CE889– Neural Network and Deep Learning

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Abstract

These days, a wide variety of neural network topologies are being developed. This neural network investigates the working of the human brain. Numerous uses for this network exist, including as in the automotives and medical fields. We classified workload using a dataset dataset provided by the professor using ECG signals. To learn this, the logistic model and deep learning model will be employed. We will compare and discuss the results of each model. A deep learning model and logistic regression model are the two different modelling methodologies are being used for the classification task. For complex data, like ECG signals, deep learning models especially neural networks are more suited than logistic regression, which is more of a traditional statistical modelling technique. The purpose of the project is to compare the workload categorization problem's outcome and the performance of the logistic regression models. Metrics such as accuracy, precision, recall, and F1 score scores are evaluated. The discussion will likely focus on benefits and drawbacks of each model as well as a logical justification for any observed variations in performance.

Background

Electroencephalography (EEG), a neurophysiological approach, is employed in this experiment to calculate mental workload. It uses scalp to identify electrical activity in the brain. Certain EEG frequency bands, loke theta and alpha, have been found to associated with cognition load and attention levels. EEG’s high temporal precision makes it useful for tracking abrupt changes in cognitive state. Functional near-infrared spectroscopy is another neuroimaging technique that monitors changes in oxygenated and deoxygenated hemoglobin concentrations in the brain that are likely to neuronal activity. Compared to EEG, fNIRS is more immune to electrical noise and motion distortions. The regions of the brain that light up during cognitive tasks are shown in detail. Pupillometry can also shown signs of cognitive strain because it measures pupil dilation via eye tracking. When performing cognitively demanding tasks, the pupil tends to widen due to increased brain activity. Coulometric measures that can be useful include eye blink rates and gaze patterns. Research has been done on heart rate variability as a mental effort metric. The electrocardiogram data are used to calculate HRV. Higher exertion is associated with reduced HRV as the sympathetic nervous system becomes more active. Multimodal approaches , which combine many physiological signals include EEG, fNIRS, eye tracking, and ECG/GSR, can provide a more comprehensive picture of cognitive state than can be obtained from any one measure alone. Machine learning techniques are often used to aggregate data from these numerous sources to estimate mental workload.

Methods

We have used both a logical and deep learning model to categorize mental workload. Dataset was provided by the professor. Data was first taken from the MATLAB file. The package we have been using to load and read data is called SciPy, then after label separation and data analysis. Total, 180 samples are available, with 180 samples in each of the two classes. There are 20% for testing and 80% for training. The form needs to be changed because we want the samples to be columns. We have defined functions for accuracy, sigmoid, feedforward, backpropagation, prediction, and accuracy report in class that we have built. Using the weights dot product and the train data, we ran a sigmoid analysis. Ascertain the error and modify the bias and weight. We have created a CNN model and Added the sigmoid functions and activation layer to each dense layer. 0.1 and 0.2 dropout functions have now been introduced to every layer. This will help lower the overfitting. Use 5-fold cross-validation with an accuracy score for assessment.

Results

I have thoroughly contrasted these model's output. The Accuracy of CNN model is 0.805% and while that of logistic model accuracy is 0.52% .

Conclusion

We conclude from the above result, we should experiment with additional models. Our model needs to have several layers added or removed as well as some features extraction and selection techniques.

Reflections

I want to use this dataset for other operations in the future in an effort to achieve high accuracy. In order to prepare model appropriately. I need to gain a deeper grasp of data.

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