# EEG SIGNAL DIMENSIONALITY REDUCTION AND CLASSIFICATION USING TENSOR DECOMPOSITION AND DEEP CONVOLUTIONAL NEURAL NETWORKS

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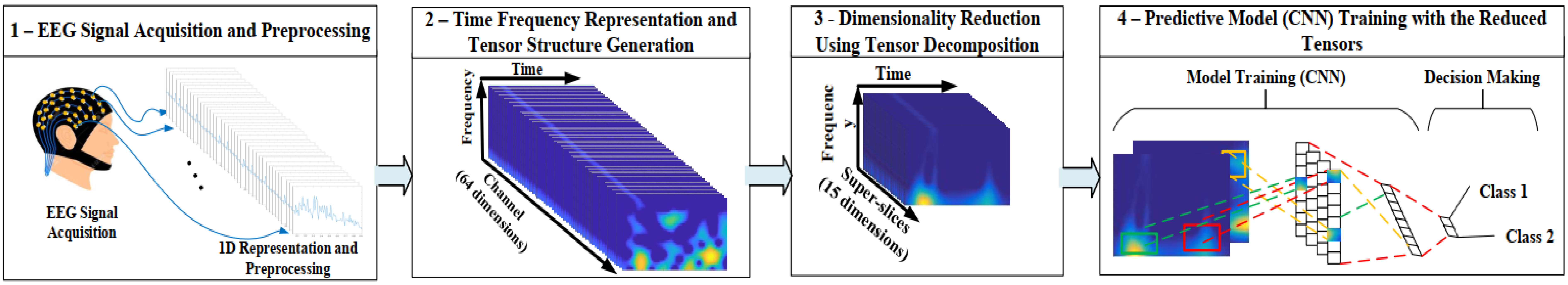
## Block Diagram of the Proposed Framework




## 1- Problem Statement

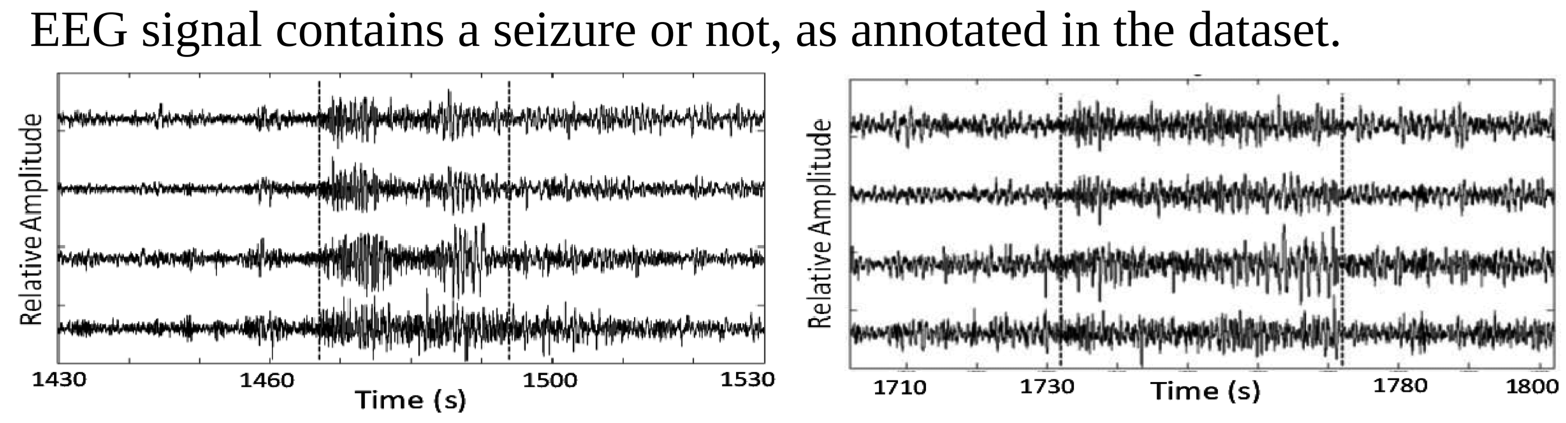
- **Problem:** EEG signals suffer from high dimensionality. This makes the signal analysis task more difficult, and even impossible for on-line processing and decision making.
- **Goal:** To design a novel framework for reducing the dimension of the EEG signals, without affecting the classification accurately to detect the epileptic seizure in EEG signals.

