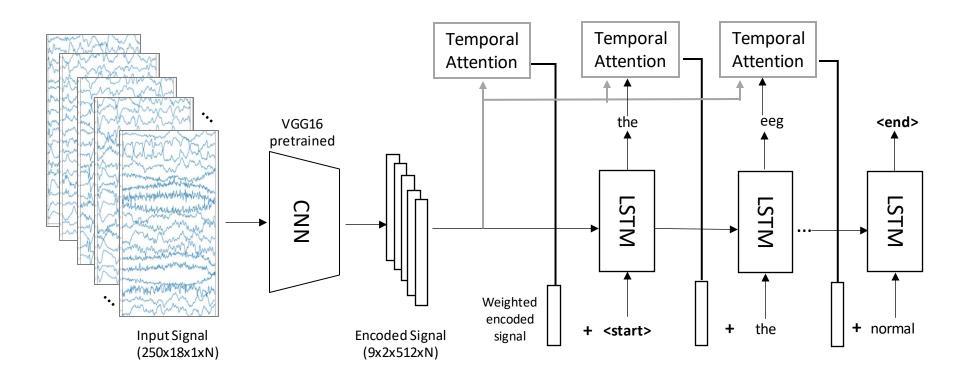




## Sequence to Sequence (Seq2seq)

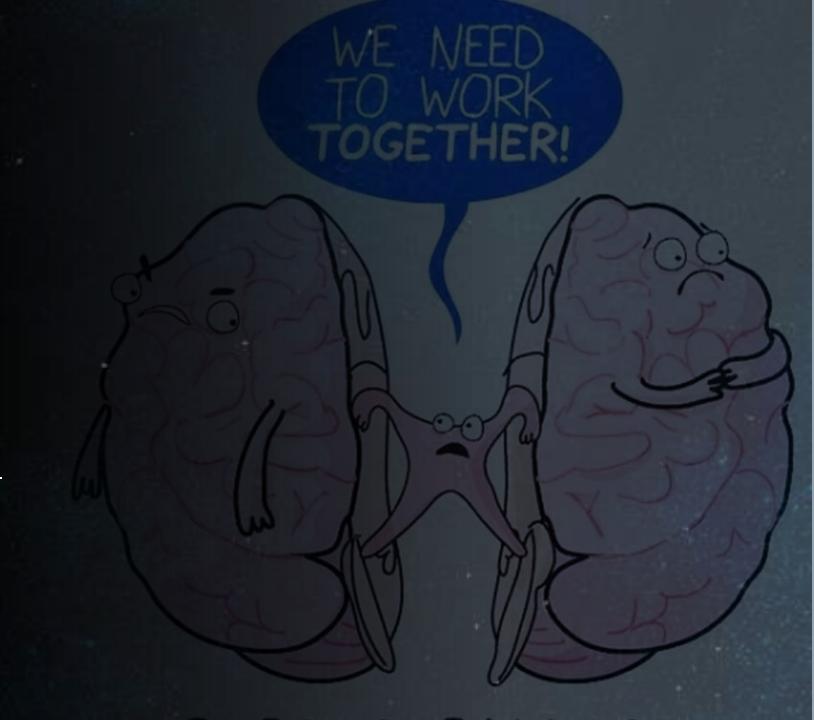


## Temporal Attention Mechanism (TAM)

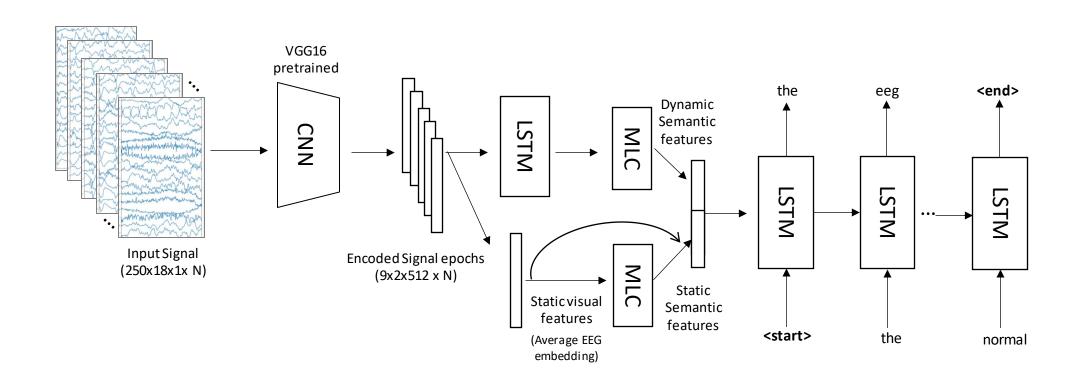




Maybe combine static and dynamic?

