Lie Detection based on EEG Signals and Ensembles

Team 31:

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Introduction

- Electroencephalogram(EEG): A non-invasive method to record electrical activity of the brain along the scalp.
- We record this data by asking few sets of questions and the subject responds with either yes or no, we run this a couple of times and take an average.
- We then use this data to see patterns using machine learning to predict based on past data.
- The fundamental concept is of pattern matching.

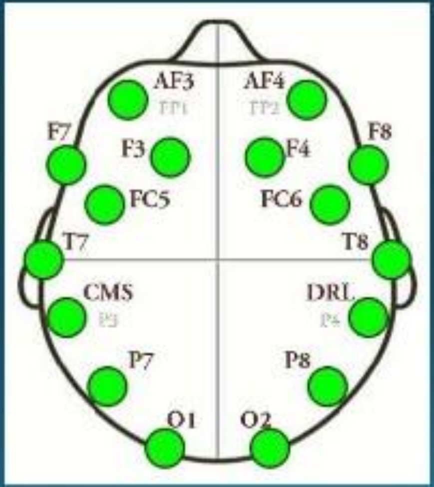
Motivation

The concept of pattern matching has various use cases:

- We could use this to map certain action to perform certain tasks like biting your tongue to turn off the lights in a room.
- Helpful for handicapped people to navigate using a wheelchair, wherein their facial right/left eye blink could be mapped to turn the wheelchair right/left resp.
- We're using this for Lie Detection because Lie Detection is traditionally done by measuring heart rate, skin conductance and rate of breathing etc. which requires a lot of setup. So, we wanted to use EEG and make this a handy process

Testing

Sensor Positions



Problem Statement

We model the task of Lie Detection as a classification problem.

Let *D* be the dataset containing EEG signals captured for each subject and where x_i is the data collected by $\boldsymbol{i^{th}}$ channel where $\boldsymbol{i \in \{1, 2, 3 \ldots . 16\}}$ and y be the output class label where if $\boldsymbol{y} = \mathbf{1}$ then the subject is guilty and if $\boldsymbol{y} = \mathbf{2}$ then subject is innocent.

Let $\boldsymbol{y_{act}}$ be the actual output class label and let $\boldsymbol{y_{pred}}$ be the predicted output class labe using the proposed model. Then the Accuracy A can be defined as:

$$\boldsymbol{A} = \frac{(\boldsymbol{y_{act}} - \boldsymbol{y_{pred}}\ is\ 0)}{total\ class\ labels}$$

Design an optimum model that classifies $\boldsymbol{y}$ using the dataset *D* containing input feature $\boldsymbol{x_i}$ such that the A is maximized.

Dataset

- The dataset was recorded from 10 healthy subjects. The recording was performed for two sessions: Guilty and Innocent.
- The EEG data recording is done by placing 16 Ag/AgCl electrodes at Fz, FC1, FC2, C3, Cz, C4, CP5, CP1, CP2, CP6, P3, Pz, P4, O1, Oz and O2 sites following 10-10 international system for electrode placement.
- Three types of stimuli (target, irrelevant and probe) are presented to the subject. Instead of asking question, we have shown certain images to subjects
- The subject has to recognize those images and has to answer in a “yes” or a “no”.

Format of Data

We have a 10 fold dataset.

Each fold represents each subject as the testing data, for example fold 1 consists of subject 1 as test data and rest all subjects from 2 to 10 as train similarly for fold 2 and so on.

Fold 1 train - contains all the data from subject 2 to 10

Fold 1 test - contains data from subject 1

- For each subject in the ten-fold EEG dataset we do the following in each classifier model:
- For each fold i:
- Test data = train fold i
- Train data = train fold j for all j where $1 \le j \le 10$ and $j \neq i$.

Key Concepts

Weighted Voting Classifier

Weighted voting works on the ideology of giving power to the stronger. In weighted voting, the weights are assigned to classifier on the bases of some specific characteristics. In this report, the weight is assigned based on the test accuracy of the classifier. The below equation can be used to assign weights to each classifier:

$$\text{Weight of the classifier} = \frac{\text{Accuracy of the classfier}}{\text{summation of Accuracy of all the classifiers}}$$

After the weights are assigned, the class which gets the highest vote is produced as the final output.

