BS6200 Project Report: Machine Learning-based EEG siganl classification for seizure detection

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1 Introduction

Epilepsy is a neurological disease characterised by recurrent, unprovoked seizures. It is one of the most common neurological disease, affecting 70 million worldwide (Paul, 2018). About 30% of people with epilepsy are medically intractable, which is associated with adverse outcomes, such as serious comorbidities, injury and death (Kuhlmann et al., 2018).Clinically, seizure can be recorded in electroencephalogram (EEG), which is an electrophysiological monitoring method that measures brain electrical activity. Since the disease onset is considered to be potentially dangerous and largely unpredictable, careful monitoring of EEG signals for early detection of seizure is important to avoiding severe adverse outcomes caused by the disease. Thus, developing an automated approach for seizure detection based on machine learning has drawn great interest in the field of both biomedical sciences and data science.

Technically, EEG signals measures voltage fluctuations due to intra-neuron ionic current, which can be caused by seizure and a variety of non-seizure states, such as eye open and eye close with different patterns. Distinguishing the signals from each other can improve our understanding of brain function with the different patterns identified to be involved in the signals, which will increases our knowledge of neuropathological processes, eventually contributing to better seizure detection, prediction and treatment. Thus, lately various machine learning approaches have been proposed to decode the signals. In this paper, we will construct and assess a series of supervised learning approaches, along with different feature engineering approaches, to classify EEG signals into 5 different classes.

2 Problem Statement

The project aims to apply and develop suitable machine learning approaches to perform multi-class classification of EEG signals with a simplified, machine learning-ready version of EEG dataset from the University of Bonn (Andrzejak et al., 2001), which is acquired through UCI Machine Learning Repository (Asuncion & Newman, 2007), to order to compare and contrast how different data preprocessing approach may affect choices and accuracy of different machine learning models. Thus, we propose hypotheses as follows:

1. Different machine learning approaches can classify EEG signals into 2+ classes with good accuracy.
2. Dimension reduction methods such as principal component analysis (PCA) can retain the accuracy of machine learning models despite reduced size of input data
3. Feature engineering methods based on wave analysis can increase the accuracy of machine learning classifiers.

Our ultimate aim is develop optimised models for the multi-class classification of EEG signals and compare and analyse their results with insights into model choices.

3 Dataset Description

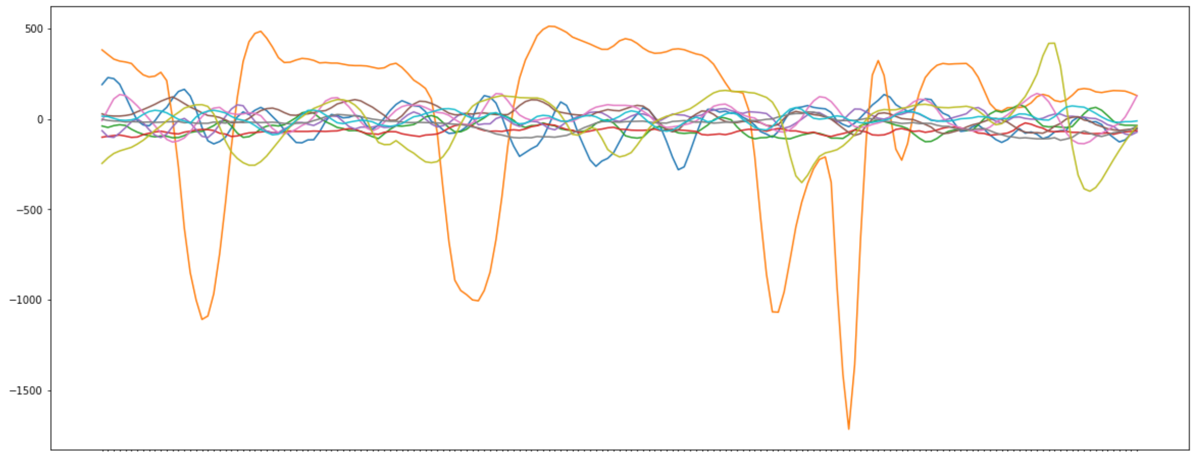


Figure 1. Example EEG signals

As illustrated in Figure 1, EEG signals are time-series data involving fluctuations and waves. According to the description on UCI Machine Learning Repository, the whole dataset consists of 11500 pieces of EEG signals data from 500 individuals. Each piece of data measures a time period of 23.6 seconds with 178 data points. The dataset classify all EEG data into five distinct types by biological significance:

1. during seizure activity
2. in brain tumour sites
3. in healthy brain
4. during eye close
5. during eye open

Among the data classes, only Class 1 is considered to have seizure activity, while the rest are non-seizure but related to other defined biological states. As illustrated in Figure 2, recordings of seizure activity have much more volatile curves than other classes of recordings. Thus, a good number of works have been aimed to perform binary classification of the signals, which can achieve high accuracy (Resque et al., 2019).

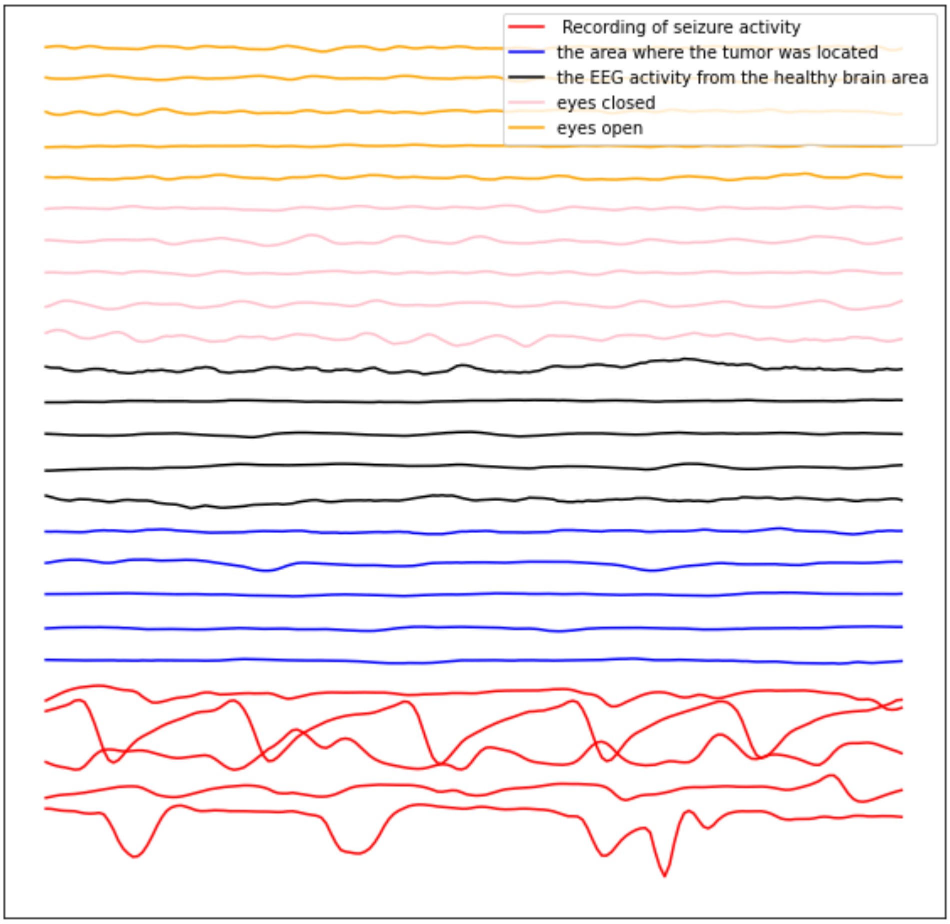
