CE889-SP Neural Networks and Deep Learning

University of Essex

Department of Computer Science and Electronics Engineering

Report on Neural Network Models

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1 ABSTRACT

Measuring mental effort is a fundamental problem in the science of human-computer interaction (HCI). With the rapid growth of technology in the field of HCI, systems that accurately evaluate mental workload automatically are in high demand. One method is to classify levels of mental strain using physiological markers like electroencephalograms (EEG).

As a result, the assignments's purpose is to employ a logistic model and a deep learning model to improve classification accuracy utilising an existing dataset of people who had their EEG signals collected. The dataset comprises two workload classes (low and medium), and we'll compare the performance (accuracies) of both models to learn more about how deep learning models are parameterized and how performance varies among them.

2 BACKGROUNDS

The degree of cognitive engagement that might have a direct impact on the quality and efficacy of task performance is referred to as mental workload [1]. Excessive cognitive engagement in mental activity can be beneficial, resulting in enhanced adaptability, or harmful, resulting in mental overload. The mental effort that is being measured is a combination of innate abilities, internal interpretation, and situational variables that manifest when these tasks are completed.

Young and Stanton proposed that the quantity of attention-related resources required for both subjective and objective performance criteria can be modified by external assistance, task demands, and previous experiences [10]. As a result, it may be deduced that mental workload can be quantified using performance data. When a person puts forth mental effort to complete a task, physiological reactions should be elicited, allowing mental strain to be measured for better awareness of mental workload.

Related works on Workload Evaluation methods

Evaluation of cognitive workload used to be performed with subjective measures, for example, based on interviews or questionnaires, where the amount of mental effort put into a task is assessed. These methods, on the other hand, rely on participants' subjective opinions, which are acquired by psycho-physiological measurement or subjective scales, and they rarely provide accurate, comparable results.

Other more efficient alternative approaches seen in previous studies covers monitoring the cognitive workload changes with neurophysiological measures such as (For references, see the following sources [5, 12]);

- Galvanic Skin Response (GSR)
- Electroencephalogram (EEG)
- pupillometry or cardiogram (ECG)

Studies on brain activity measurement has proven to be effective in visualizing cognitive state changes. Widely used approach of cognitive workload level estimation takes advantage of the EEG signals, and one of the most popular types of features extracted from EEG signals is power spectrum [9]. Due to the sensitivity of theta and alpha oscillations to task difficulty, their variations were also analyzed by Putze et al. in the paper [6], where EEG, GSR, and breathing rate were combined to estimate mental fatigue among drivers in a driving simulator performing a secondary cognitive task. Frontal theta power was also proved to be positively related to working memory engagement and attentions control in a study of different difficulty tasks combined with practice. Holm et al.[3] proposed the EEG-based measure of the overall brain load and it was determined as

$$\frac{\theta(Fz)}{\alpha(Pz)} ratio, \tag{1}$$

Where Fz and Pz are electrodes. In [14] the mental state of individuals was analyzed on the basis of changes in EEG power spectral density, especially in the theta and alpha bands, where the average classification accuracy reached, respectively, 79% and 78%. The classifier applied was based on SVM. The results show that both the alpha and theta powers decrease in central and posterior regions with the increase of the level of difficulty

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Different classification techniques have been applied to the problem of cognitive workload classification, one of such techniques is Artificial Neural Networks(ANN). In [15] Wilson et al. performed two-class classification based on Artificial Neural Networks (ANNs), achieving 86% of accuracy, whereas in another article, the same authors reported 98.5% accuracy achieved with the model built on EEG data in combination with heart rate, respiration, and eye movement measures.

Other classifications technique applied in the cognitive workload research cover SVM and Random forest classifiers. In [13], Yu et al. presented classification of four levels of cognitive workload with a linear probabilistic support vector machine (LIPSVM) at the level of 87%. Mahmoud et al. in [4] classified four cognitive levels achieving the accuracy equal to 92% using linear classification.

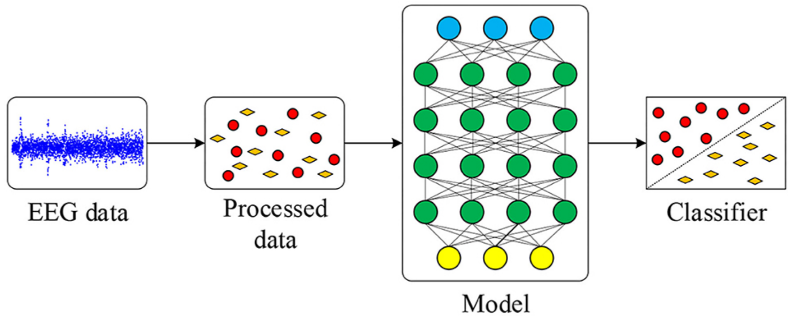


Figure 1: Classification procedure.