## 2- Contributions

- Proposing a new framework for reducing the dimensionality of EEG data based on the *tensor decomposition*, and feeding the *dimension-reduced data* to a *convolutional neural network* (CNN) to increase the model's efficiency and to decrease the training complexity.
- Handling noise, artifacts, and redundancies of EEG signals by tensor decomposition-based dimensionality reduction.
- Providing a comprehensive comparison and evaluation of different time-frequency representation approaches for CNN-based EEG signal analysis.

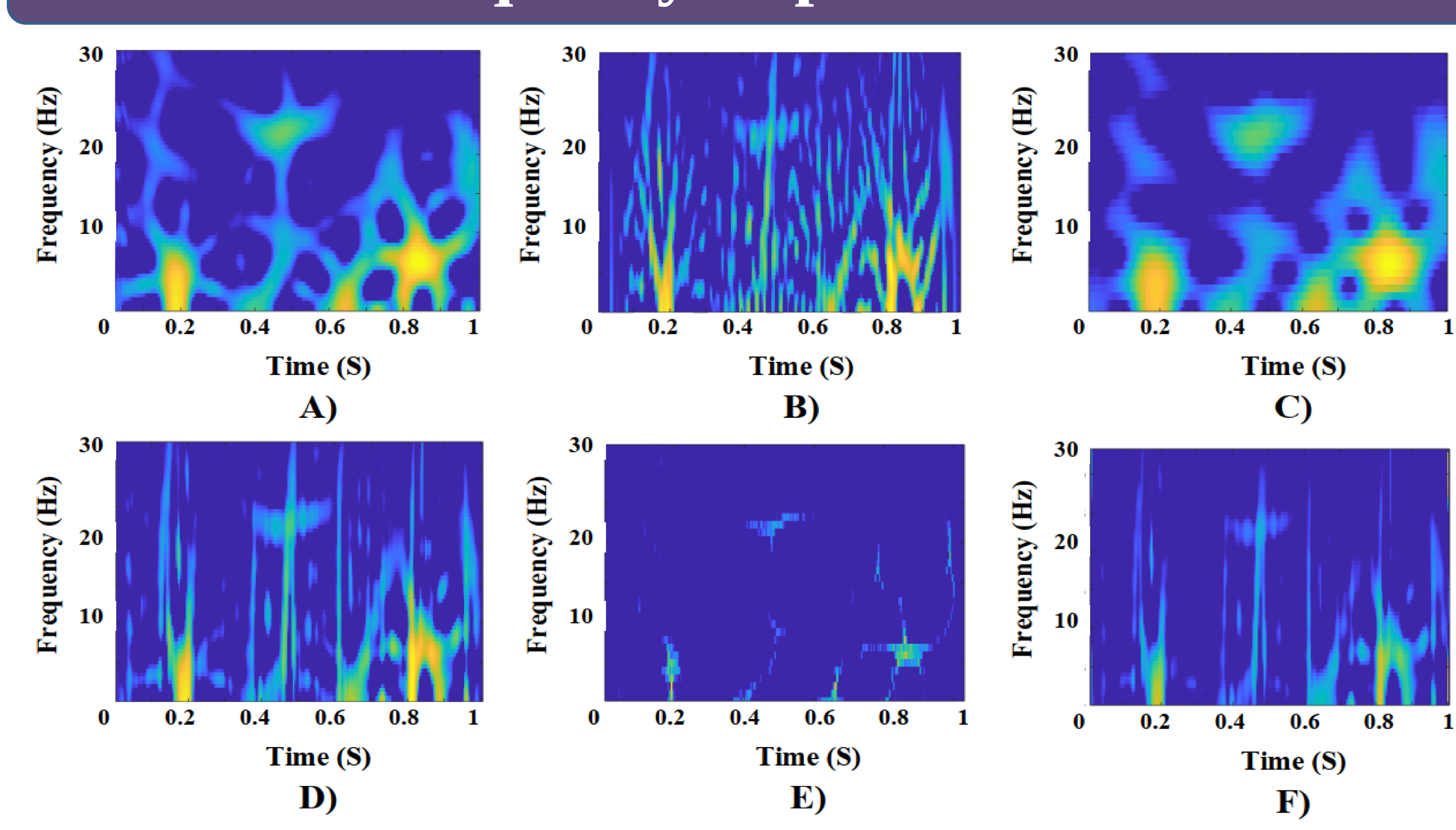
## 3- EEG Data-set

We evaluate our method on the **CHB-MIT** [1] dataset. In this study, for cross-patient detection, the goal is to detect whether a 30 second segment of EEG signal contains a seizure or not, as annotated in the dataset.