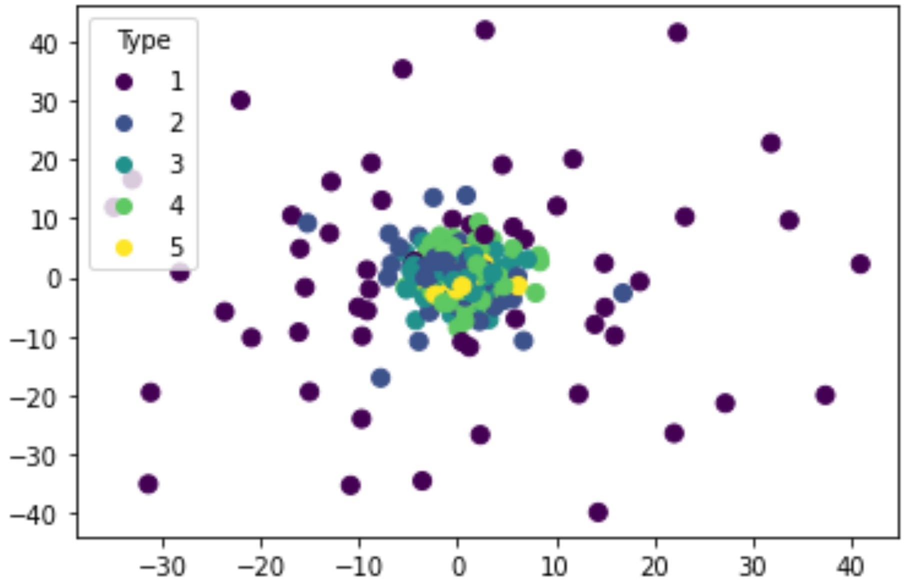
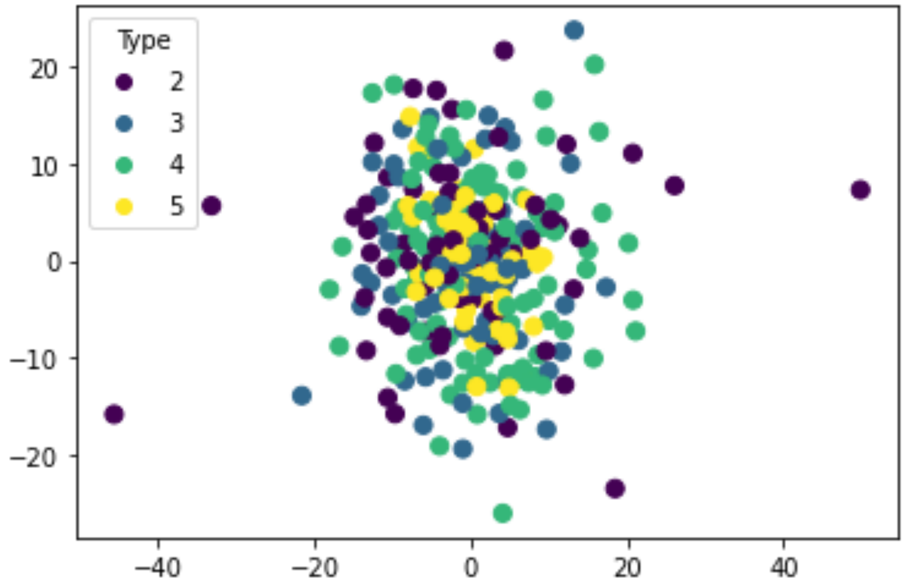


Figure 2. Classification of EEG signals

To further visualise the differences between data classes, we leverage multidimensional scaling (MDS) to visualise the high dimensional data of EEG, as shown in Figure 3. In Figure 3a, it is all non-seizure cases cluster in the centre, whereas the rest sparsely located off the central cluster are mostly seizure cases. In Figure 3b, we further aims to visualise high-dimensional non-seizure data with MDS, where different classes of data tend to mix with each other.



