Cognitive Analysis of Working Memory Load from EEG, by a Deep Recurrent Neural Network

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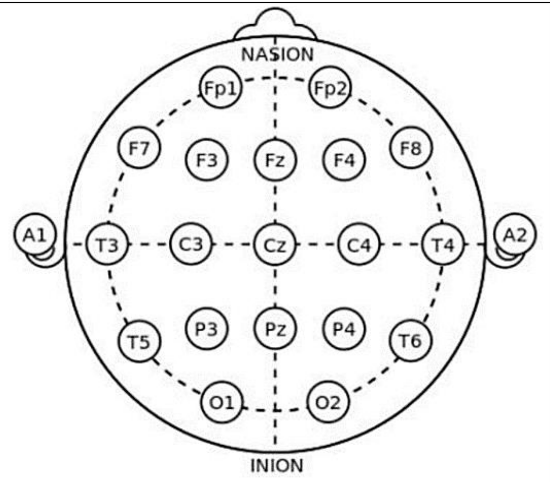
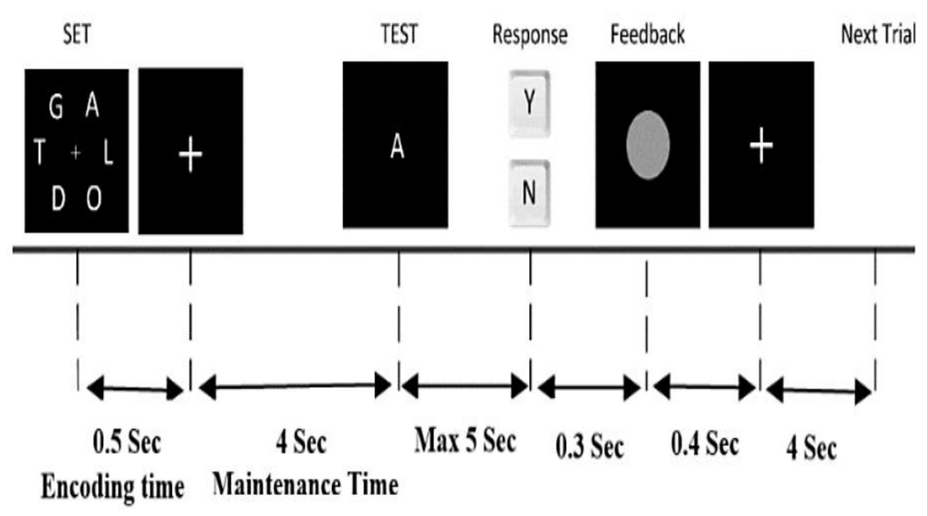
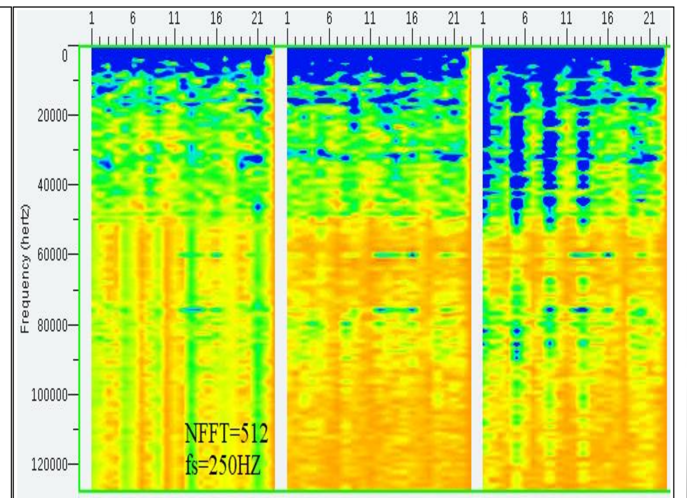
Setting: To find a robust representations from EEG multi-channel time bound series by using a deep recurrent neural network (RNN) and predict the levels of cognitive load from EEG recordings.
Goal: <u>Accuracy</u> and <u>efficiency</u>.



