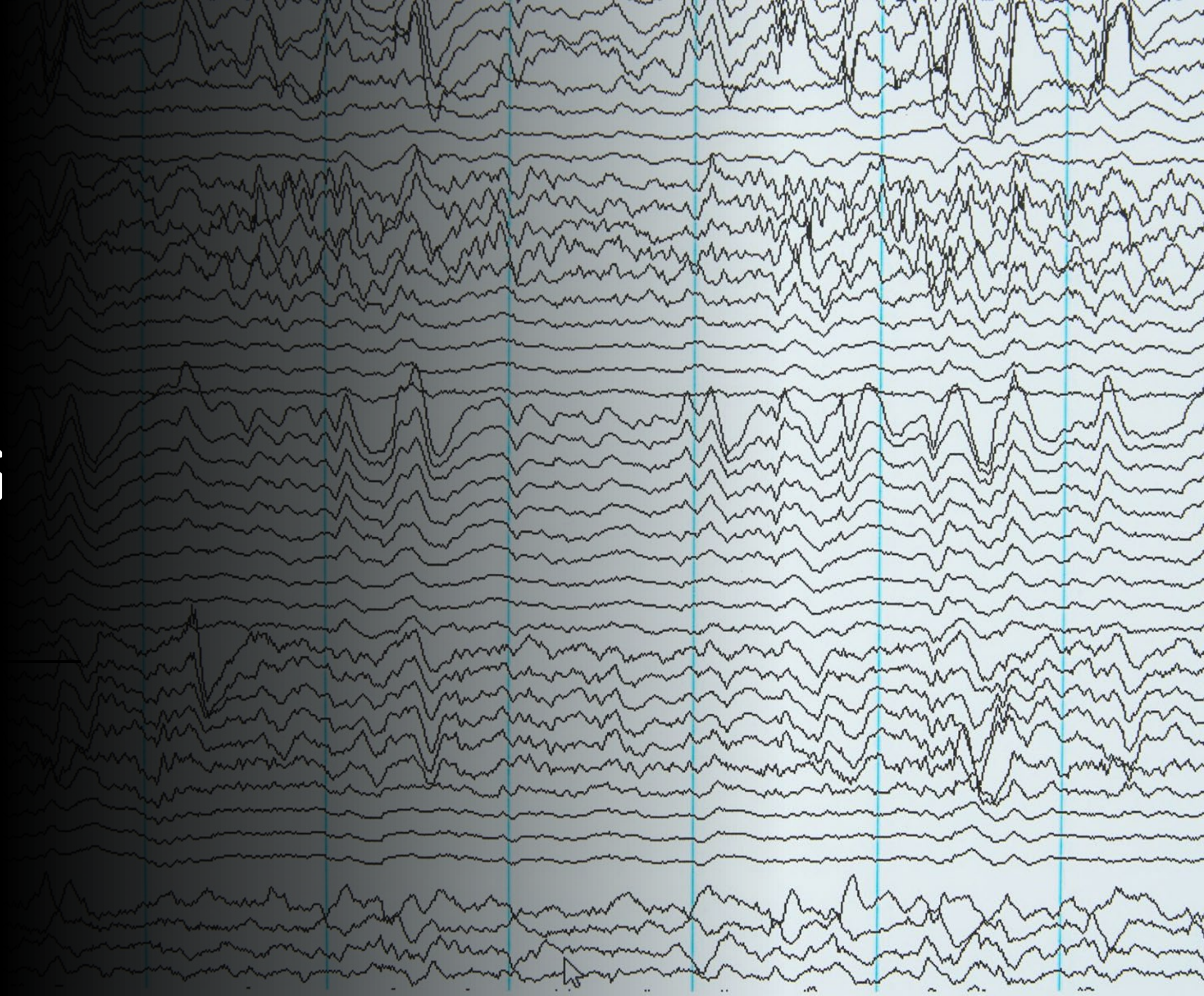
Mice Sleep Staging from EEG and EMG signals



ECE 408 Project Presentation

Fazla, Paul, Yixuan, Yanlong

Introduction: Background and Motivation

Sleep Staging and Its Importance

- Sleep, a fundamental behavior with vast biological implications, is typically classified into stages: Wakefulness, REM, and non-REM.