3a) visualisation of all classes of EEG data (Class 1-5)



3b) visualisation of non-seizure classes (Class 2-5)

Figure 3. Visualisation of different types of EEG signal clustering using MDS

Thus, the cluster suggests relatively higher difficulty of 5-class classification when compared with binary classification, where most models used can reach accuracy as high as more than 90%. Also, for binary classification, the chance of getting accurate results are 50%, which suggests a much higher baseline than 20%-baseline in the 5-class classification question. Thus, any model with > 20% accuracy outperforms random guess. In this model, we will validate whether most machine learning techniques can outperform this and further compare the models.

4 Data Preprocessing

4.1 Raw Data

4.1.1 Feature Scaling

Our first step is feature scaling to limit the range of the data, which gives us certain benefits. First, feature scaling can avoid feature variance from affecting the performance of models such as supported vector classifier (SVC) and K-nearest neighbours classifier that are prone to unequal variance. Second, it is known that data normalisation is known to improve performance in SVC (Liu, 2011) and other models. Third, for models not sensitive to data distribution, deploying the same data scaling method also makes it possible to compare between machine learning models using the same set of features. Lastly, it is also important to our next step, PCA, as it tries to get the data with largest variance.

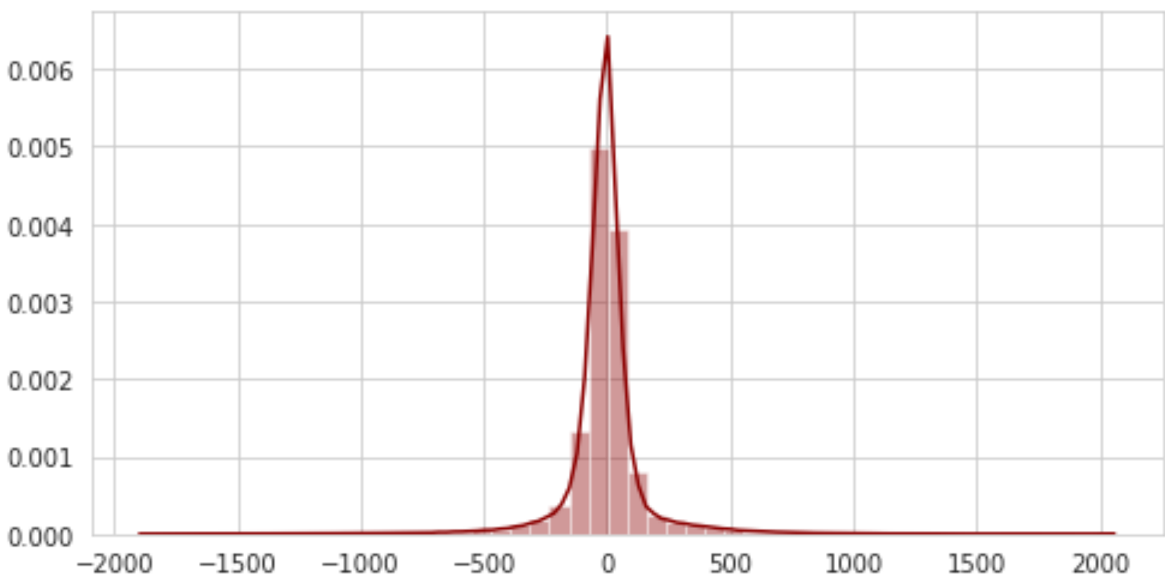


Figure 4. Distribution plot of EEG data

Thus, to choose a proper data scaling technique, we plot the data distribution in Figure 4, which the EEG data is already normally distributed. Thus, we standardise the data with StandardScaler from the scikit-learn package to create a standard normal distribution of the data and to scale the data within [0,1] for models with raw input data. Since our engineered features have quite different ranges, to normalise them, we use *normalize* function from the sckit-learn package to ensure each data have the same range and normally distributed.