64 electrodes used in the 10-20 system



Working Memory Experiment Diagram


FFT over one sec intervals in all the 64 channels

Data Recording and Preprocessing

- 25 subjects (ten female) of age 16-28 perform the standard working memory (WM) experiment.
- An array of English character in SET is shown for 0.5 seconds. After 4 seconds the TEST characters are shown.
- In each trial the number of characters are chosen from the set {4, 6, 8, 10} and repeat experiment for 320 times.
- Each of the task condition containing 4, 6, 8, 10 characters is labeled with cognitive loads 1- 4 respectively.
- Brain activity recorded during 4.5 secs trial and recognized as mental workload.
- Each trial of 4.5 sec are sliced into 0.5 sec pieces through an offline windowing process.
- An image is constructed over each time slice and produced nine frames per trail.

EEG Features

- Power spectra for each time sliced window (0.5 sec) is estimated by applying FFT.
- Frequency spectrum divided into 3 sub-bands: theta (4-7Hz), alpha (8-13Hz), beta (13-30 Hz) for EEG analysis.
- Mean spectral power within 3 sub-bands are calculated by averaging FFT magnitudes and considered as feature.
- Finally 192 features (64 channels x 3 bands) are combined to form a feature vector.
- Scalp electrode locations are projected from 3D-2D surface and transformed spatially distributed activity as frames.
- Azimuthal Equidistant (Polar) Projection technique used to preserve relative distance between electrodes.
- Clough technique applied to interpolate power over scalp and estimate intermediate values over a 32×32 mesh.

Our contribution:

- Problem: EEG recording is highly susceptible to various sources of noise and to inter subject differences.
- Approach: Introduce Bidirectional LSTM for EEG analysis and compare with other state-of-the-art CNN+LST models.
- Different: Learns robust representations from EEG video sequences using a CNN and BiLSTM hybrid network.
- Our approach preserves the spatial, spectral, and temporal structures and extracts features which are less sensitive to variations along each dimension.
- <u>Plus:</u> Significant gains in efficiency.
  - **Find better classification accuracy i.e. up to 92.5% over various existing LSTM models**

