

## MOTIVATION

Develop a computational basis for developing real-time brain controlled actions, such as thought-controlled prosthetic limbs or electronic devices.

Whenever we execute, or even think of executing a motor activity, neurons in certain sections of the brain get fired up, which eventually manifests itself into the change in the averaged electrical activity of the region, as recorded by the EEG device [1].

Signal:  $f(t): t \rightarrow X^n$ , where  $n$  is a large dimension.

Can we guess the action by interpreting the signal  $f$ ?

## PROBLEM

- ❖ EEG Signal has a poor signal-to-noise ratio [2].
- ❖ The real signal is masked by other neural activity.

## SOLUTION

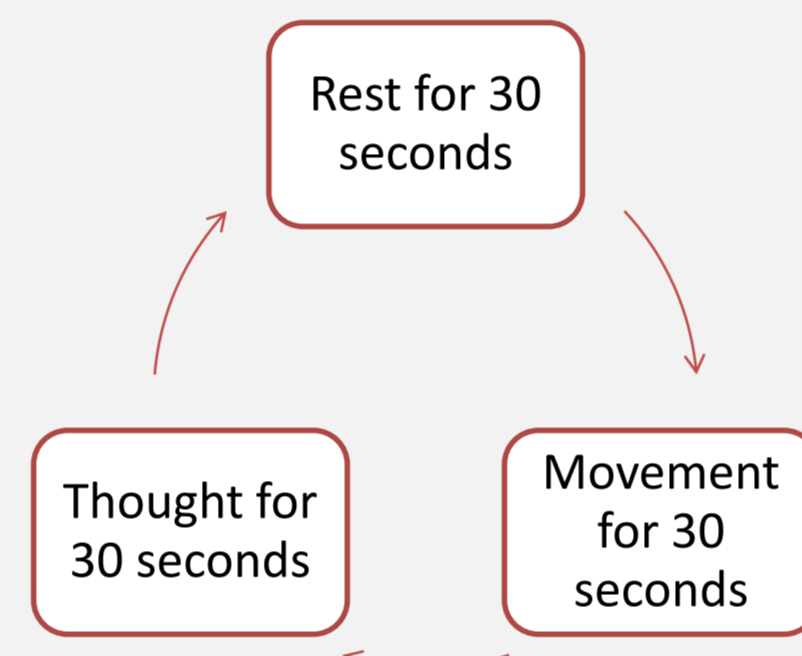
Use Artificial Neural Networks, inspired by the way the Brain works.

- ❖ Based on past data (collected in experiments), train the ANN model.
- ❖ Based on new data, predict the stimulus using the trained model.

## EXPERIMENTS

Using a 14-channel wireless EEG headset, we conducted experiments across multiple sittings with the same subject. *Block* format [3], which is common in EEG experiments was used. Data was collected for 3 actions:

1. Rest **R**
2. Right arm movement **M**
3. Thought of right arm movement **T**



## DATA ANALYSIS

Since the data is high-dimensional and noisy, we need to reduce this dimensionality for efficient computation. For this, we converted the signal into *frequency domain* by binning it into signal ranges. [Closely related to the idea of *information content* of a signal.] The so formed size-140 vectors were fed to an ANN (whose hyperparameters like learning rate and number of hidden neurons were appropriately adjusted for highest prediction rates) for training, which learns by backpropagating errors [4]. Some part of the data was reserved for validation and testing, and the error values were reasonably small for even the testing data.

## RESULTS

We were successful in:

- ❖ Devising a suitable experiment structure while respecting the real-time nature of the study's application.
  - ❖ Expressing any arbitrary EEG signal parameterised to just 3 dimensions.
  - ❖ Rudimentary differentiation of movement from thought-of-movement.
- Further work can be done to deal with discrete instead of continuous motor activities, and extending the action set to more number of activities.

## REFERENCES

- [1] Tatum, W. O. (2008). *Handbook of EEG Interpretation*. Demos Medical Publishing.
- [2] Alois Schlögl, M. S. (2002). *Presence research and EEG*.
- [3] Anne Porbadnigk, M. W.-P. (n.d.). *EEG-based Speech Recognition - Impact of Temporal Effects*.
- [4] Jain, A. K. (1996). *Artificial Neural Networks: A Tutorial*. IEEE.

