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Abstract

A high mental workload decreases work efficiency, while a low mental workload wastes human resources. It is critical to investigate the mental workload of operators. The current method for classifying mental workload is based on electroencephalogram (EEG) features as it has promising psychophysiological measures to determine the amount of workload. In this study, the proposed method is to perform Binary Classification to classify between low workload and medium workload. In order to do so we have performed Fourier transform (FT) on the signals to obtain power features in four frequency bands theta, 4~8 Hz; alpha, 8~12 Hz; beta, 12~30 Hz; and gamma, 30~45 Hz. For each frequency band, there were two power features. Band power and relative band power. The extracted features were fed to two models a Logistic model and a deep learning model Multilayer perceptron. Both the models were trained and tested to understand the Classification Accuracy and was evaluated using 5-Fold Cross-Validation.

Literature Review

The Section illustrates the background of this project, the current and related work through this Literature Review:

2.1 Background

2.1.1 Electroencephalogram (EEG) Signals

A recording of brain activity is called an electroencephalogram (EEG). Small sensors/electrodes are attached to the scalp during the test to pick up the electrical signals created as brain cells communicate with one another. A machine is used to record these signals. [1].

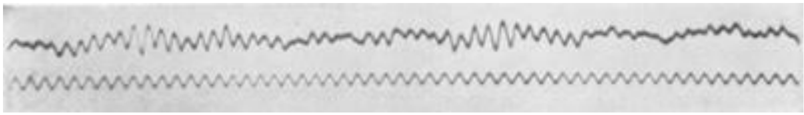


Fig. 2.1.1.a The first human EEG recording obtained by Hans Berger in 1924. [1]

EEG signals have different frequency bands. The main frequencies of Human EEG waves are as follows *delta*, 1~4 Hz; *theta*, 4~8 Hz; *alpha*, 8~12 Hz; *beta*, 12~30 Hz; and *gamma*, 30~45 Hz.

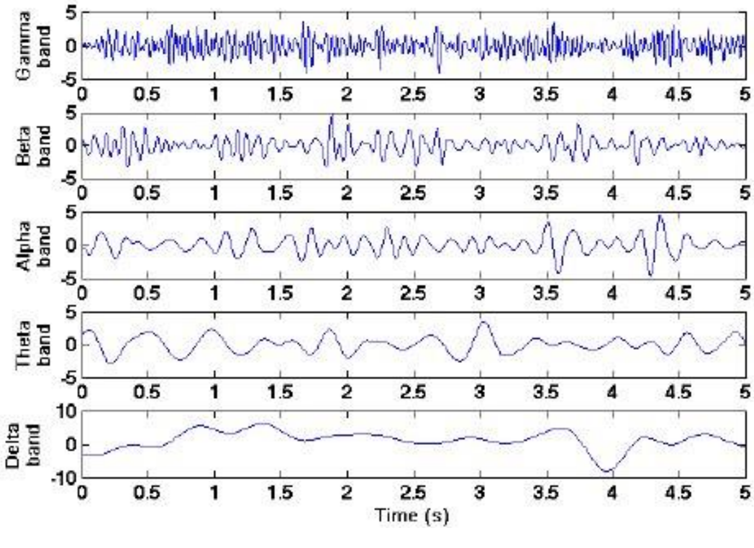


Fig. 2.1.1.b The five frequency bands of EEG signal [2]

Fourier transforms are often used to decompose EEG signals into frequency components. In this method we have performed Fast Fourier transform on the EEG signal to extract Power features Band Power and Relative Band power.

2.1.2 Current and Related Work

Several techniques have been developed to study the EEG signal and classify the workload.

Different types of working memory workload can be distinguished via spectral analysis of changes in hemispheric asymmetry in EEG activity. Davidson et al. (1990) used spectrum analysis to find consistent changes in spectral power in the right and left hemispheres as a function of whether subjects were performing a verbal or spatial working memory test. [3].

Wilson and Russell (2003a) used artificial neural networks to classify workload among highly trained air traffic control personnel on a simulated task. ANNs trained on all seven circumstances had an average classification accuracy of 80%, with the overload condition (91%) having much higher classification rates than any of the other difficulty levels. For ANNs trained on within-difficulty manipulation types, classification accuracies improved to an average of 85.8%. ANNs trained solely on traffic complexity data identified traffic complexity data more accurately than when volume level data was included.[4]

Pang, Guo (2021) used stochastic configuration network (SCN). Individual EEG data were used to create subject-specific classifiers (SSCs). The accuracy of SSC tests ranged from 56.5 percent to 90.2 percent, with an average of 75.9 percent, according to the findings. The operational accuracy and the SSC accuracy have a favourable relationship. [5]