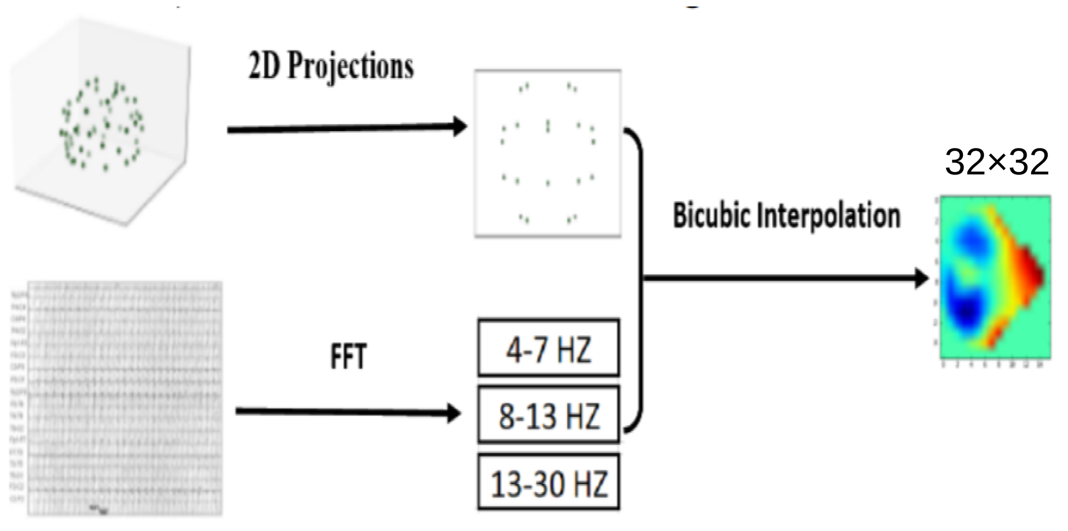
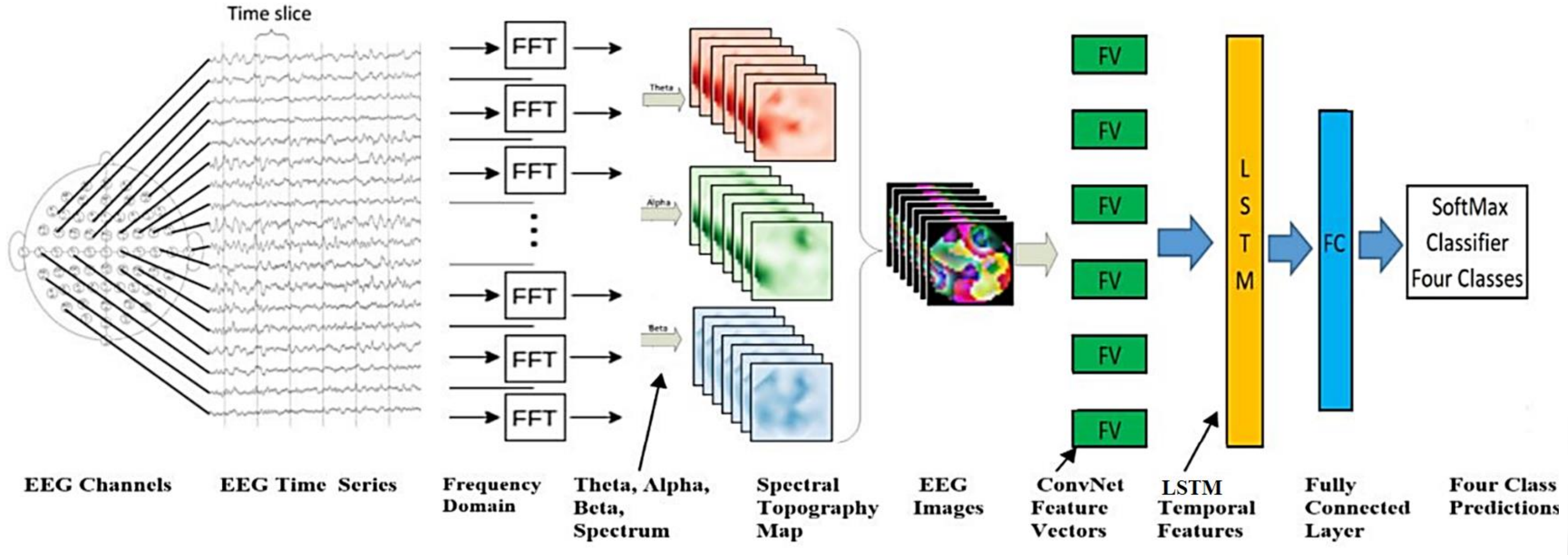
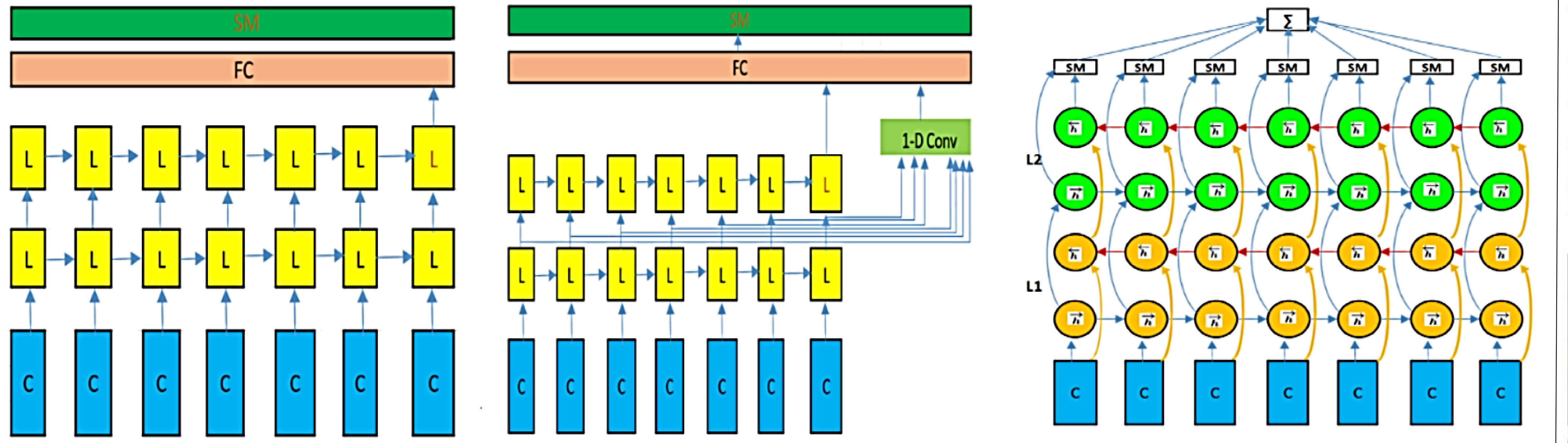