- Understanding sleep stages is critical for both preclinical and clinical research, providing insights into sleep architecture and related disorders for mice.

Introduction: Background and Motivation

Challenges in Sleep Staging

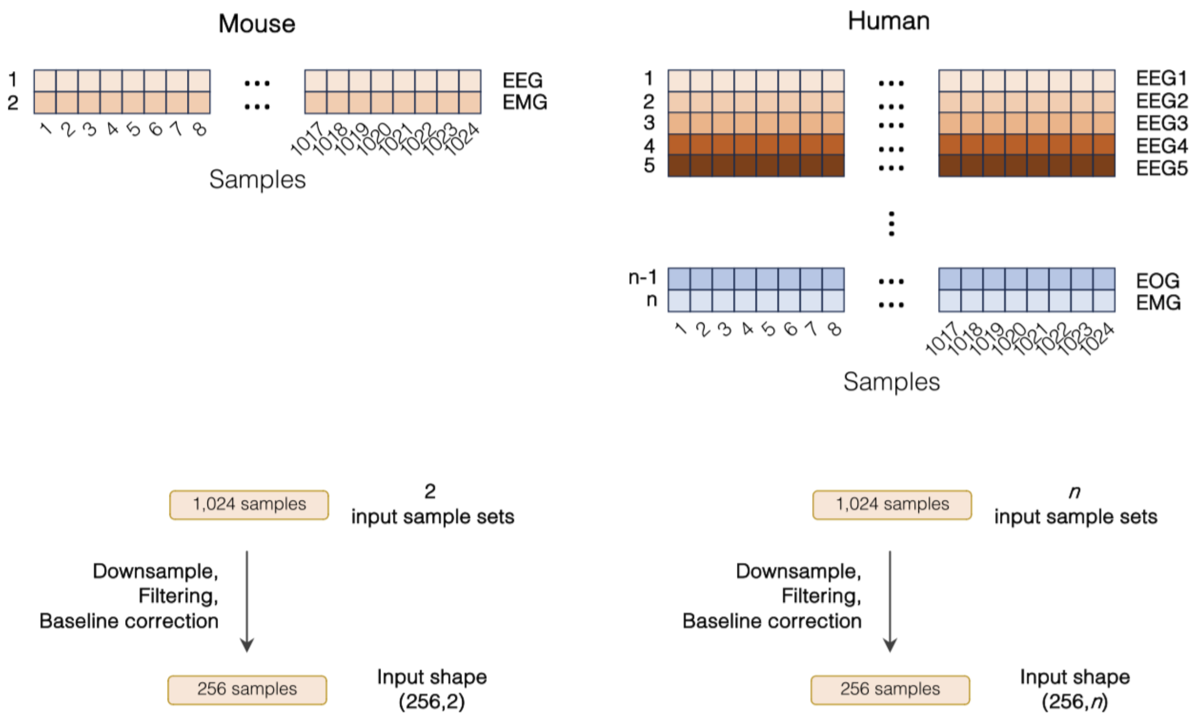
- Traditional methods are labor-intensive and require expertise, making automated solutions a necessity.
- However, current automated methods face challenges, such as larger resolution (4 sec - 10 sec) and a lack of unified models that can handle various input sources.

Literture review

The research paper by Justus T. C. Schwabedal et al. focuses on sleep stage classification and EEG artifact detection in mice using a deep neural network model

artifact-free data VS artifact data

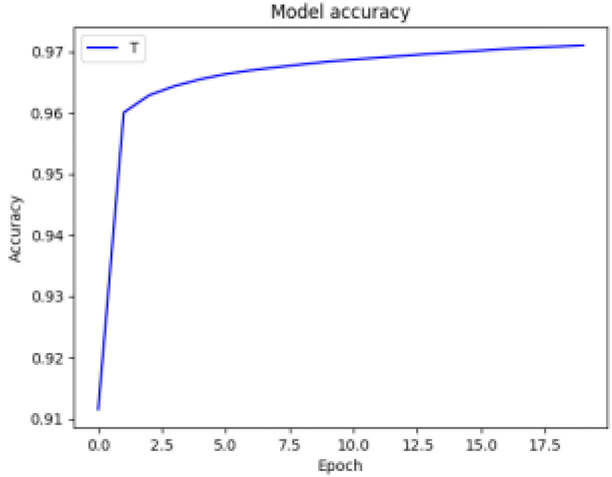
Research by Akara Suprata et al. introduces a deep learning model that utilizes Convolutional Neural Networks (CNNs) to extract time-invariant features from raw single-channel EEG data