4.1.2 Dimension reduction with principal component analysis (PCA)

As is mentioned above, PCA is a technique used for dimension reduction by identifying components with largest variance. For our data with 178 dimensions in the input, with PCA can be beneficial in several aspects. First, it can remove correlated features in the dataset, which simplifies the input dimensions. Second, with less features, the speed of algorithm execution is faster. Third, it is likely that PCA can reduces overfitting when often occurs when there are too many variables, which may contribute to better model performance. Here we plot the scree plot of our PCA result as illustrated in Figure 5. To get 95% of the explained variance ratio, we select 39 principal components with largest variance.

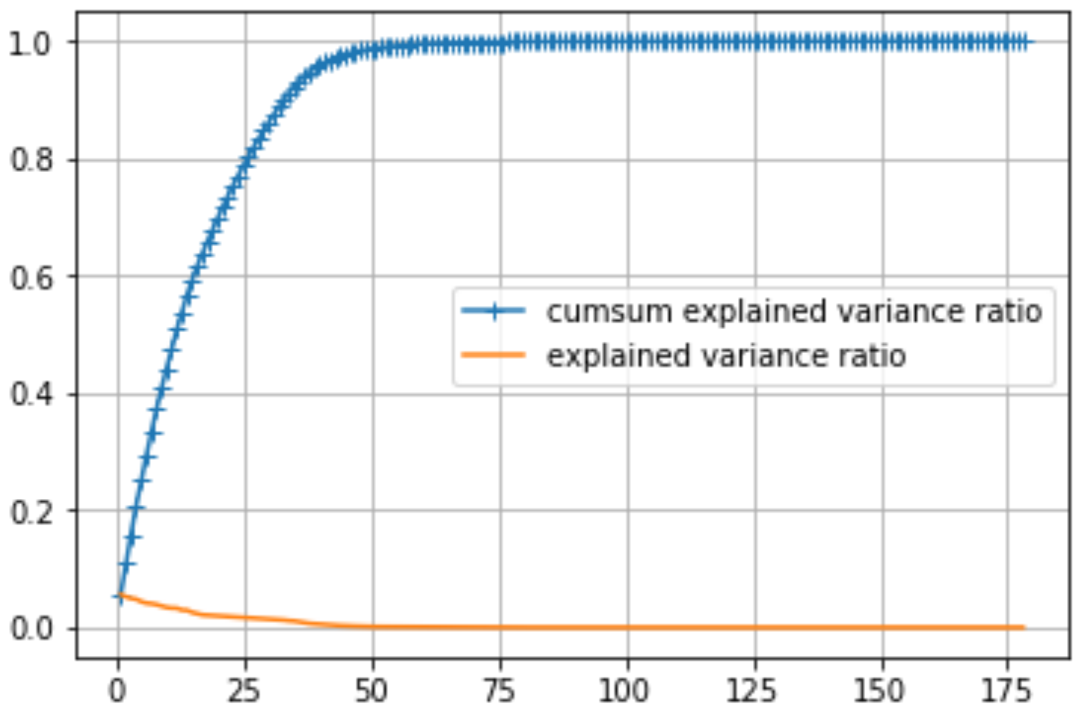


Figure 5. PCA scree plot

4.2 Feature construction with fast Furrier transformation (FFT)

Although it is possible for machine learning models to learn the features in the dataset with relatively good accuracy, we also try to dissect the EEG signals based on existing knowledge of EEG analysis, which may help us to build more interpretable models. EEG signals are typically separated by 4 pre-defined frequency bands, namely alpha, beta, gamma, theta and delta waves, which are considered to be correlated with different spectra of neurological diseases (Newson & Thiagarajan, 2019).

Thus, we engineer a series of variables based on FFT, which can be illustrated in the heatmap below (Figure 6), which is based in a previous work (see Jupyter Notebook for details) and analyse a variety of wave features of the signals. This is actually superior to our previous methods which treat the data as an array, ignoring the time-series nature of the data, thus building on more interpretability of the models.