Image Based Representation of EEG Signal

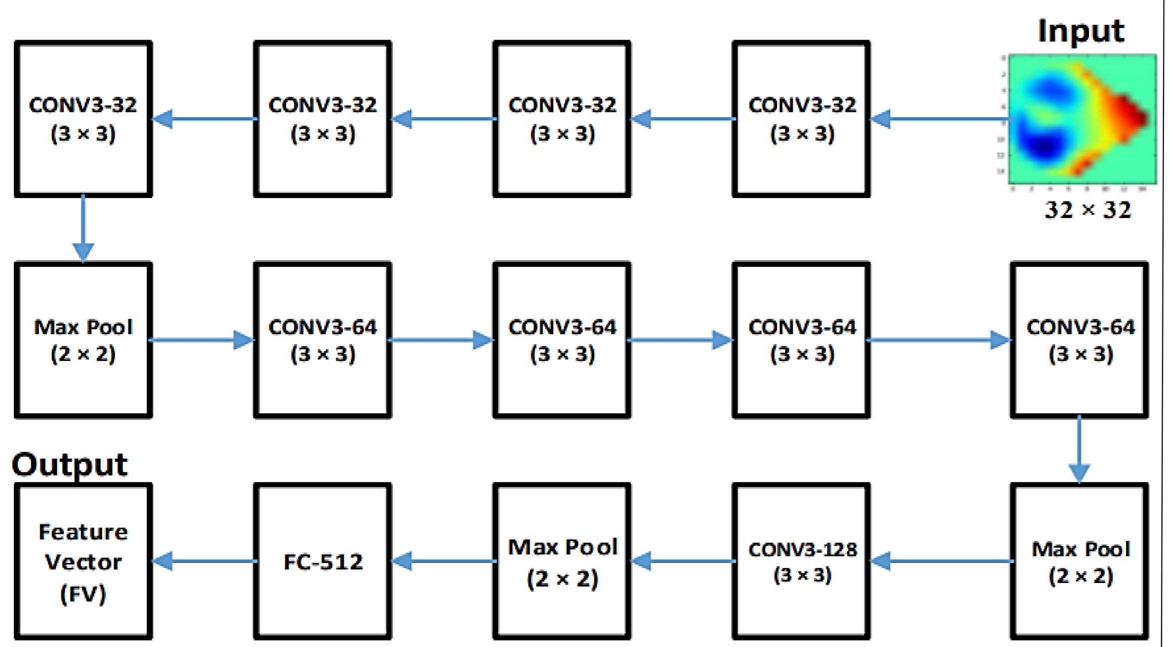
Neural Network Models



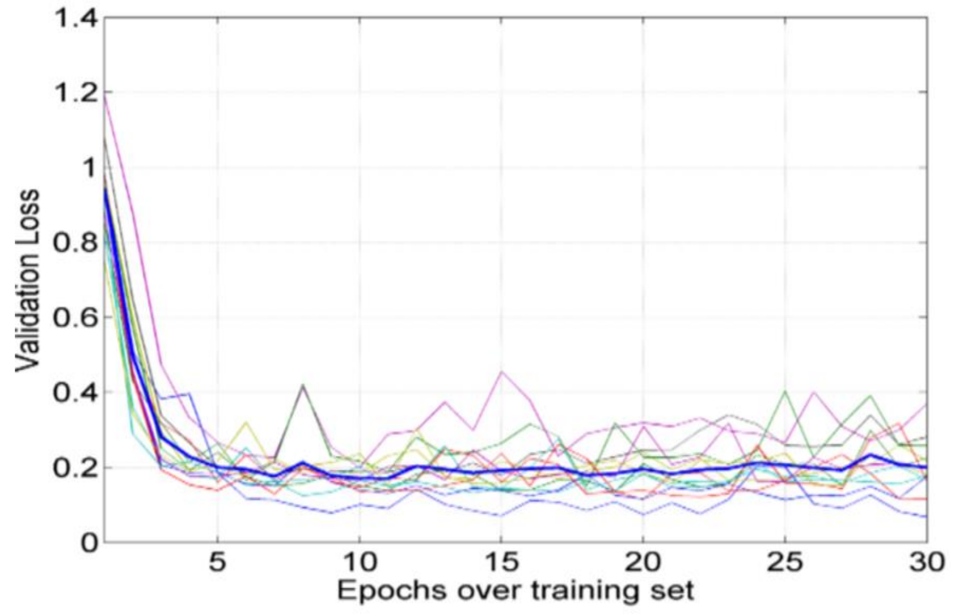
Framework overview: (i) EEG signals from multiple cortex locations (ii) FFT and topographical maps (iii) Spectral maps combined to form 3 channel images, (iv) CNN (ConvNet) FV and LSTM for representation learning (v) Softmax classification.