Key Concepts

Majority Voting Classifier

This is one of the best voting classifiers that uses the ensembling technique. In this classifier, the results of several classifiers producing class labels are counted and the class label that gets produced the maximum number of times is chosen as the final output. In majority voting classifier, the number of constituent classifiers should be odd to keep the logic behind getting the majority voting. Figure 3.8 clearly explains the working of majority voting classifiers.

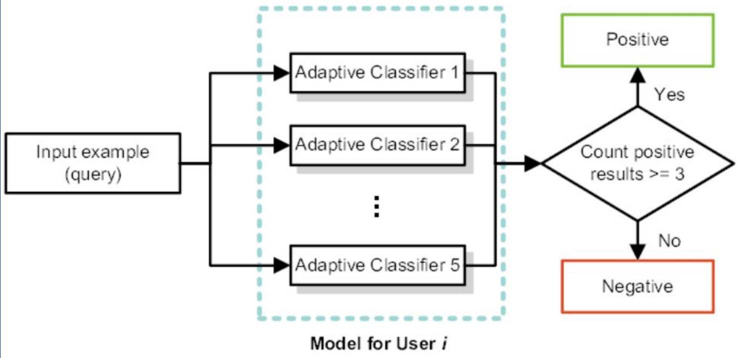


Figure 3.8 Majority voting classifier

Key Concepts

Unanimous Voting Classifier

Unanimous voting classifier is unique classifier where all classifier needs to agree on a particular class label to produce output as that class label. It means that if any classifiers disagree, then the decision will be turned. In this report if every classifier but one agrees upon the subject being innocent then also the output label will be innocent. In simple terms, if any classifier output subject as guilty then output will be guilty.

Key Concepts

Hyperparameter Tuning: The hyperparameters define how our model is structured whereas the model parameters specify how to transform the input data into the desired output. Unfortunately, there's no way to calculate “which way should the hyperparameter be updated to reduce the loss?” (i.e., gradients) to find the optimal model architecture; thus, we generally try out different experiments to figure out what works best. In general, this process includes:

- Start by defining a model
- Then define the range for the hyperparameter with all possible values
- Go on to define a method for sampling hyperparameter values
- Now define some evaluation criteria to judge our model
- Finally, define a cross-validation method

Key Concepts

K-fold cross-validation

In K-fold cross-validation, from the whole data first, the test data is kept aside. The remaining data is divided into K number of folds, where each one of the k-folds is taken as the validation set and the remaining k-1 folds are used as the training set. This will be repeated k times until every fold is made and validation set exactly once. The 5-fold cross-validation is shown in figure 3.9. K-fold cross-validation helps to increase the accuracy of the data that it has not seen before as it applies k number of times on the same dataset with subsets of data.