Saadati, Nelson (2019) use CNN, CNNs use two-dimensional pictures as input, which differ in structure from the neural time series collected via EEG and fNIRS on the scalp surface. To allow fNIRS-EEG input to a CNN, both existing CNN designs and fNIRS-EEG input must be modified. With a three-second window and the ELU activation function, the best performance is attained, with the CNN yielding 89%. [6]

In this paper, examined and clarified the roles of feature fusion and feature selection in workload identification by comparing each type of features that contribute to workload identification. When compared to individual feature categories (i.e., band power features, 75.90 percent; conn) the results showed that feature combination (83.12 percent in terms of accuracy) improved classification performance. The classification accuracy was enhanced to 83.47 percent with the Fscore feature option.[7]

<u>**Methodology**</u>

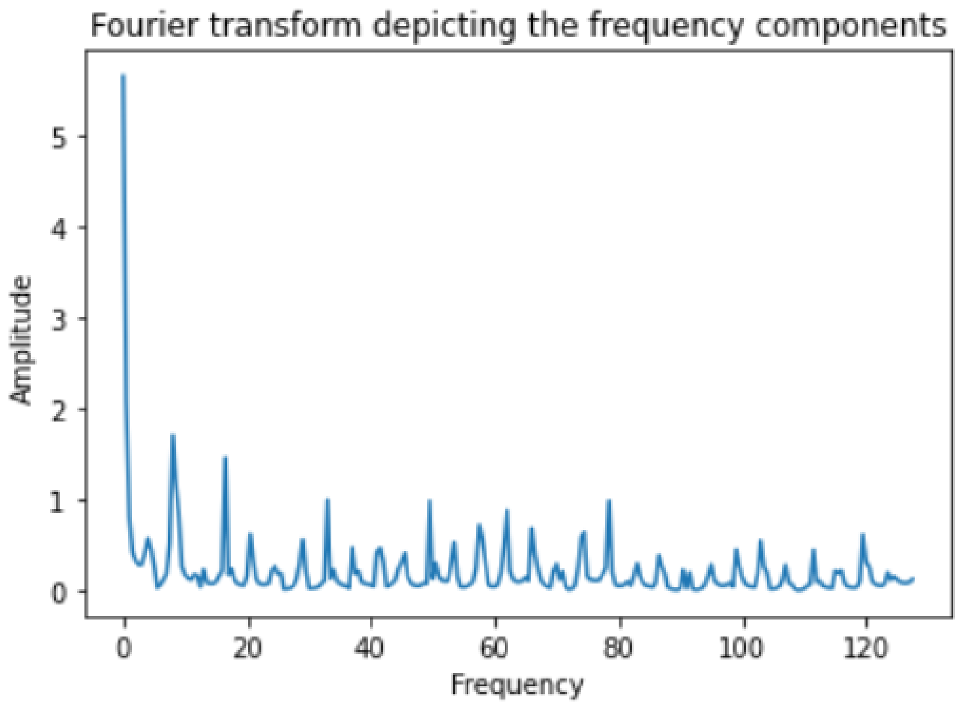
About the Dataset:

This study uses dataset for training and validation of the system for workload classification. This database consists of EEG records of both low workload and medium workload. There are 360 recordings, 180 for each class.
Two Classes: Low Workload versus Medium Workload
Number of Samples: 180 for each class
Sampling Rate: 256Hz

For each sample
- Number of Channels: 62
- Number of Data Points: 512

Proposed Plan:

Data Pre-processing: The EEG signals were transformed using Fast Fourier Transform.



Fi 3.1a: FFT on an EEG signal

<u>**Feature Extraction**</u>

We have extracted the Power features of the signal for frequency bands theta, alpha, beta and gamma that is from 4 Hz to 45 Hz. The delta band was removed as it is not needed for workload Classification.

Power Features

To get the Band Power:

We took absolute value of FFT and squared it and got the magnitude and got the Band power for theta, alpha, beta, and gamma that is from 4 Hz to 45 Hz.

To get Relative band power:

Relative band power = Band Power/Total Power

Models:

Logistic Model from scratch:

A simple version of a neural network that categorises data is logistic regression. Logistic regression takes an input, runs it through a sigmoid function, and then returns a probability between 0 and 1 as an output. This sigmoid function is responsible for classifying the input.