Examples of two epileptic seizures from CHB-MIT Scalp EEG database

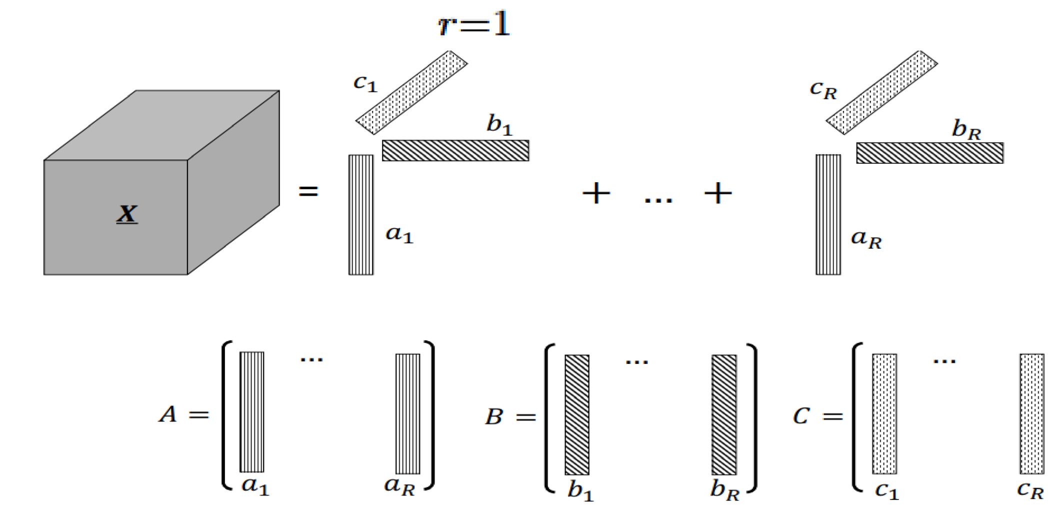
## 4- Time Frequency Representation Methods




Time-frequency representations of 1 second of EEG signal using different methods including:
A) smoothed-WV (SWV), B) Gaussian kernel (GK), C) Wigner–Ville (WV),
D) spectrogram (SPEC), E) modified-B (MB), and F) separable kernel (SPEK).

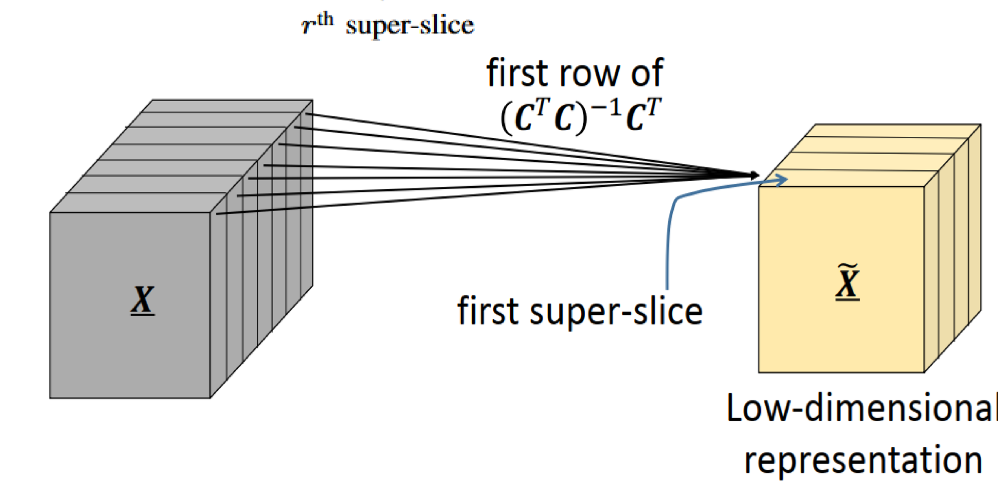
## 5- Tensor Decomposition

$$\underline{X} = \sum_{r=1}^{R} a_r \circ b_r \circ c_r$$



Decomposition of a rank-R tensor to a summation of R rank-1 tensors. Symbol o indicates the outer product.