3 METHODS

We will be using two approaches to classify the mental workload levels for this assignment. The logistic regression model and an existing deep learning models, of which the Keras model has been selected.

Logistic Regression Model

Logistic regression is a method of binary classification. It can be represented as a function that accepts any number of inputs and limits the output to values between 0 and 1. This means that we can think of Logistic Regression as a one-layer neural network, with its sigmoid functions acting as activation functions in the neural network's hidden layer. [7]

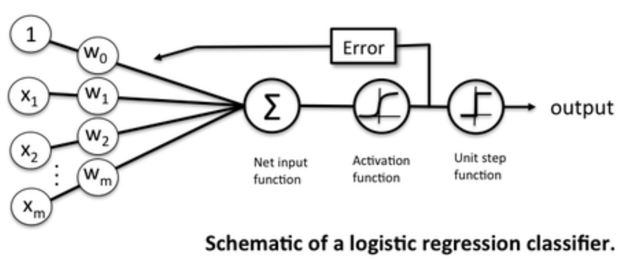


Figure 2: Logistic regression classifier

Keras Deep Learning Model

Keras is a high-level API that integrates with the Tensorflow, Theano, and CNTK backends. It includes a good and easy-to-use API for implementing neural network tests, as well as 10 different neural network modelling and training API modules. The Models API allows you to construct complex neural networks by adding and removing layers. The model could be sequential, which means the layers are stacked one on top of the other with a single input and output. The model can also be operational, which means it can be changed completely. The API also includes a training module, which includes methods for generating the model, as well as the optimizer and loss function, fitting the model, and evaluating and forecasting input messages. It also includes methods for batch data training, testing, and forecasting. Models API also allows you to save and pre-process your models.[8]

Fourier transform (FFT) for Feature extraction

The accuracy of EEG signal detection in signal processing remains a serious issue, and integrating feature extraction for classification has shown to improve performance accuracy. Currently, the Fast Fourier transform (FFT) method, the Fourier spectral feature derived by the Welch method, and the windowed Fourier signal segment transformation are the most common feature extraction methods for EEG images.[2]

4 RESULTS

Below is the results from obtaining classification accuracy using:

(a) Logistic regression model

Using this model, after loading the data, we then transpose, flatten and place the data in a dataframe using pandas. After training, at best, we see the accuracy ranging between 45-52%

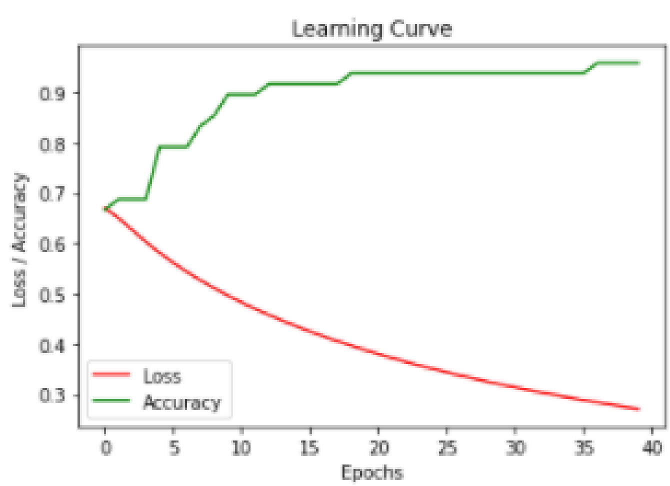


Figure 3: Accuracy/Loss graph using Logistic regression model

(b) Logistic model including Fourier Transform for feature extraction

In this test case, we have used Fourier transform as a methods of feature extraction. thereby reducing the size of the features from 31744 to 6200, this implies that the model is been trained based on relevant features, and the accuracy for prediction was increased giving approximately 96%

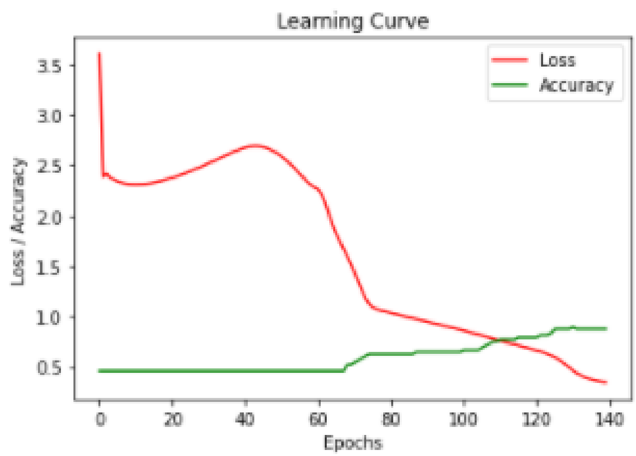


Figure 4: Accuracy/Loss graph using Logistic regression model with FT

(c) Keras model for deep learning

Using this model we see a significant improvement in using this model as the accuracy increases to 60% on the classification accuracy after training the model