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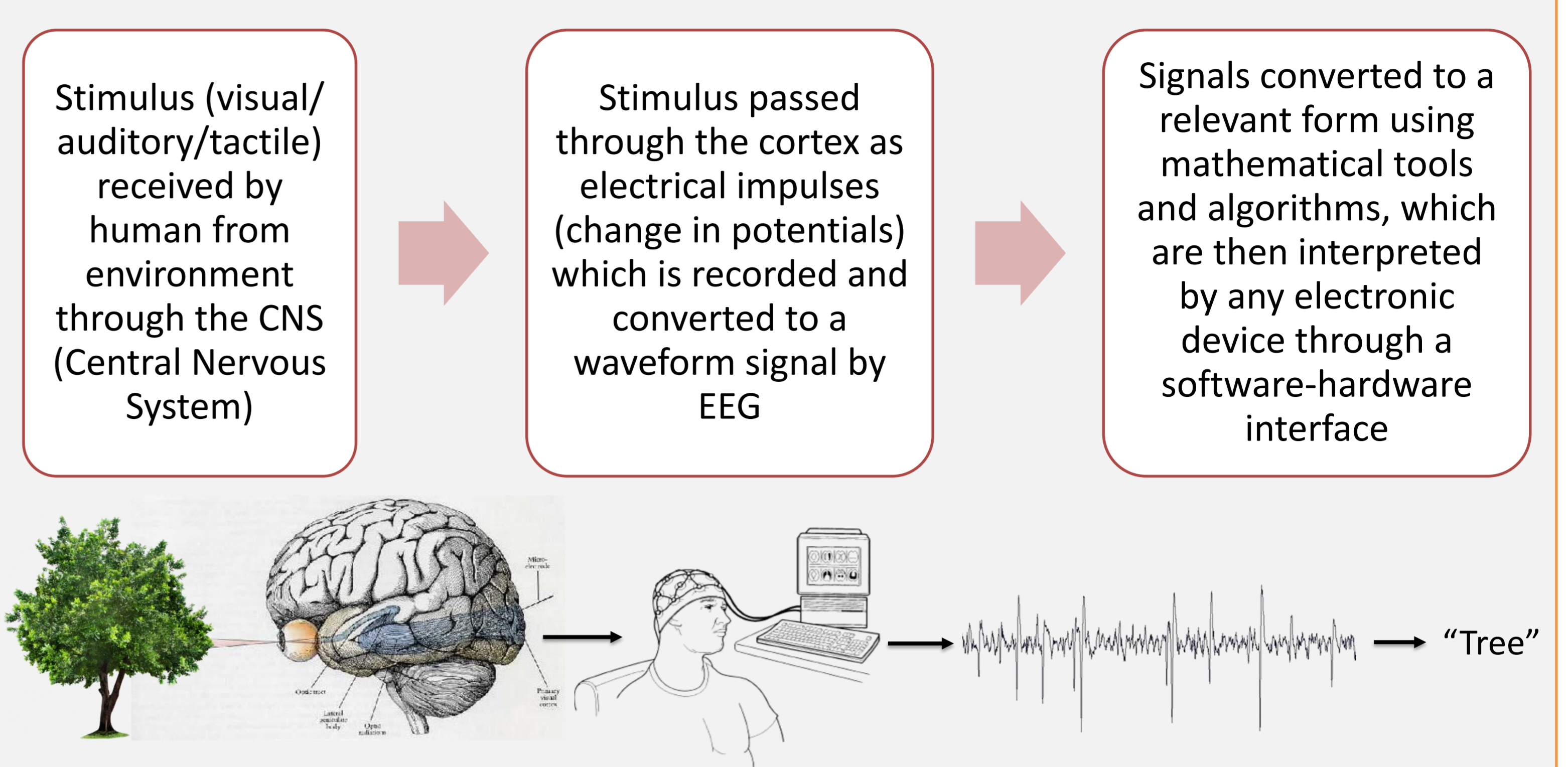