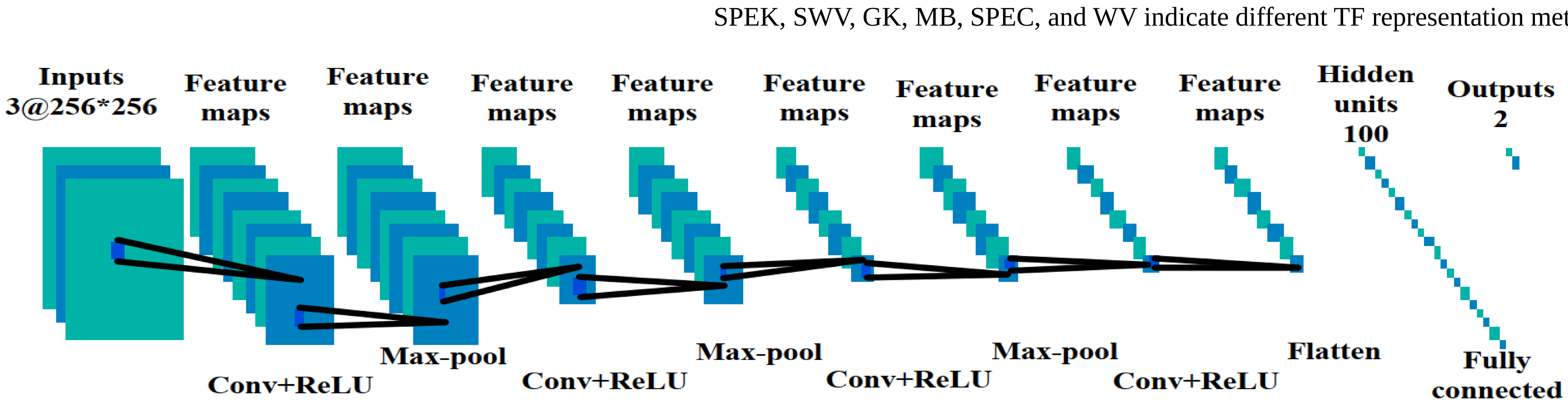
$$\underbrace{\tilde{\underline{X}}_{:,:,r}}_{r^{th}\text{ super-slice}} = \underline{X} \times_3 P_{r,:}$$