Connection between mice and human

Baseline and Implement
A novel approach- SlumberNet

Implementation of the SlumberNet

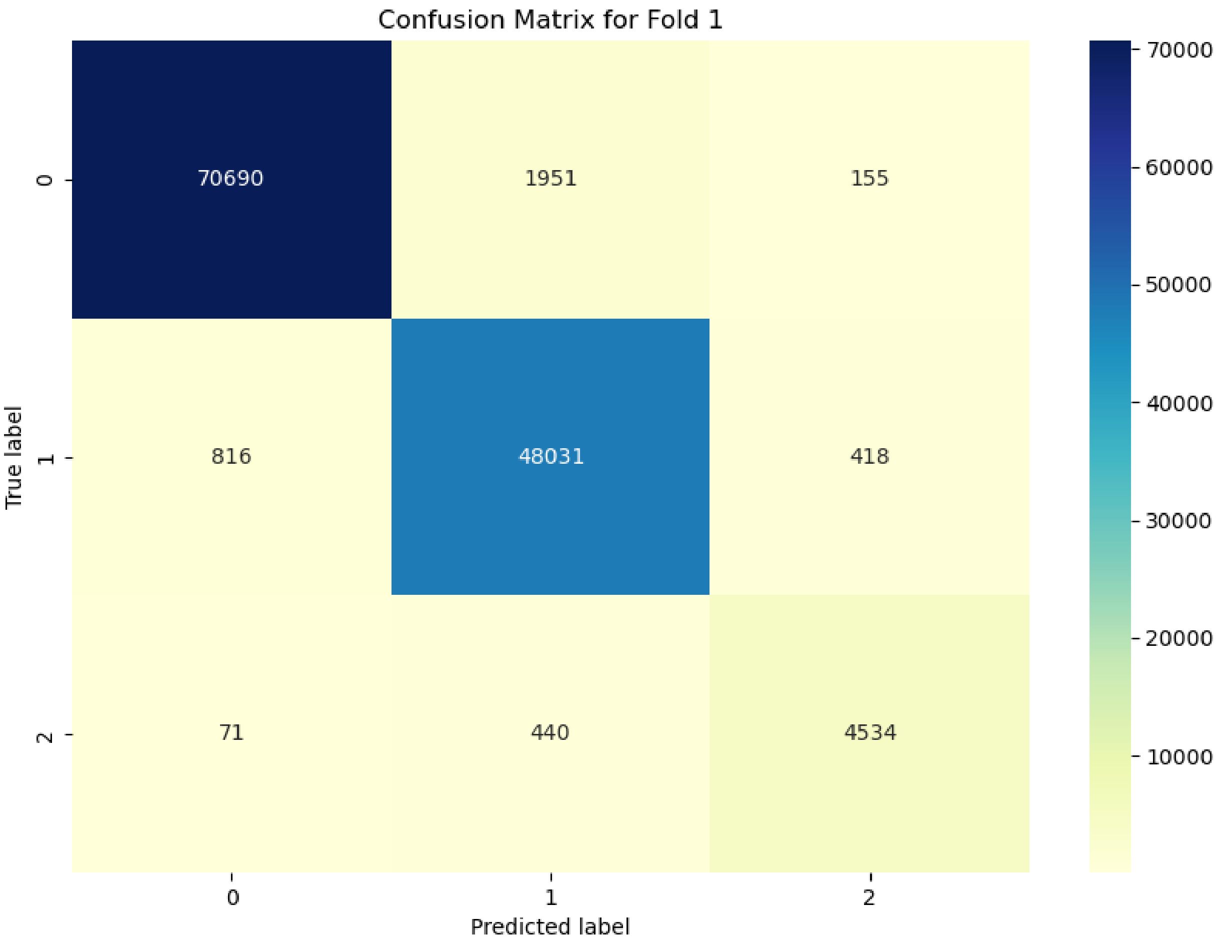


Residual Neural Network

Data preprocess

```
Epoch 20/20
4966/4966 [==============================] - 435s 88ms/step - loss: 0.0838 - accuracy: 0.9710 - lr: 1.0000e-06
```