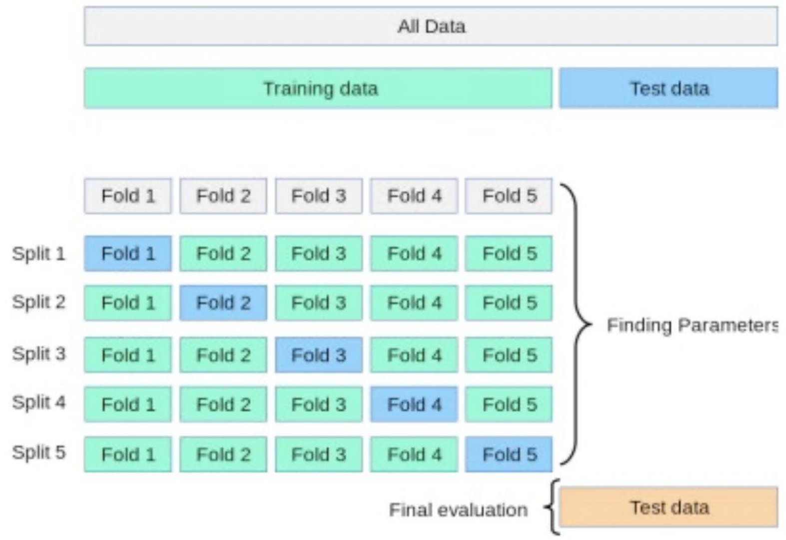
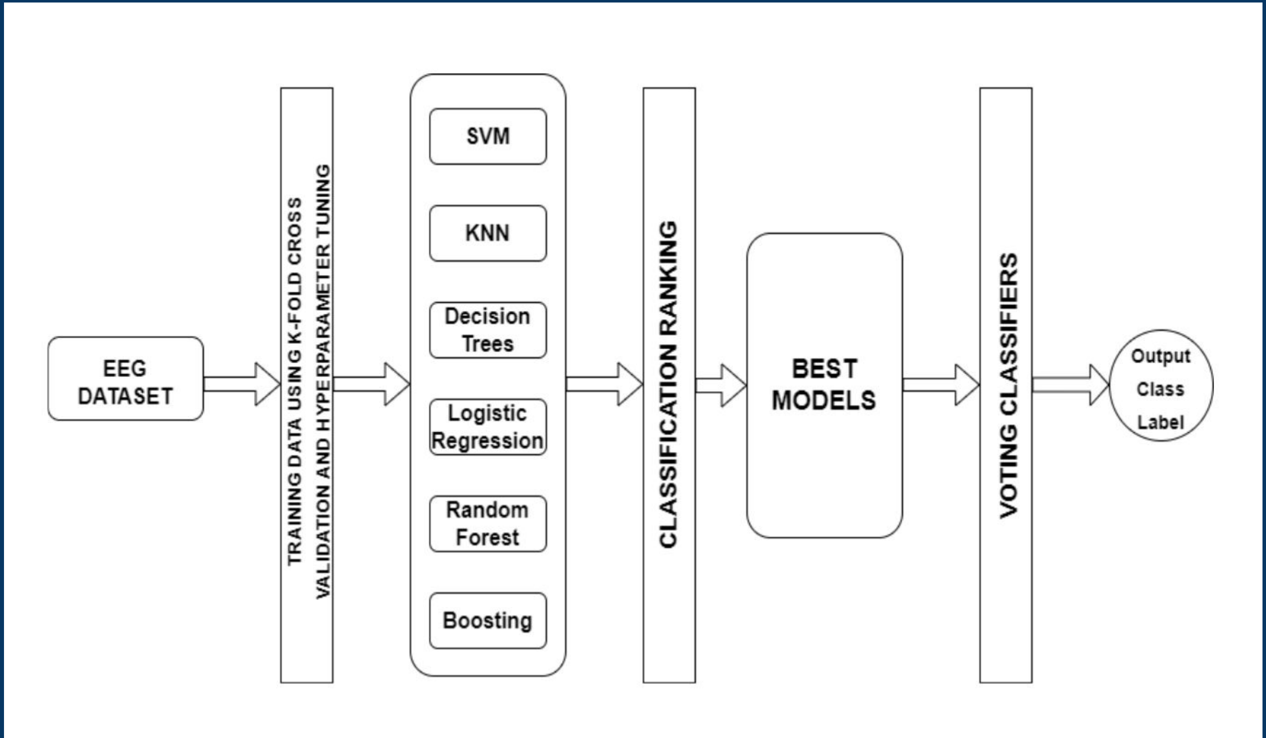


Figure 3.9 5-fold cross validation

Literature Survey

There are several papers which have used the raw EEG data. Using the data, time and frequency domain information was extracted using techniques like wavelet transform, BAT algorithm, Binary BAT Algorithm etc. [1] [3] [4] [5] [6] [8] [11] that helped to get optimal feature extraction from the dataset and hence the accuracy gets increased. The raw EEG dataset contains numerical data in the time series format, using deep neural networks techniques were used to classify EEG signals with accuracy reaching till 95% [11]. Using Deep belief networks instead of the deep neural network did not work well leading to an average accuracy of 85% even after apply wavelet transform technique for feature extraction [8]. Also using K means clustering and feed forward neural network after wavelet transform produces only an accuracy of 83.1% [6]. Another work including wavelet transformation for feature extraction and then applying Support vector machine for classification achieved 84.29% as the accuracy [3]. Another work that has used frequency and time domain representation the data and uses LDA for classification instead of SVM achieved accuracy of 86% [1]. However, our project scope is limited to the potential (or amplitude) information of the EEG data that means each cell in the data represents the maximum peak value achieved at any instant of time for that recorded signal.