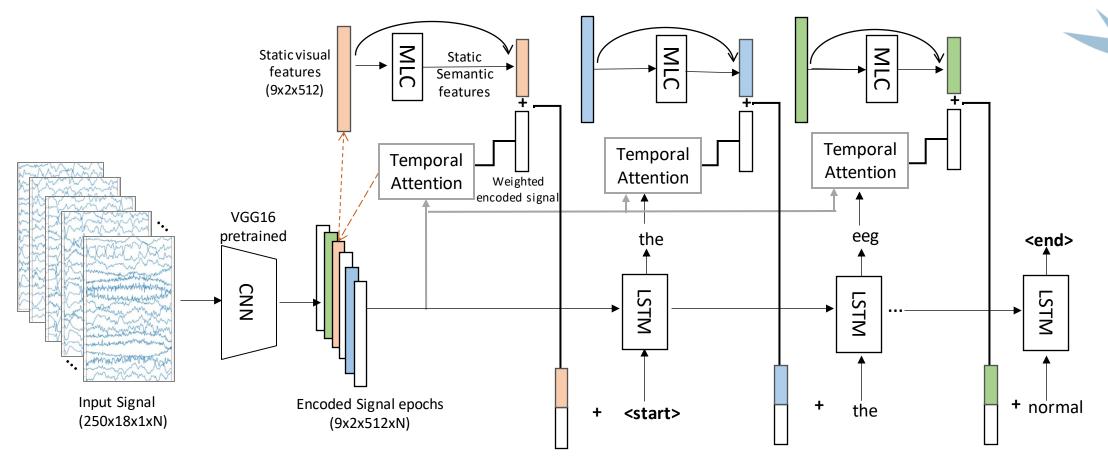


### Multi-Stream Models (Multi-stream-Avg)



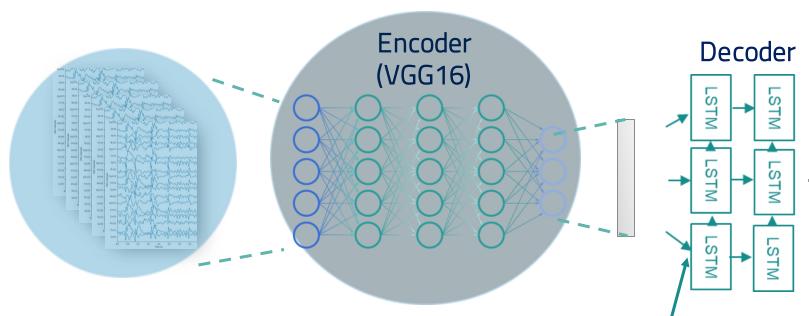


### Multi-Stream Models (Multi-stream-TAM)





#### Encoder-Decoder architecture

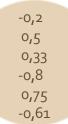


How to combine variable length time series information?

- 1. Average EEG Embedding
- 2. Sequence to Sequence
- 3. Temporal Attention mechanism
- 4. Multi-stream

How can the encoder learn to extract significant features with few examples?

Pre-train model (classification)



Does the vectorization technique impact the (quality of) report generation?

Prediction

- 1. One-hot encoding
- 2. Random initialization
- 3. Word2Vec
  - . fastText





#### Classification Task

Table 2. VGG16 Model performance for binary classification (SPSW and BCKG)

Set	AUC	Sensitivity	Specifity	Precision	F1-score
Train	0,81	88%	75%	25%	0,39
Test	0,80	82%	77%	28%	0,42

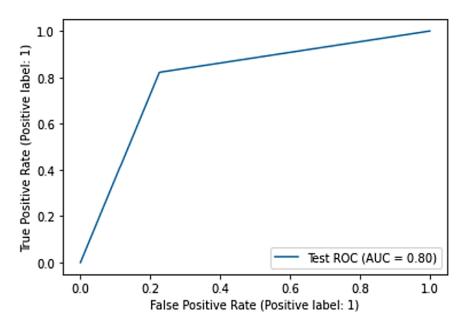


Fig 1. ROC curve on test set

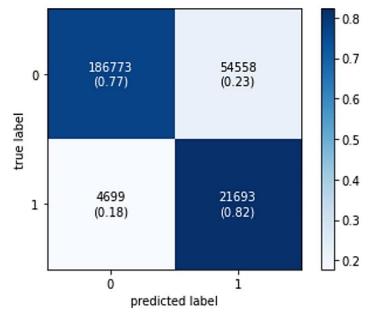


Fig 2. Confusion matrix (0-negative, 1-positive)

## Impact of text representation approaches

Table 3: Results from CNN-LSTM using different word embeddings

Method	BLEU1	BLEU2	BLEU3	BLEU4	METEOR	ROUGE_L	CIDEr	SPICE
One-Hot encod.	53,5	39,7	31,6	25,1	21,4	44,2	15,5	18,2
Random init.	54,1	40,6	32,4	25,7	21,6	44,3	22,3	17,3
Word2Vec	54,6	39,1	25,6	14,7	17,6	35,8	14,2	17,4
fastText	49,5	37,1	25,4	15,7	17,8	37,2	14,0	16,8

Table 4. Model performance of all captioning approaches with random embedding initialization