complex

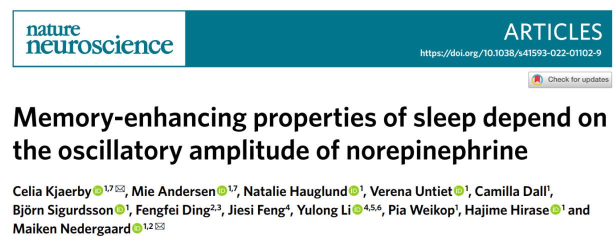


Confusion Matrix for Fold 1
70690
1951
155
816
48031
418
71
440
4534
True label
Predicted label
0
1
2
70000
60000
50000
40000
30000
20000
10000

Dataset

Data Collection

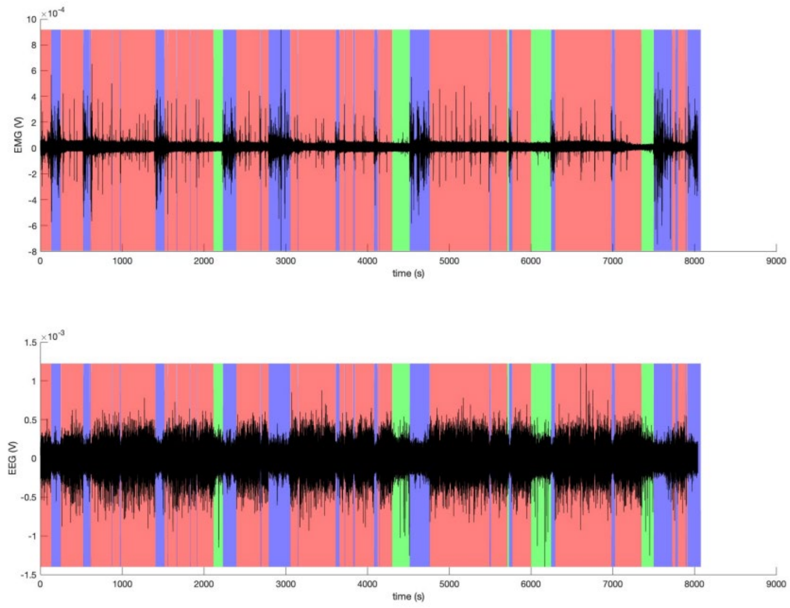
- The dataset comprises electrophysiological **time-series data, specifically EEG and EMG** signals collected during sleep studies on mice.
- Expert annotations provide second-by-second sleep stage labels corresponding to Wake, SWS (slow-wave sleep), or REM (rapid eye movement) states.



nature neuroscience
ARTICLES
https://doi.org/10.1038/s41593-022-01102-9
Check for updates

Memory-enhancing properties of sleep depend on the oscillatory amplitude of norepinephrine

Celia Kjaerby[1,7] ✉, Mie Andersen[1,7], Natalie Hauglund[1], Verena Untiet[1], Camilla Dall[1], Björn Sigurdsson[1], Fengfei Ding[2,3], Jiesi Feng[4], Yulong Li[4,5,6], Pia Weikop[1], Hajime Hirase[1] and Maiken Nedergaard[1,2] ✉



Dataset

Dataset Statistics

- Subjects: Data from 8 mouse subjects, both male and female.
- Sampling Rate: EEG and EMG signals sampled at 512 Hz.
- Duration: Approximately 4 hours per subject, leading to millions of data points.
- Labels: Expert-scored stages for rigorous evaluation.

Data Preprocessing

- Irregularity Removal: Periods with uncertain stage classification are excluded to ensure data consistency.
- Notch filtering
- Bandpass filtering EEG (.5 to 70 Hz), EMG (1 to 250 Hz)
- Subject-wise Normalization: Signal normalization accounts for individual variability in electrophysiological signal features.
- Temporal Slicing: Signals are segmented into one-second epochs to match the temporal resolution of sleep stage labels.