Figure 1. System Description

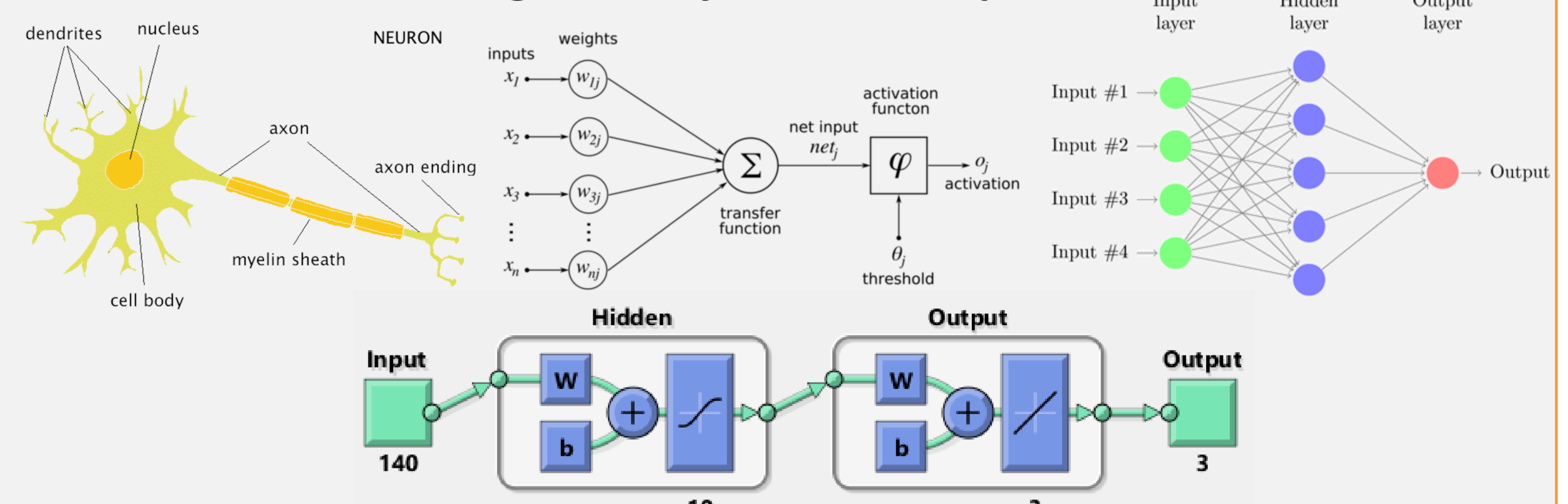


Figure 2. Structure of the Neural Network

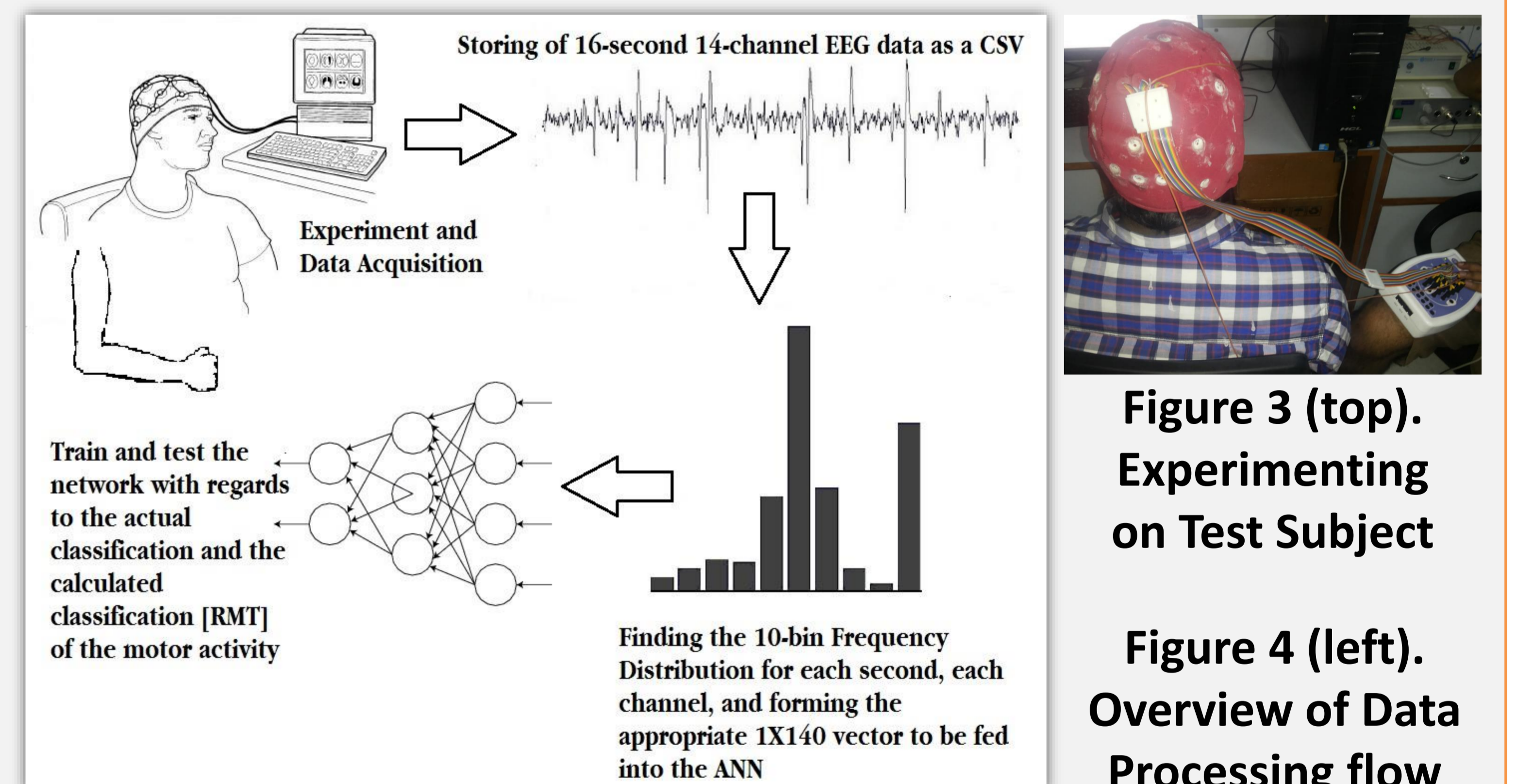


