# Investigating the Impact of Calibration Time On Classifier Accuracy in c-VEP BCI Systems


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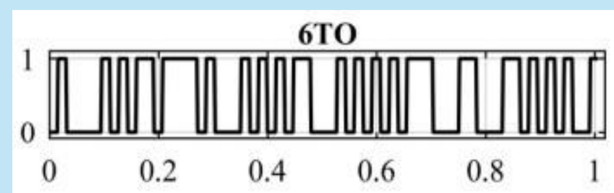
## Introduction

**Goal of this study:**

To examine the impact of increasing the amount of EEG training data on the classification accuracy of c-VEP BCI systems across various classifiers

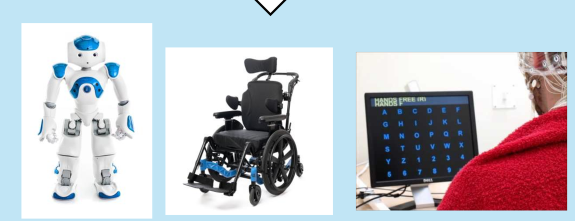



EEG recorder

Pre-processing

c-VEP BCI calibration

Classification

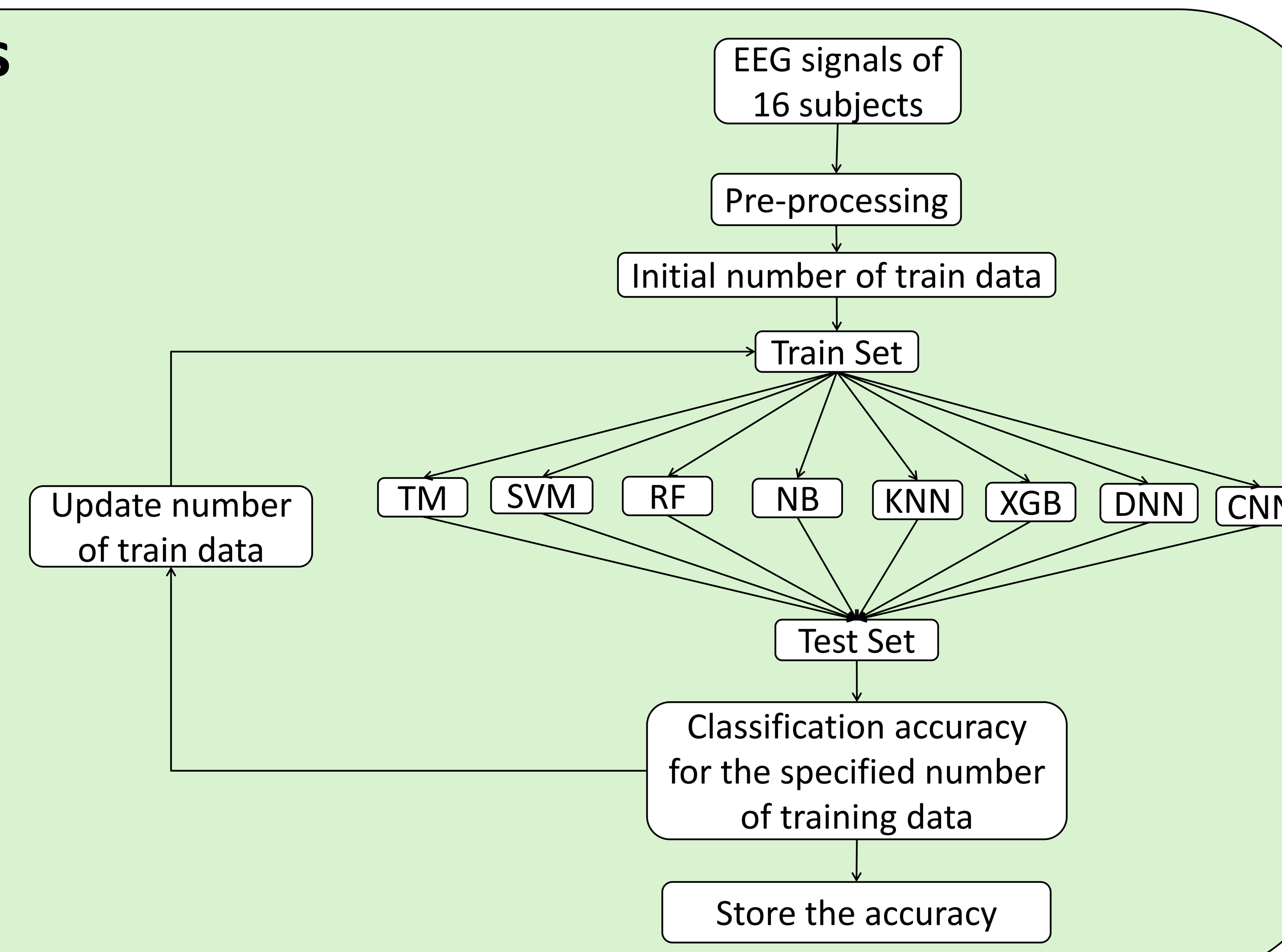


C-VEP BCI Calibration

| Ensemble Approach | Circular shift Approach |
|---|---|
| Each subject repeatedly focuses on various visual stimuli | Each subject repeatedly focuses on a single visual stimulus |
| EEG trials for each stimulus obtains individually | EEG trials of other stimuli are obtained using circular shift |

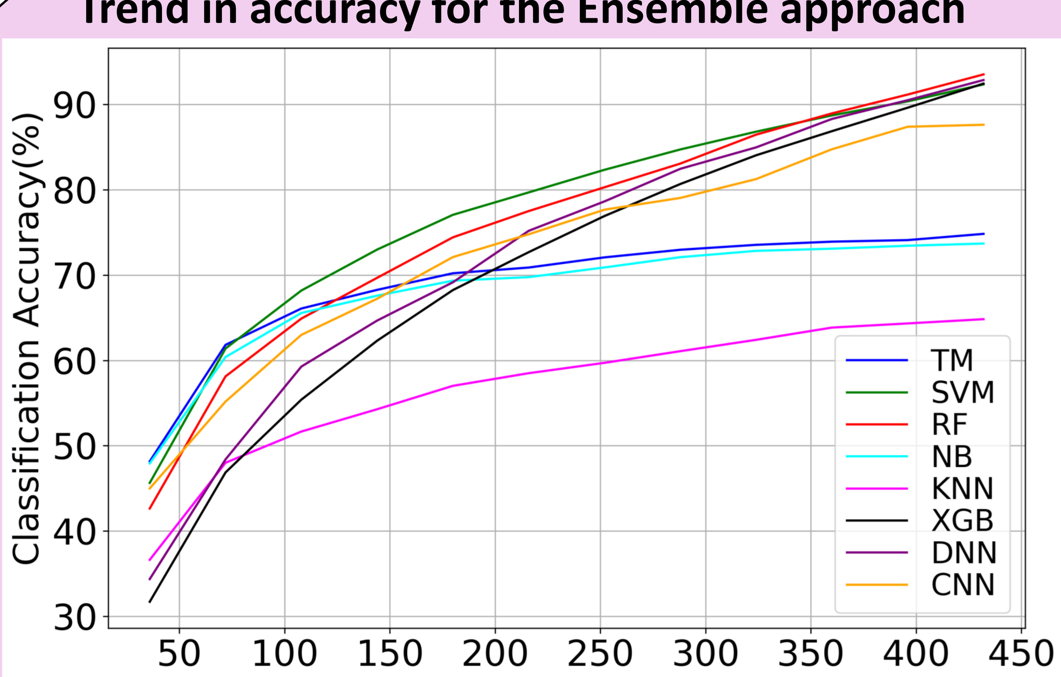
## Methods

- **EEG recording**
  - # of subjects N = 16 (healthy)
  - Single EEG channel recording (bipolarly from Oz relative to Pz with ground at FPz)
- **Preprocessing:**
  - Butterworth bandpass filter (2 and 40Hz)
  - Extracting EEG trials, removing the DC value
  - Dividing data to train set and test set with a designed cross-validation strategy (different number of training data, but the same number of test data)
- **Different classifiers:**
  - Template Matching (TM): Traditional classifier for c-VEP BCIs
  - Support Vector Machine (SVM): With Radial Basis Function kernel
  - Random Forest (RF): # of trees=500
  - Naïve Bayes (NB): alpha=1
  - K-Nearest Neighbours (KNN): # of neighbours= 0.18 x number of training data
  - Extreme Gradient Boost (XGB): # of trees=100
  - Deep Neural Network (DNN): 3 hidden layers with 128, 128, and 64 nodes
  - Convolutional Neural Network (CNN): 2 convolution layers (64 and 32 channels), one linear layer (128 nodes)