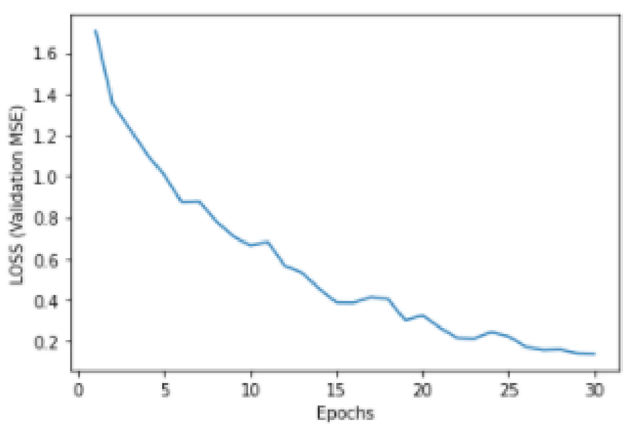
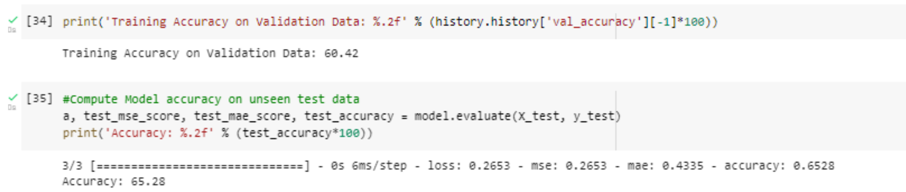


Figure 5: Loss (Mean Square Error) using Keras model



```
[34] print('Training Accuracy on Validation Data: %.2f' % (history.history['val_accuracy'][-1]*100))

Training Accuracy on Validation Data: 60.42

[35] #Compute Model accuracy on unseen test data
a, test_mse_score, test_mae_score, test_accuracy = model.evaluate(X_test, y_test)
print('Accuracy: %.2f' % (test_accuracy*100))

3/3 [==============================] - 0s 6ms/step - loss: 0.2653 - mse: 0.2653 - mae: 0.4335 - accuracy: 0.6528
Accuracy: 65.28
```

Figure 6: Classification accuracy using Keras model

(c) Keras model for deep learning including Fourier Transform for feature extraction

While the accuracy was improved when Fourier transform was introduced to extract features using the Logistic regression model, this is not the case with the keras model. I also tried increasing the number of Epochs but the accuracy stayed within the 50% range for this model

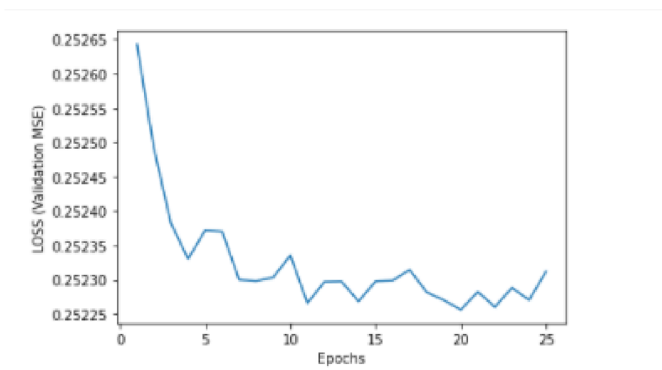
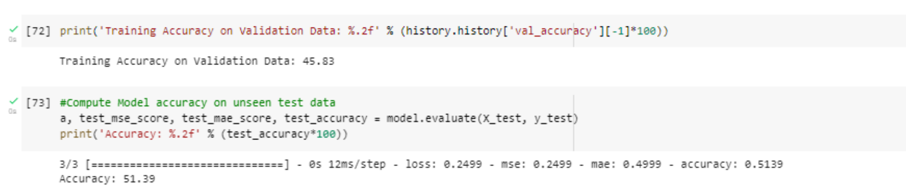


Figure 7: Loss (Mean Square Error) using Keras model with FFT



```
[72] print('Training Accuracy on Validation Data: %.2f' % (history.history['val_accuracy'][-1]*100))

Training Accuracy on Validation Data: 45.83

[73] #Compute Model accuracy on unseen test data
a, test_mse_score, test_mae_score, test_accuracy = model.evaluate(X_test, y_test)
print('Accuracy: %.2f' % (test_accuracy*100))

3/3 [==============================] - 0s 12ms/step - loss: 0.2499 - mse: 0.2499 - mae: 0.4999 - accuracy: 0.5139
Accuracy: 51.39
```

Figure 8: Classification accuracy using Keras model with FFT

5 CONCLUSION/REFLECTION

In conclusion, we can deduce from this assessment that when the Fourier Transform is used to extract features in the Logistic regression model, the classification accuracy improves to 96 percent. When combined with the Keras model, however, the classification accuracy does not improve. In order to yield better results, future study will look at acceptable strategies for feature extraction and classification of EEG signals.

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