Figure 3 (top). Experimenting on Test Subject

Figure 4 (left). Overview of Data Processing flow

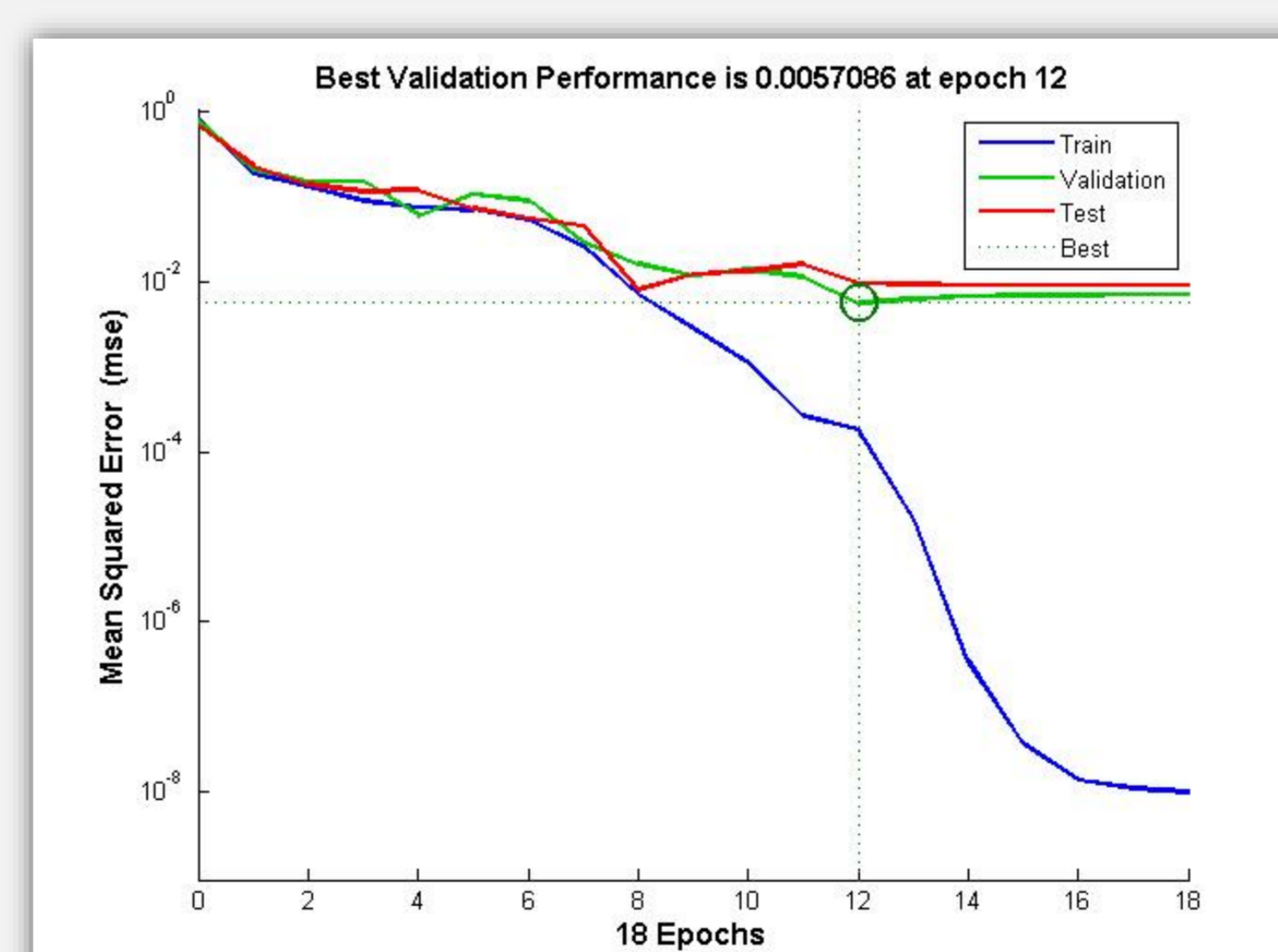