## Results

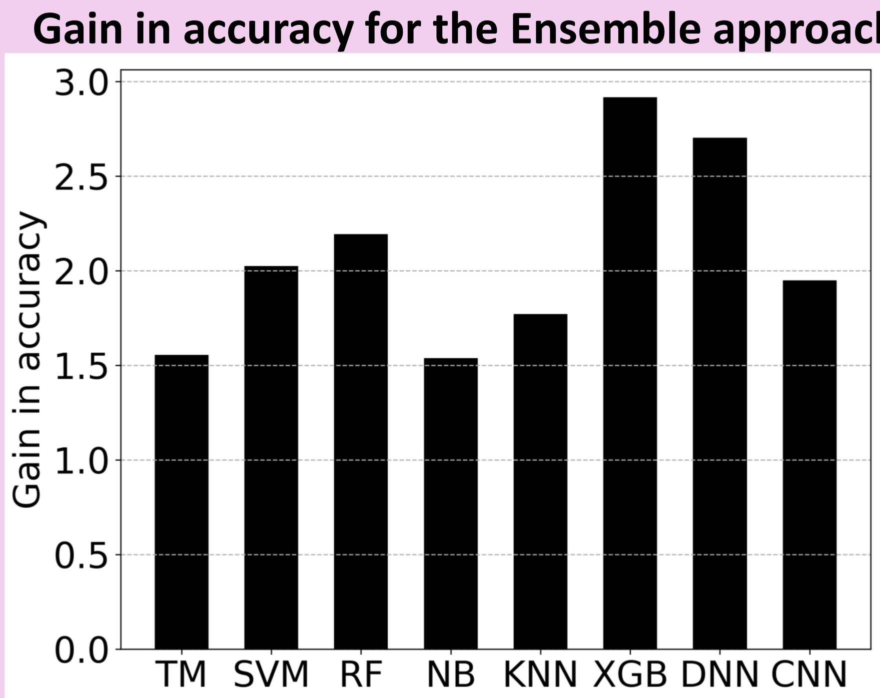
**Trend in accuracy for the Ensemble approach**