Method	BLEU1	BLEU2	BLEU3	BLEU4	METEOR	ROUGE L	CIDEr	SPICE
CNN-LSTM	54,1	40,6	32,4	25,7	21,6	44,3	22,3	17,3
CNN-Att-LSTM	50,5	38,9	31,3	25,0	20,7	42,5	16,9	17,1
Seq2seq	51,2	35,9	26,9	19,9	17,6	40,1	16,4	13,6
TAM	52,2	39,8	32,0	25,7	20,0	44,1	16,5	16,9
Multi-stream-Avg	56,3	43,4	35,0	28,3	23,3	46,0	21,8	18,4
Multi-stream-TAM	54,8	41,4	32,9	26,3	23,2	44,7	21,5	19,3

Table 5. Model performance of average embedding-based models

Method	BLEU1	BLEU2	BLEU3	BLEU4	METEOR	ROUGE_L	CIDEr	SPICE
CNN-LSTM	54,1	40,6	32,4	25,7	21,6	44,3	22,3	17,3
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Table 6. Qualitative model evaluation of average embedding-based models

Methods	Generated report
CNN-LSTM	this eeg is marked by the occurrence of sharp waves and generalized slowing.
CNN-Att-LSTM	this eeg is marked by the occurrence of several <b>seizures</b> , in addition to the <b>focal slowing</b> in the right posterior quadrant.

**Ground truth:** abnormal eeg due to the arising of intermittent left occipital focal **seizures**, in addition to **background slowing** and focal left hemispheric **slowing** 

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### Could models.elfhattiaelyuthtaratteetizattiere?eg re

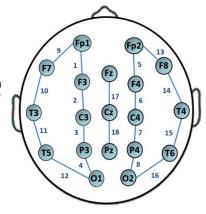


Table 7. Qualitative model evaluation of all captioning approaches

Methods	Generated report
CNN-LSTM	this eeg is marked by the occurrence of sharp waves and generalized slowing.
CNN-Att-LSTM	this eeg is marked by the occurrence of several seizures , in addition to the <b>focal slowing</b> in the <u>right posterior</u> quadrant.
Seq2Seq	this eeg is remarkable for <b>focal</b> <u>right hemispheric</u> slowing, mild to moderate diffuse slowing and focal voltage attenuation.
TAM	abnormal eeg due to the arising of multiple frequent seizures and moderate diffuse slowing.
Multi-stream-Avg	this eeg is marked by the occurrence of seizure, in addition to continuous <b>focal slowing</b> and moderate diffuse background slowing.
Multi-stream-TAM	this eeg is marked by the occurrence of seizure , in addition to <b>focal slowing</b> in the <u>left</u> <u>anterior temporal</u> region with diffuse background slowing .

Ground truth: abnormal eeg due to the arising of intermittent left occipital focal seizures, in addition to background slowing and focal <u>left hemispheric</u> slowing

### Could models effectively characterize the EEG recording?

Table 8. Qualitative evaluation of model performance, generating clinical report from a normal EEG

Methods	Generated report
CNN-LSTM	this eeg is remarkable for focal delta activity in the right hemisphere and marked background slowing.
CNN-Att-LSTM	this eeg is remarkable for focal slowing in the right temporal region.
Seq2Seq	abnormal eeg because of multiple left frontal electrographic seizures , in addition to focal slowing in the left hemisphere.
TAM	this eeg is marked by the occurrence of seizure , in addition to the focal slowing from the right hemisphere .
Multi-stream-Avg	this eeg is marked by the occurrence of seizure, in addition to continuous focal slowing and moderate diffuse background slowing.
Multi-stream-TAM	this eeg is marked by the occurrence of seizure, in addition to focal slowing in the left anterior temporal region with diffuse background slowing.

**Ground truth:** eeg within the normal limits.

#### Conclusions

It is possible and there is a **great potential** in generating clinical reports from EEGs, but EEG captioning models are **not yet ready for** implementation in **clinical practice** 

- The main limitations are related to the dataset
- Compromise between the amount of data and the complexity of the models
- Feature extraction and summarization in global embeddings are one of the major challenges
- Models are restricted regarding the diversity of phenotypes
- Models generate incomplete reports and have difficulty in identifying locations
- Model performance is still far from optimal

#### Conclusions → Future work

- Feature extraction and summarization in global embeddings are one of the major challenges
- → Multi-stream-Avg seem promissing but need to be further studied and improved :
  - Datasets
  - Assess the efficiency of feature extraction
  - Pre-training the streams
  - Use 3D-CNN instead of 2D-CNN

- Model are restricted regarding the diversity of phenotypes
- → Train in a more comprehensive database
- Model Generate incomplete reports and have difficulty in identifying locations.
- → Dense Captioning approach

Model performance is still far from optimal

- → Training with larger datasets;
- Transformer-based architectures:
  - Multiple stack transform layers
  - ClinicalBERT or BioBERT



#### Future work

- Multi-stream-Avg seem promissing but need to be further studied and improved
- Train in a more comprehensive database
- Dense Captioning approach
- Training with larger datasets
- Transformer-based architectures
- GANs

How far are we from the implementation of such a system in the clinic?

- Clinical validation by a group of experts
- Model interpretability (XAI)