Architecture



Implementation

- The hyperparameters, cross validation accuracy and cross validation f-measure for the above training data are found using k-fold cross validation.
- Now the models are trained with train data and tested with the test data to get the metrics (accuracy, sensitivity, specificity, f-measure) for all the models.
- Then all the models are ranked in descending order of their cross-validation f-measure values.
- From those models only the top models are passed to the voting classifier.
- Finally, the voting classifier produce the output class label with the final accuracy.
- This whole process is repeated for each fold, and we will get the accuracies for all ten subjects. The final accuracy is achieved by taking average of each subject's accuracy.

Observations

- Average accuracy for the subjects for the three weighted voting was observed to be 85.06% and for five weighted it was observed to be 86.04%. Hence it can be that five weighted voting classifier is performing better than three weighted voting classifiers.

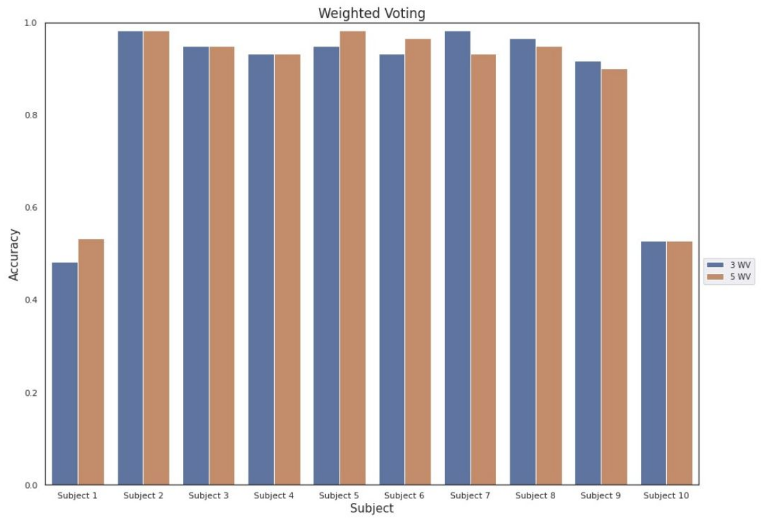


Figure 4.1 Weighted voting for all subjects

Observations

- Average accuracy for the subjects for the three-majority voting was observed to be 86.06% and for five majority it was observed to be 86.04%. Hence it can be that three-majority voting classifier is performing better than five majority voting classifiers.

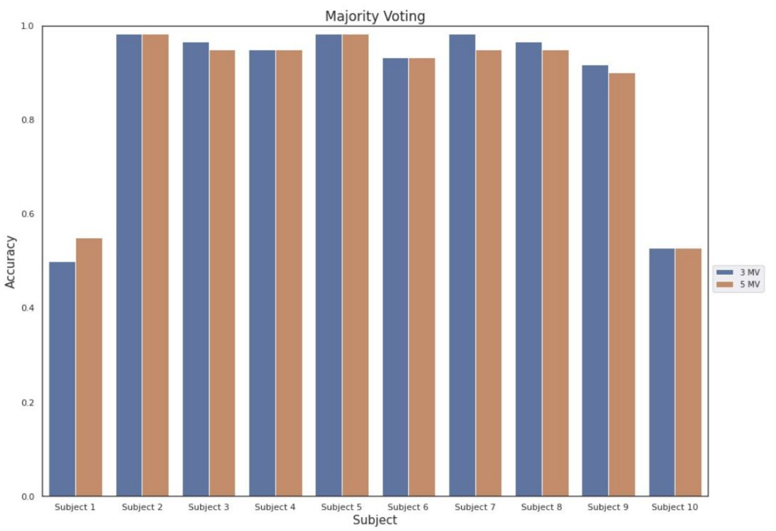


Figure 4.2 Majority voting for all subjects

Observations

- Average accuracy for the subjects for the three unanimous voting was observed to be 83.71% and for five unanimous it was observed to be 79.87%. Hence it can be that three unanimous voting classifier has performed similar to five unanimous voting classifiers.