CNN-based model

```python
def conv_1d(ni, nf, kernel_size, stride, padding, drop=None):
    return nn.Sequential(
        nn.Conv1d(ni, nf, kernel_size=kernel_size, stride=stride, padding=padding),
        nn.PReLU(),
        nn.BatchNorm1d(nf),
        nn.Dropout(drop) if drop else nn.Identity()
    )

# Modify the Classifier class for regular 1D convolutions
class Classifier(nn.Module):
    def __init__(self, raw_ni_EEG, fft_ni_EEG, raw_ni_EMG, fft_ni_EMG, no, drop=.5):
        super().__init__()

        self.raw_EEG = nn.Sequential(
            conv_1d(raw_ni_EEG, 32, 8, 1, 3, drop=drop),
            conv_1d(32, 64, 3, 1, 1, drop=drop),
            conv_1d(64, 128, 8, 2, 2, drop=drop),
            conv_1d(128, 128, 3, 1, 1, drop=drop),
            conv_1d(128, 256, 8, 2, 2),
            conv_1d(256, 256, 3, 1, 1),
            nn.AdaptiveAvgPool1d(1),
            nn.Flatten(),
            nn.Dropout(drop),
            nn.Linear(256, 64),
            nn.PReLU(),
            nn.BatchNorm1d(64)
        )
```

Design Approach

Utilize 1D convolutional layers to extract temporal features from raw time-series data.

Apply ReLU activation for non-linearity and Batch Normalization to stabilize training.

Implement Dropout for regularization and to prevent overfitting.

Architecture Components:

Raw Signal Pathways (EEG & EMG):

1. Capture features from raw EEG and EMG signals.
2. Sequential layers of 1D convolutions with progressive downsampling.
3. Adaptive Average Pooling to convert feature maps into a flat vector.

Fourier Transformed Signal Pathways (FFT-EEG & FFT-EMG)

1. Process FFT-transformed signals to exploit frequency domain information.
2. Similar layer structure as raw signal pathways for feature extraction.

Output Layer

1. Concatenates outputs from all pathways.
2. Final classification performed with fully connected layers.

Result for CNN-based Approach

Class Name	Precision	1-Precision	Recall	1-Recall	f1-score
Awake	0.8414	0.1586	0.9321	0.0679	0.8844
NREM	0.9177	0.0823	0.8518	0.1482	0.8835
REM	0.4629	0.5371	0.5413	0.4587	0.4990

Training Set

TARGET / OUTPUT	Awake	NREM	REM	SUM
Awake	32895 29.57%	6073 5.46%	127 0.11%	39095 84.14% 15.86%
NREM	2258 2.03%	58863 52.91%	3019 2.71%	64140 91.77% 8.23%
REM	138 0.12%	4169 3.75%	3712 3.34%	8019 46.29% 53.71%
SUM	35291 93.21% 6.79%	69105 85.18% 14.82%	6858 54.13% 45.87%	95470 / 111254 85.81% 14.19%

Awake:NREM:REM(4:8:1)

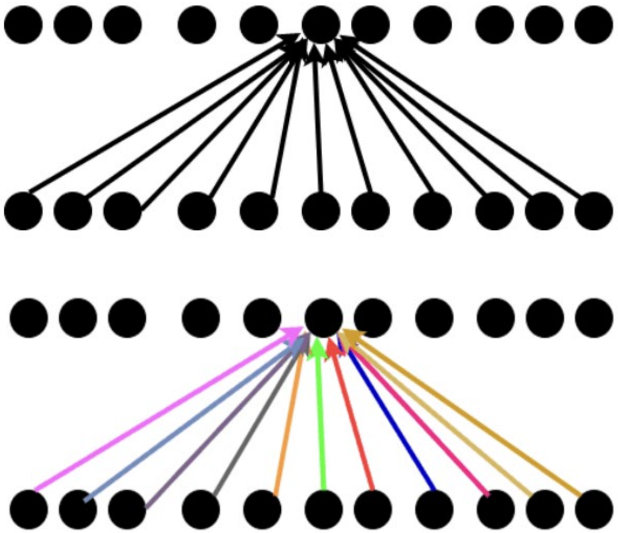
Mice	CNN-Based model
1	90.92
2	82.3
3	87.97
4	83.23
5	89.83
6	91.2
7	71.73
8	84.79
Avg	85.5

Adding Attention mechanisms

- Using self-attention for contextual learning
    - Ie past/future stages affect probabilities of current stage

Architecture:

- Placed after 1D convolutional layers for more global context
- Tuned number of embeddings and heads for different datasets



Adaloglou, N., & Karagiannakos, S. (2020). https://theaisummer.com/attention/

Adding Attention mechanisms

Results:

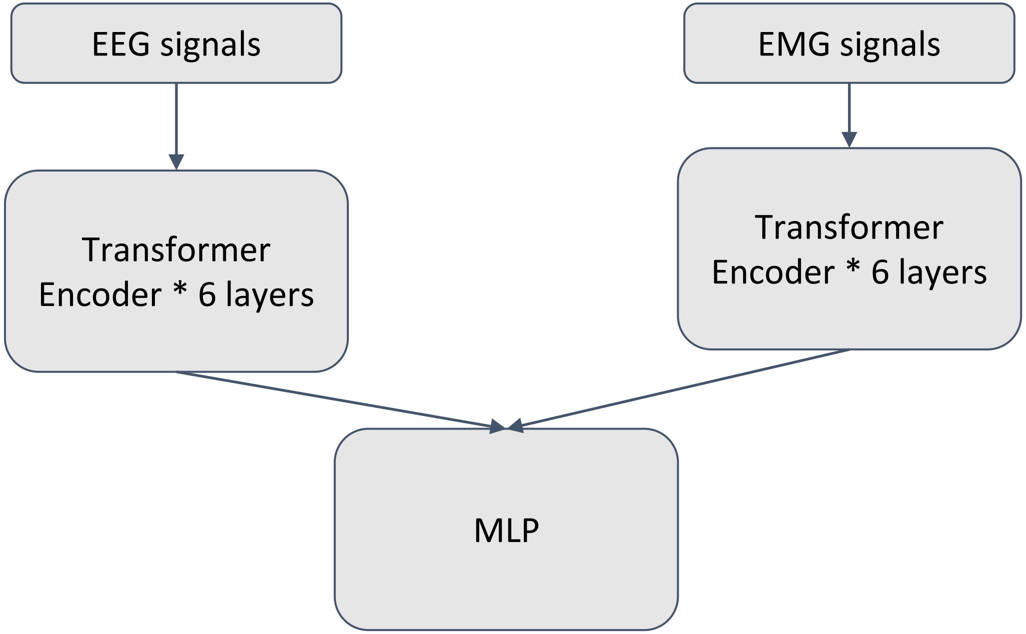
- Slight decrease in average accuracy:
  - 85.5% -> 84.65%
  - Limitation in dataset size
  - REM precision decreased

Class Name	Precision	1-Precision	Recall	1-Recall	f1-score
Awake	0.7725	0.2275	0.8558	0.1442	0.8120
NREM	0.9064	0.0936	0.8087	0.1913	0.8548
REM	0.2667	0.7333	0.4084	0.5916	0.3227

Confusion matrix:

Training Set				
TARGET / OUTPUT	Awake	NREM	REM	SUM
Awake	30202 27.14%	7219 6.49%	1674 1.50%	39095 77.25% 22.75%
NREM	3389 3.05%	55895 50.24%	2383 2.14%	61667 90.64% 9.36%
REM	1700 1.53%	6001 5.39%	2801 2.52%	10502 26.67% 73.33%
SUM	35291 85.58% 14.42%	69115 80.87% 19.13%	6858 40.84% 59.16%	88898 / 111264 79.90% 20.10%

Transformer-based model - Model architecture



Transformer-based model - Results

Index	1	2	3	4	5	6	7	8	Average
ACC (%)	77.88	85.20	62.25	51.42	80.37	84.29	82.27	84.76	76.05

Matrix	Avg-acc	Avg-precision	Avg-recall	avg-specificity	Avg-F1
Result	76.05%	0.5382	0.5307	0.8285	0.4997

Transformer-based model - discussion

Result discussion:

Transformer-based models tend to underperform compared to traditional CNN-based models when data is limited, as transformers require larger datasets to achieve optimal results.

Limitations

- Amount of data
  - Only 8 mice
  - Impacts attention and transformer performance
- Quality of data
  - Class imbalance
  - Impacts REM performance

Future work

- Investigating different species of mice
  - General model
- Detecting changes in sleep stage
- Combine transformer and CNN models
- Generating synthetic data to overcome class imbalance
  - REM sleep data is limited

Questions?