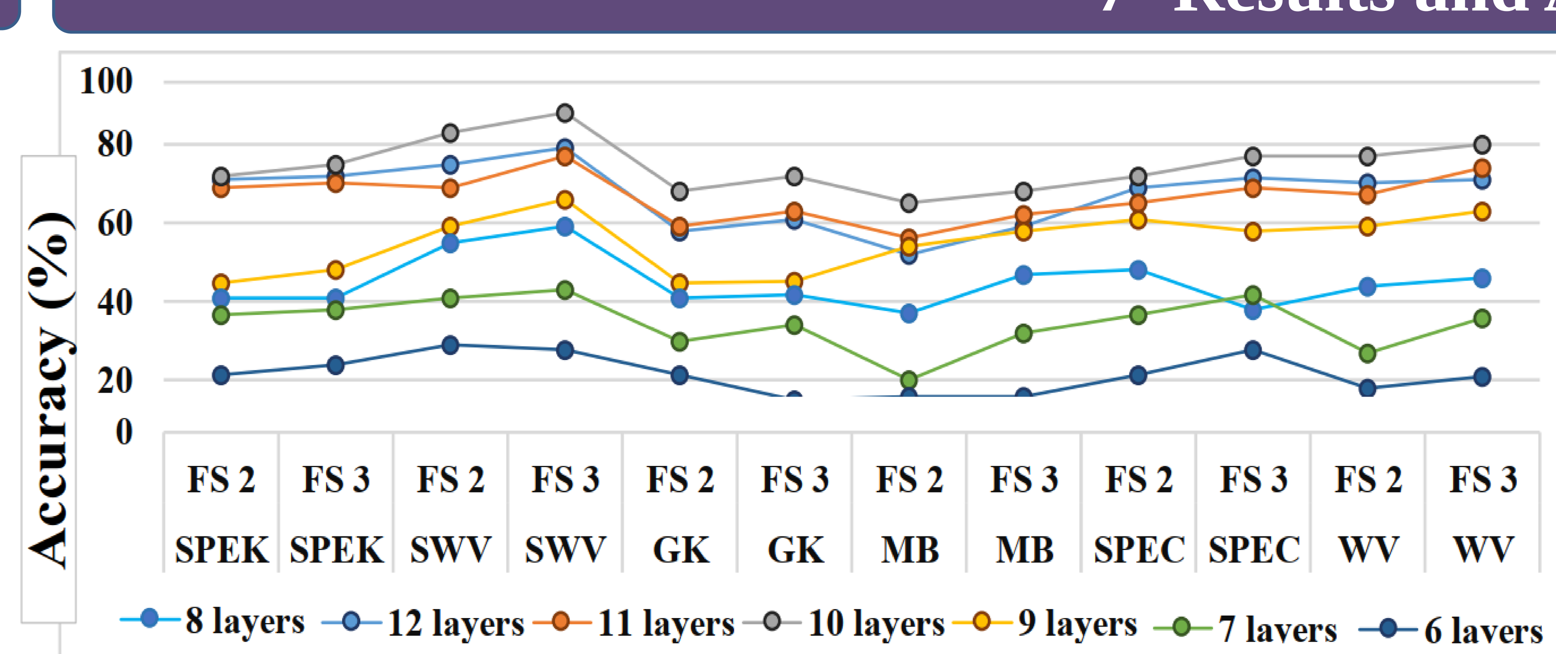

The input tensor as a collection of slices is transformed to a set of super-slices. Each super-slice is a superposition of all slices and weights are driven from Matrix $P = (C^TC)^{-1}C^T$. For example, the first super-slice is summation of all slices weighted by the first row of P. $\times_3$ indicates mod-3 product.

## 6- CNN Structure & Parameters

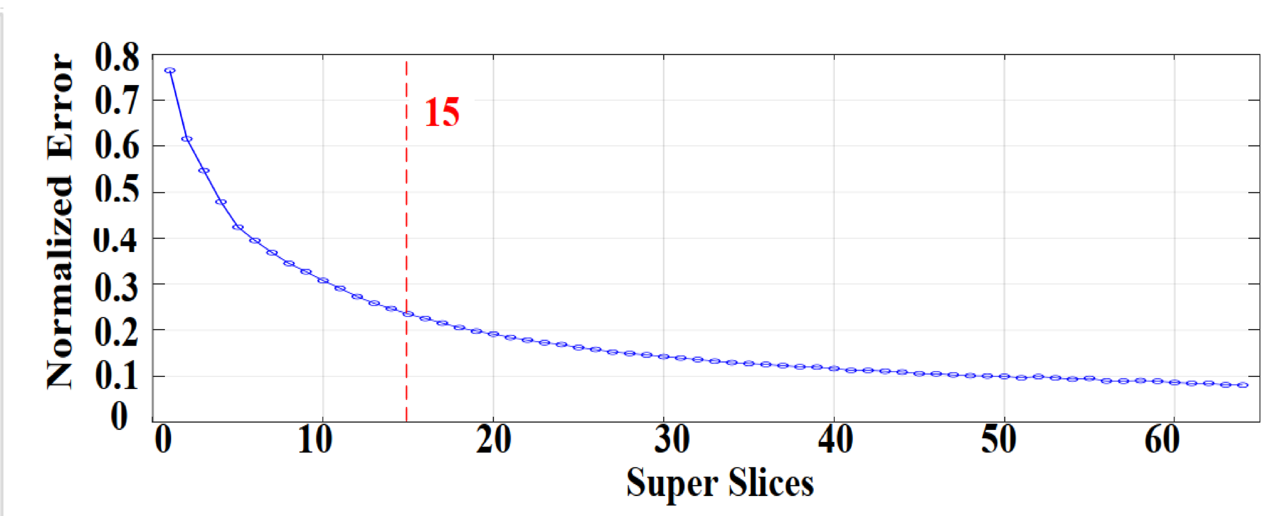
| CNN Parameter | Values |
|---|---|
| Learning Rate | 0.001 |
| Momentum Coefficient | 0.9 |
| No. of Feature Maps | 32 and 64 |
| No. of Neurons in Fully Connected Layer | 64 |
| Batch Size | 40 |