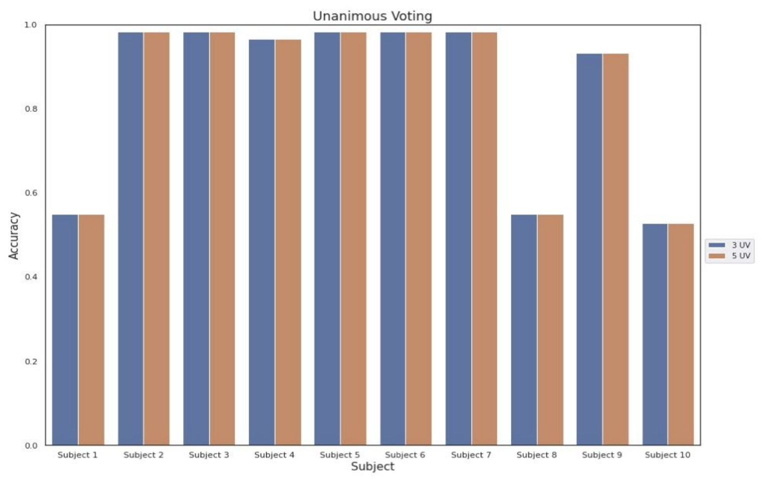
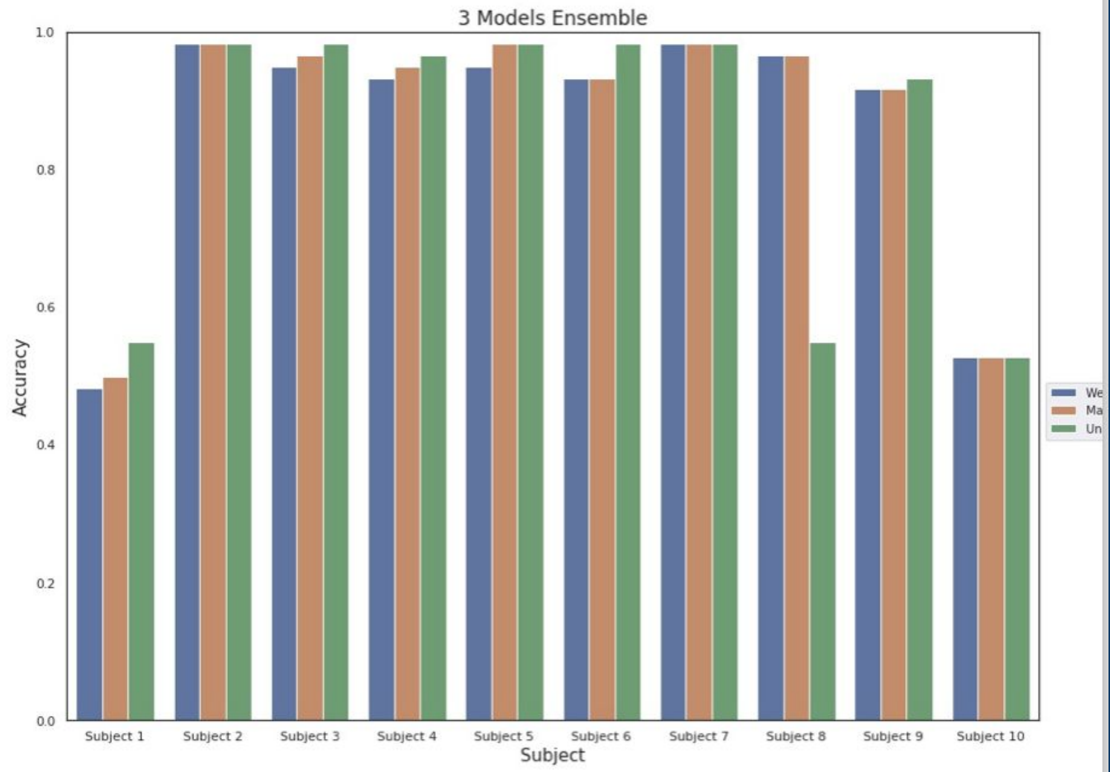