Different LSTM (L) models with ConvNet (C); BiLSTM (L1, L2); FC: Fully Connected; SM: Softmax



Convolutional neural network architecture with 9 conv layers + 1fully connected layer



Validation Loss along the number of training set epochs. Average loss→ Blue line

RNN Model

- CNN handles space and frequency variations, and learns 2D representations.
- CNN output feature vectors are fed into recurrent LSTM layers to learn temporal variations.
- LSTM frames propagated to FC layer and prediction is made by Softmax classifiers.
- Bidirectional LSTM process the EEG data in both forward and backward directions using two separate hidden layers and access long frames in both directions.
- Three different combination of LSTM models are explored for experiment.

Classification Algorithm

- RNN receives sequence of CNN activations.
- Forward inputs x = $\{x_1 \ldots x_T\}$, compute hidden vector h = $\{h_1 \ldots h_T\}$ and output vector y = $\{y_1 \ldots y_T\}$ by iterating from time t = 1 to T.
- h_t = H $(W_{xh} \times x_t + W_{hh} \times h_{t-1} + b_h)$ computed by a set of equations with components input, forget, cell activation and output gates
- $y_t = W_{hy} \times h_t + b_y$
- Trained by optimizing the cross entropy cost function using SGD and backpropagation.
- Compare results w.r.t. commonly used classifiers: Random Forest (RF), Support Vector Machines and Logistic Regression.

Experiments

Architecture	Test Errors (%)	Validation Error	Number of Parameters
SVM	14.96	-	-
Logistic Regression (L1)	14.45	-	-
Random Forest	12.23	-	-
ConvNet + LSTM	9.87	6.13	1.29 Mil
ConvNet+ LSTM+1D-Conv	8.34	8.32	1.47 Mil
ConvNet + Bidirectional LSTM	7.61	8.11	1.66 Mil

Classification Results of Different Architectures

Test Subjects	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11
LSTM	88.45	71.27	93.22	97.43	98.2	81.1	94.5	93	86	85.25	87.4
LSTM + 1D Conv	89.9	75.3	92.5	96.4	95.4	94.5	96.4	95.8	91.8	93.45	90.5
BiLSTM	94.5	86.5	96.8	98.5	97.3	95.3	99.25	97.7	99.5	97.5	94.5

Test Subjects	S12	S13	S14	S15	S16	S17	S18	S19	S20	S21	S22
LSTM	80.5	46.7	81.45	92.53	89.3	100	91.4	90.5	82.4	80.5	47.5
LSTM + 1D Conv	81.7	50.62	92.5	87	96.5	100	93.5	95	87.2	81.65	51.4
BiLSTM (Mix)	89.8	78.5	95.2	92.5	98.45	97.3	94.34	96.34	75.4	88.6	71.3

Average Accuracy (%):	BiLSTM (Mix) = 92.5	LSTM + 1D Conv = 87.68	LSTM = 84.48

Classification Accuracy Results for Subjects Fold

Results

- Accuracies on individual subjects show that our three models achieved consistent improvement on classification except at S3, S4, S5, S6, S15, S20.
- Classification errors lowered significantly when temporal LSTM models are added.
- Cognitive memory load prediction across four different levels with a better accuracy of 92.5% during the memory task execution.
- Reduce classification error to 7.61% in comparison to other state-of-art techniques.

Concluding Comments

- We defined a methodology to learn spatial, spectral and temporal representations from EEG datasets and demonstrated its advantages in context of cognitive memory load
- In future, we would like to experiment on the unsupervised generative frameworks with large number of unlabeled task-specific datasets.

Acknowledgments

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