While reading the 2023 research paper called “A Systemic Comparison of Deep Learning Methods for EEG Time Series Analysis”, published in Frontiers in Neuroinformatics, introduces Electroencephalography (EEG) as a non-invasive method for recording and analyzing brain activity. It discusses the challenges of low amplitude signals and noise interference in EEG recordings, complicating patient mental condition identification. Traditional research has focused on handcrafted feature extraction methods, such as STFT, DWT, and tensor decomposition, to isolate relevant signals from noise. The paper also touches on the representation of generated spectrograms as images, classified by networks like FFNs, and the importance of high accuracy and efficient processing for applications in neurofeedback and BCIs. The methodology details the process for EEG signal recording and analysis. It emphasizes the challenges of low signal amplitude and noise in EEG recordings. The paper discusses traditional handcrafted feature extraction methods (STFT, DWT, tensor decomposition) and their role in noise reduction and signal isolation. The generated spectrograms are classified using networks like FFNs highlighting the necessity of high accuracy in automated analyses and the challenges posed by manual calibration in image generation, requiring expert knowledge to avoid overlooking important features.

Their evaluations were focused on three questions:

Which recurrent topology has advantages for EEG time series classification in between non-gated, gated, and random high dimensional mapping approaches?

Are feed-forward topologies based on self-attention convolutional (SACOrec), suitable without further preprocessing?

Can Bi-Directional Attention Flow (BiDAF) and adding attention weights, additional extension for LSTMs, improve performance for EEG time series classification?

They used linear regression and blind source separation to remove artifacts and interferences from their datasets for preprocessing in addition to traditional preprocessing methods. Experimental results indicate that TCN outperforms RNNs for EEG data and is less reliant on large training datasets, unlike the Transformer-Encoder. Feed-forward architectures were found to be easier to train, and networks with recurrence sometimes suffered from poor initialization leading to no learning progress, an issue not observed in feed-forward networks. The study further examines the effects of bidirectional and attention mechanisms on model performance. It was found that attention mechanisms improve LSTM performance, sometimes even surpassing TCN, while bidirectional mechanisms were generally not beneficial. Because of this, the authors suggest avoiding bidirectional mechanisms in RNNs for EEG classification. Overall, the study trained and compared ten different neural network topologies on three datasets (a seizure dataset, the emotion dataset DEAP, and a frequency entrainment dataset), evaluating their classification performance without handcrafted feature extraction. The results indicate the feasibility of solving different tasks with minimal adjustments to the training pipeline, although overfitting was a challenge, particularly on the DEAP dataset.