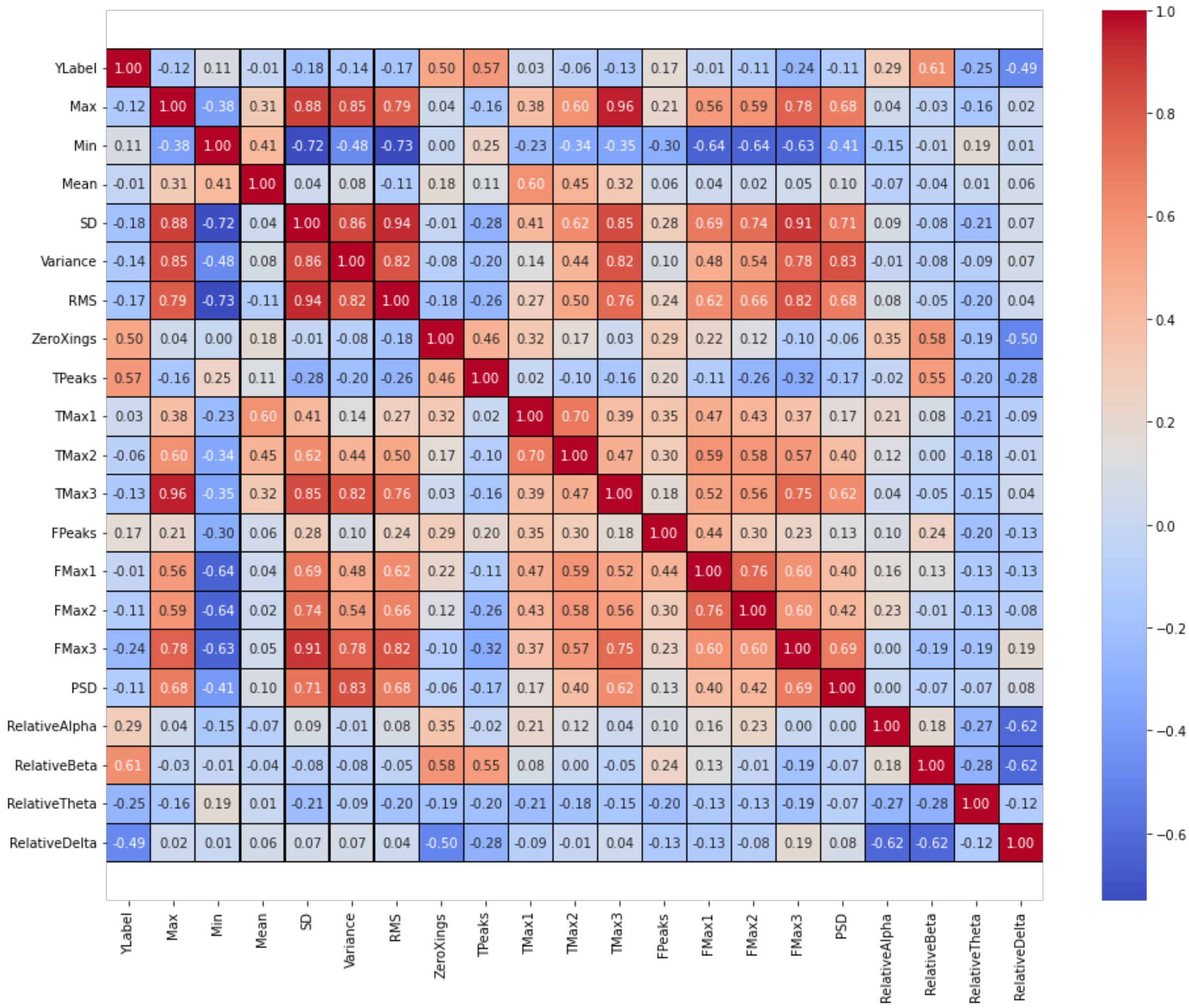


Figure 6. Heatmap of engineered features

With the feature constructed, we further perform lasso to select features with importance > 0. Thus, 10 of the 20 features are selected, which includes Max, Min, ZeroXings, TPeaks, TMax1, TMax2, FMax1, RelativeAlpha, RelativeBeta, RelativeTheta. Thus, we can simplify the input dimension, which is believed to increase model training speed for our models.