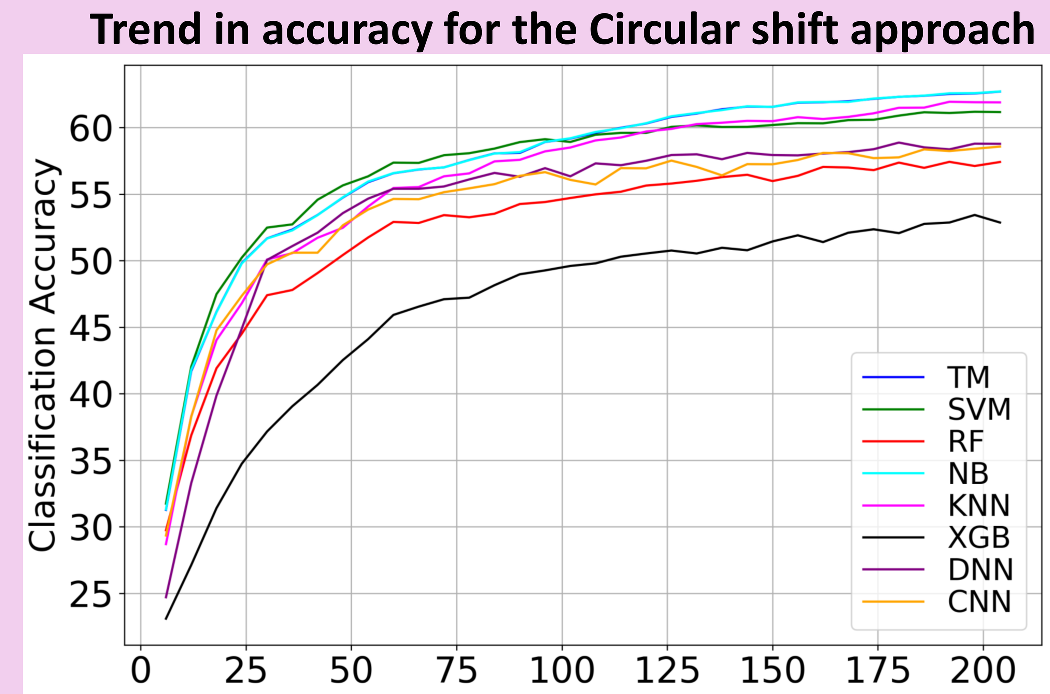

**Increase in accuracy for the Ensemble approach**

| | |
|---|---|
| TM | 26.6% |
| SVM | 46.7% |
| RF | 50.9% |
| NB | 25.8% |
| KNN | 28.2% |
| XGB | 60.7% |
| DNN | 58.5% |
| CNN | 42.6% |

**Gain in accuracy for the Ensemble approach**



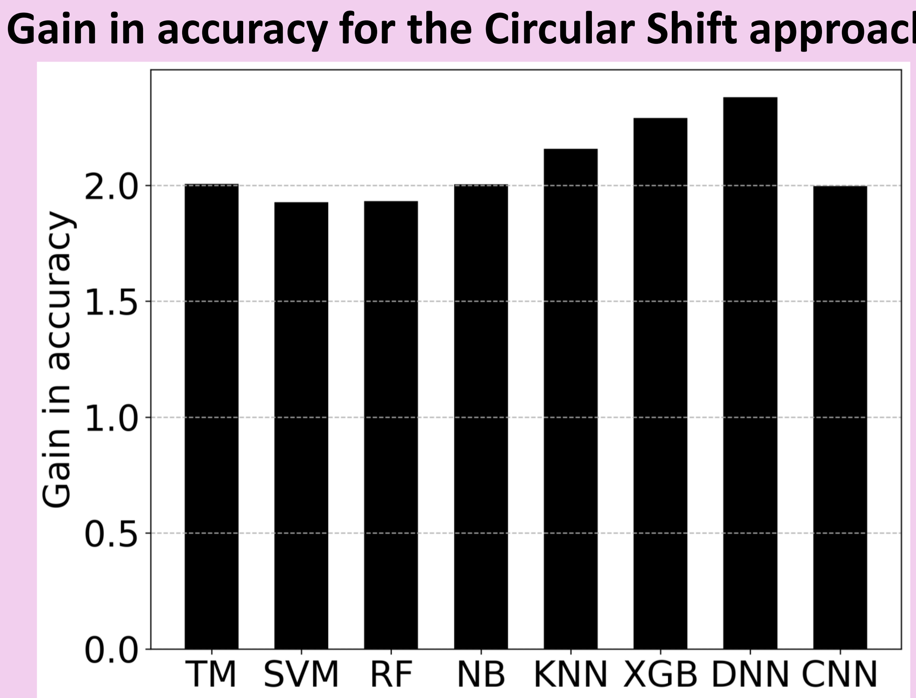

**Trend in accuracy for the Circular shift approach**




**Increase in accuracy for the Circular shift approach**

| | |
|---|---|
| TM | 31.4% |
| SVM | 29.5% |
| RF | 27.7% |
| NB | 31.4% |
| KNN | 33.2% |
| XGB | 29.8% |
| DNN | 34.1% |
| CNN | 29.3% |

**Gain in accuracy for the Circular Shift approach**




## Discussion

- Both the Ensemble and Circular-Shift approaches show increasing trends, with the Ensemble approach having a steeper slope
- Even though all classifiers improved in accuracy, the improvement rate gradually diminished
- Among the classifiers, DNN exhibited the highest sensitivity to increased EEG training data
- The TM and NB were the least sensitive to changes in the amount of EEG training data

## Future Work

- Using traditional data augmentation techniques to increase the EEG training data
- Utilize generative models to synthesize additional EEG training data for augmentation
- Apply transfer learning to augment each subject's EEG data using data from other subjects
- Apply regression techniques to predict the amount of EEG training data needed for 100% accuracy

## References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