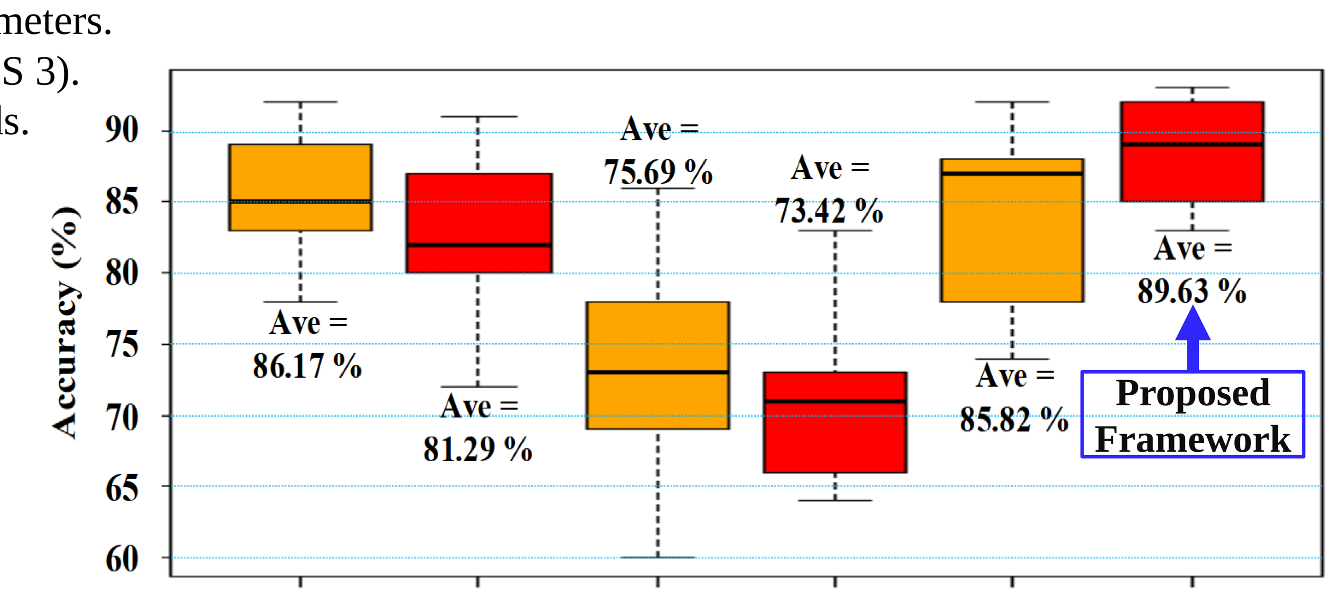

## 7- Results and Analysis




Accuracy of EEG signal classification for different TF methods and different CNN parameters. Parameters are different number of layers, and filter sizes are 2×2 (FS 2) and 3×3 (FS 3). SPEK, SWV, GK, MB, SPEC, and WV indicate different TF representation methods.




Normalized error of CP decomposition versus assumed rank of decomposition




Comparison of the classification accuracy of cross-patient seizure detection on CHB-MIT EEG dataset. Each box plot shows 10 iterations of 10 cross validation of the predictive model for the associated method.

**Reference:** 1- Ali Shoeb. Application of Machine Learning to Epileptic Seizure Onset Detection and Treatment. PhD Thesis, Massachusetts Institute of Technology, September 2009.

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