Figure 4.3 Unanimous voting for all subjects

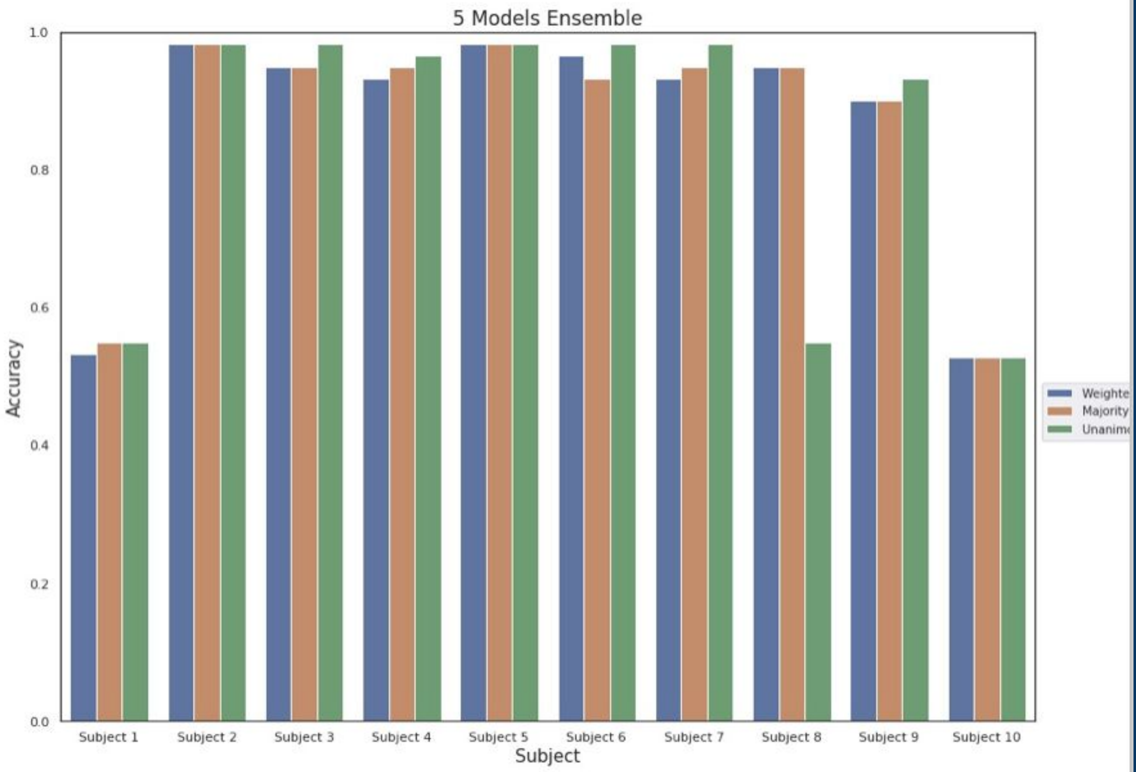
Observations

Figure 4.4 3 model ensemble for all subjects



Observations

Figure 4.5 5 model ensemble for all subjects



Result

From the observations and analysis of each voting classifier considering different number of best models the best accuracy is achieved by three majority voting classifiers with accuracy 86.06%.

Future Plan

Following are the improvements that can be made to increase the efficiency –

- **Refining Dataset –** After performing the experiment, our observations have clearly shown that there are some biases/faultiness in some part of the dataset. The outliers of data set have to be removed and data has to be refined. This process will result in significant improvement in the accuracy.
- **Channel selection –** From the 16 channels that are reading and capturing the brain waves, only those optimal channels can be selected that contains significant information, these channels be selected with some optimization techniques to produce better results.
- Instead of using the accuracy as a measure to choose best model, application specific measures can take into account.

THANK YOU

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