Figure 5. Decrease in Mean Squared Error with Training

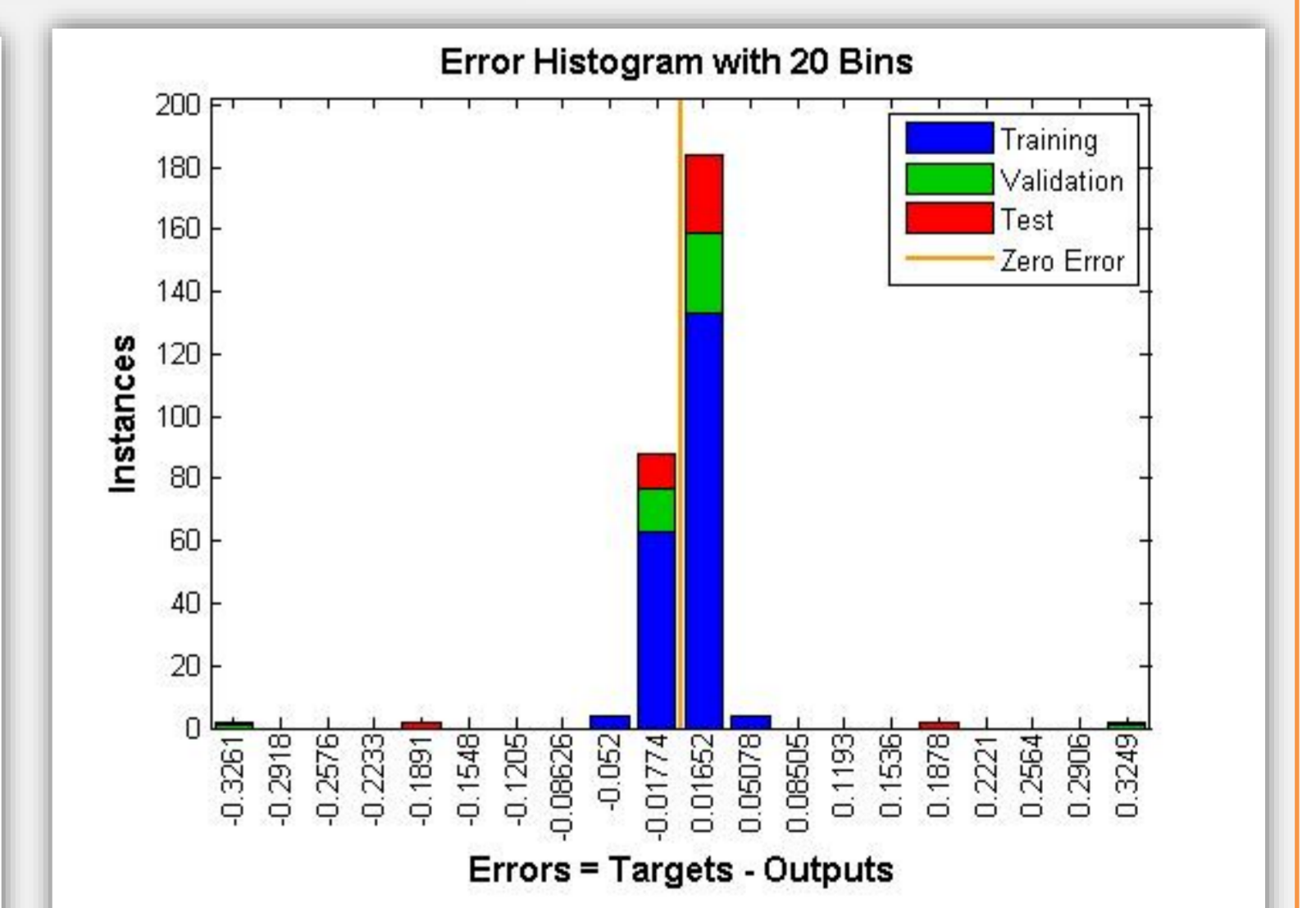


Figure 6. Error Histogram