5 EEG Signal Classification

5.1 Classification with raw data input

Here we use a variety of models which include logistic regression, supported vector classifier, naïve Bayes classifier, multilayer perceptron (MLP), random forest classifier, gradient boosting classifier for processing the data without feature engineering.

We first take a grid search approach with cross validation to tune hyperparameters of our models. With the tuned parameters, we further divide the data into 70% training and 30% testing and then re-run the model for training and testing, which produces the model accuracy in the raw dataset and PCA-based dataset. Below is a summary of training results.

Models	**Accuracy (raw input)**	**Accuracy (PCA-based)**	**Change**
Logistic regression	0.25645	0.25732	0%
Supported Vector Classifier	0.68792	0.69922	1%
K Nearest Neighbour	0.49406	0.51898	2%
Naïve Bayes	0.44538	0.62967	18%
Multilayer Perceptron	0.69284	0.71544	2%
Random Forest	0.51463	0.62417	11%
Gradient Boost	0.68937	0.72675	4%

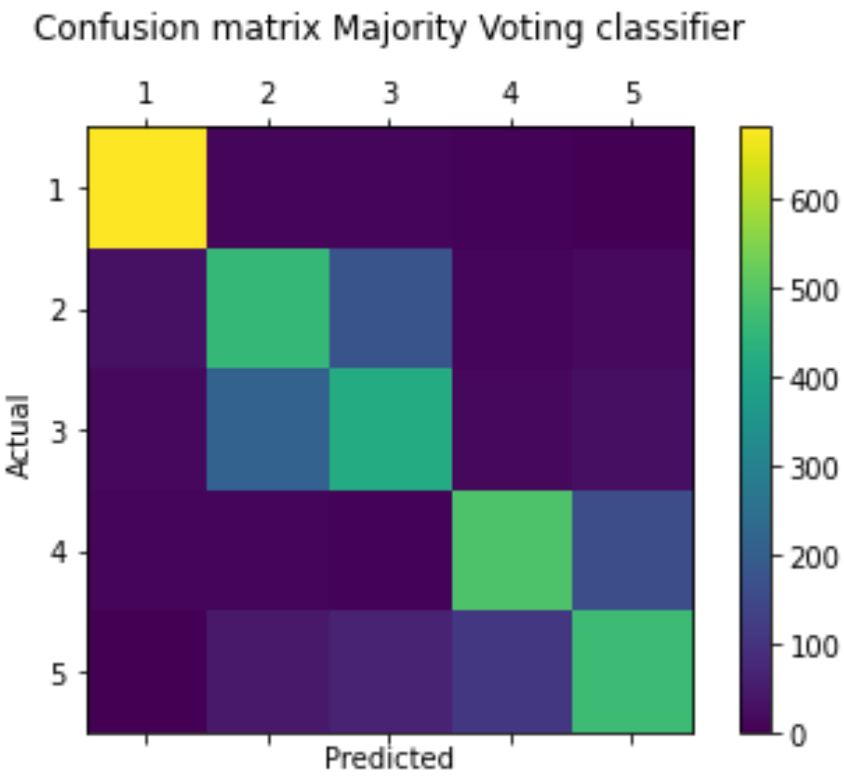
Table 1. Accuracy change of models before and after PCA

As mentioned in the Data Preprocessing section, PCA increases training results to different extent, as discussed in the Data Preprocessing section. Although all models are better classifiers than guessing, logistic regression always have the worst performance, which may suggest nonlinear nature of the categorical data which may be unsuitable for working with logistic regression. K nearest neighbour, which is an algorithm that classifies data according to majority voting or averaging of distance between the data point and different clusters can always correctly classify around half of the result. However, the distance-based method may be subject to the mixed-up data points between clusters, thus contributing to a lower performance.

