Evaluating the ML Models for MindBigData (IMAGENET) of the Brain Signals

Priyanka Jain, Mayuresh Panchpor, Saumya Kushwaha and Naveen Kumar Jain
Artificial Intelligence Group, CDAC, Delhi
priyankaj@cdac.in

Human-machine interaction is frequently seen as a reflection of human experience; speech recognition, human activity classification, facial identification, sentiment analysis, and so on are all based on sound and sights. Interaction with machines can often exceed the capabilities of the natural human experience, because of the availability of sensors that collect data that the human body cannot. Electroencephalographic brainwaves are a good example of this. The brain has a distinct pattern of electrical activity that comes from the aggregate firing patterns of billions of individual neurons, depending on what a person is thinking, experiencing, or doing. In principle, these electrical impulses can be recognized and processed to infer a discriminative brain activity over a wide range of visual categories in an attempt to read people's minds. This capability is useful for brain-machine interaction, among other things, in addition to clinical uses. In brain-machine interface, more effective classification approaches are critical, because better performing models can read human brain activity with greater accuracy.

Our proposed research focuses on comparing and implementing several machine learning and deep learning methods in order to achieve improved classification accuracy of EEG signals. The key contribution is to extract information (features) from EEG signals in order to classify or differentiate them based on the images used to trigger brain activity. This paper shows how to classify EEG brain waves using an image classification approach. The proposed method works by representing images and classifying brain waves signals using Machine Learning and Deep Learning algorithms. The authors have used the publicly available EEG data from MindBigData (http://www.mindbigdata.com/). The version 1.04 of MindBigData "IMAGENET" of The Brain, open Database contains 70,060 brain signals of 3 seconds each, captured with the stimulus of seeing a random image (14,012 so far) from the Imagenet ILSVRC2013 train dataset and thinking about it. All the signals have been captured using commercial EEGs (not medical grade), with the Emotiv Insight headset, covering a total of 5 Brain (10/20) locations. We have used dataset Insight v1.0 EEG with Spectrogram. The data is saved in a plain text format, with one CSV file for each EEG recording associated with a single image. There are a total of 14012 CSV files which contain data of 5 channels each, this data consists of 26,850,320 data points. These 14012 files are merged into a single CSV file creating a data frame encompassing all the required features from data.

In this research, we have used Time Series Feature Extraction Library (TSFEL) for feature extraction. TSFEL is a Python library for extracting features from time series data on the statistical, temporal and spectral domains. It enables users to do exploratory feature extraction operations on time series without having to write extra program. Statistical domain refers to the mathematical characteristics such as outliers, trends, and seasonal cycles in a data. Temporal domain refers to time and spectral refers to space characteristics of the data.

The implementation of Machine Learning (ML), Deep Learning (DL) and Convolutional Neural Networks (CNN) is presented in two parts: a) Implementation of ML, DL and CNN for EEG Signals Classification and b) Implementation of CNN for Spectrogram Images. We efficiently utilized CNN to classify EEG signals generated by seeing random images. We have increased the model's performance by adjusting the number of epochs, layers, data resampling, and signal noise reduction. Hyperparameter tuning and modifications to the CNN model improved the accuracy with which author read spectrograms and anticipated the proper label.

Bagging classifier had the highest accuracy of 73.24% in this proposed approach. The experiments were performed 14 times with different algorithms and with hyper parameter tuning. The results obtained for EEG signals classification without hyperparameter tuning was 0.12 for Decision Tree and with hyperparameter tuning was 0.13. We have used LSTM architectures, our approach takes less time to train and is less expensive computationally, yet provides an accuracy of 0.71. Whereas in CNN and DNN model, it provides an accuracy of 0.69 and 0.70. Bagging with Logistic Regression provides an accuracy of 0.15 which is very less in comparison to the Bagging Default provides an accuracy of 0.73. XG Boost obtained accuracy of 0.32. F1 scores 0.16, 0.75, 0.16, 0.19, 0.18 and 0.35 were obtained for Logistic Regression, Bagging Classifier, Bagging with Logistic Regression, Decision Tree, Decision Tree with tunning, and XG Boost respectively. Precision 0.19, 0.18, 0.18, 0.56, 0.49 and 0.42 were obtained for Logistic Regression, Bagging Classifier, Bagging with Logistic Regression, Decision Tree, Decision Tree with tunning, and XG Boost respectively. Recall scores 0.16, 0.15, 0.15, 0.13, 0.13 and 0.32 were obtained for Logistic Regression, Bagging Classifier, Bagging with Logistic Regression, Decision Tree, Decision Tree with tunning, and XG Boost respectively. The results obtained for spectrogram Image of CNN model1 without augmentation is 0.10 accuracy and with augmentation is 0.11 accuracy. Whereas in CNN Model2 without augmentation attained an accuracy of 0.74 which is quite higher than model with augmentation attained accuracy of 0.18.

Keywords:
Machine Learning, Convolutional Neural Networks, Deep Learning, EEG, Bagging XG boost, Random Forest, Naïve Bayes, Electroencephalography