Interestingly, naïve Bayes and Random Forest classifiers get similar accuracy at around 62%. Random forest is an ensemble learning method which fit fits a number of decision tree classifiers on a variety sub-samples of the dataset which then use averaging to improve classification accuracy. Naïve Bayes classifier is based on the Bayes theorem, which allows us to calculate *a posteriori* probability based *on a priori* probability, hence predicting the chance of variables of interest based on the data found on the hypothesis and the total data, which then classify the data according to larger *a posteriori* probability. Here removal of correlated variables may partly explain the increased accuracy in naïve Bayes classifier after PCA.

It is notable that supported vector classifier (SVC), multilayer perceptron (MLP), and gradient boosting classifiers can make classification as accuracy as around 70%. SVC calculates hyperplane that separate the data points with largest margin in a high-dimension space, where the flexibility of kernel functions are helpful to make good classification for linear and non-linear data. MLP is a class of feedforward artificial neural network, which can extract features itself with hidden layers, which are helpful to learn high dimensional, multi-class data. Gradient boosting classifier uses many weak learning models together, typically decision tree classifiers. With addition of new learners to the classifier, which produces a new output to correct for errors in the predictions, which increases classification accuracy.

Here, to leverage the three highly accurate models (SVM, MLP and Gradient boosting classifiers), we further apply them to a majority voting classifier, which produces an accuracy of 73%, outperforming the three models together with the PCA-based raw input dataset, as illustrated in Figure 7. As expected, Class 1 has very high precision, recall and F1 score, while the rest have much lower classification accuracy, which pulls down the overall performance of the classifier. Similar issues should happen in all the above-mentioned models, which is however yet to examined in further studies.



	precision	recall	f1-score	support
1	0.93	0.96	0.94	709
2	0.62	0.66	0.64	685
3	0.62	0.61	0.61	690
4	0.78	0.73	0.75	676
5	0.69	0.68	0.68	691
accuracy			0.73	3451
macro avg	0.73	0.73	0.73	3451
weighted avg	0.73	0.73	0.73	3451

Figure 7. Classification report of majority voting classifier (raw input + PCA)

5.2 Classification with engineered features

To test whether models based on engineered features can outperform those based on PCA or raw input, we train three models with grid search for hyperparameter tuning. The three models are SVC, MLP and Gradient Boosting Classifier. We use the same approach to train and test the models yet based on a engineered feature dataset scaled with normalisation. Table 2 shows the summary of the model performance.

Models	Accuracy
Supported Vector Classifier	0.7142857142857143
Multilayer Perceptron	0.6860869565217391
Gradient Boost	0.7141614906832298

Table 2. Accuracy change of models before and after PCA

It is clear that despite significantly reduced input data, the models have similar performance or outperforms those using PCA-processed or raw input data, which suggests that the constructed features are able to capture most of the features that are important to classification.

6 Conclusions and future works

In this project, we apply a number of popular machine learning methods for a 5-class classification question based on seizure detection dataset. First, we show that all the models can classify the data with better accuracy than random guess, yet we are still missing certain popular classifiers such as recurrent neural networks and convolutional neural networks. Yet, although we show that PCA can increase the classification accuracy in raw input dataset, it is unclear whether this holds true to human engineered features or whether it can do better than Lasso-based feature selection. Second, there are still a wide range of other human engineered features such as moving average that is worth constructing and testing in addition to our engineered features, which may help us to construct better, more interpretable models. Finally, a lasting question in the field is whether seizure is predictable. Although some proposed methods such GenericPred (Golestani & Gras, 2014) to predict seizure in a short time period, we have not got enough time to deploy the model to our dataset, which is a good future direction for our next step.

7 Code Availability

The code for reproducing the results are available in Jupyter Notebook format at https://github.com/ydchen17/SeizureDetection. The dataset is supplied within the notebooks. Further changes, if applicable, may be made to the GitHub repository.

8 References

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