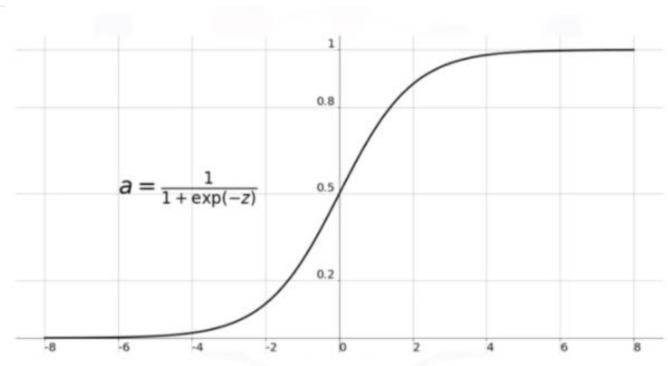


Fig 3.1b: Sigmoid Function

The purpose of a decent logistic regression algorithm is to reduce loss or weight by improving the output's correctness, which is accomplished using the Gradient Descent function. Achieving a low cost function is an excellent technique to assess the success of the logistic regression algorithm.

Steps to create Logistic Model from scratch:

- Implement Activation Function: Sigmoid Function
- Initialize Model Parameters: With x as the input feature, the model parameters are weights (w) and bias (b) initialize with zeroes.
- Build the propagate () function, which computes the cost function (forward) and its gradient to learn the parameters w, b, and y from x. (backward).
- Update Parameters with Gradient Descent
- Create the model to predict if it is low workload or Medium Workload.
- Evaluate the model using 5 fold Classification

Cost Function

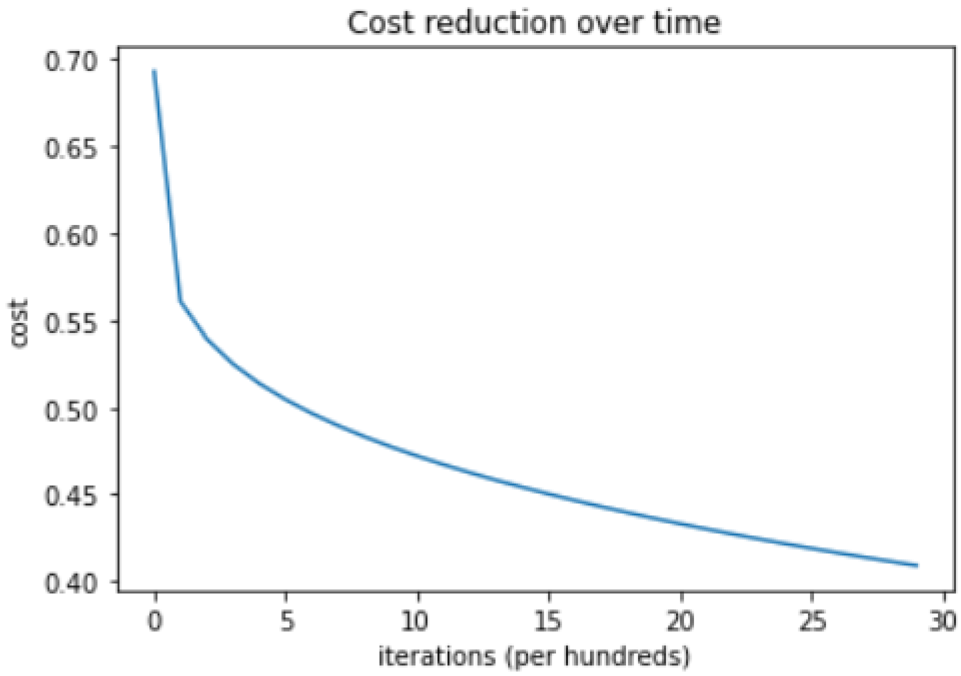


Fig 3.3 Cost Reduction over time

ANN Model – Multilayer Perceptron using Pytorch

A feedforward artificial neural network called a multilayer perceptron (MLP) is a type of feedforward artificial neural network (ANN). The name MLP is confusing, referring to networks built of multiple layers of perceptron's (with threshold activation) in some cases and any feedforward ANN in others. There are at least three levels of nodes in an MLP: an input layer, a hidden layer, and an output layer. Each node, except for the input nodes, is a neuron with a nonlinear activation function. Backpropagation is a supervised learning technique used by MLP during training.[8]

Code Referred from : https://machinelearningmastery.com/pytorch-tutorial-develop-deep-learning-models/ [9]

The sigmoid activation function is used to forecast the probability of class 1 in the model. The binary cross-entropy loss is minimised by utilising stochastic gradient descent to optimise the model.

Model = MLP(496)

Steps to update Model:

- The latest error gradient is being cleared.
- A forward pass through the model of the input.
- The loss for the model output is calculated.

- The error is propagated backwards through the model.
- To minimise loss, update the model.

Evaluation

To Evaluate both models we used 5 Fold Cross Validation:

A K-fold CV is one in which a given data set is divided into K sections/folds, with each fold serving as a testing set at some point. Let's look at a 5-fold cross validation case (K=5). The data set is divided into five folds here. The first fold is used to test the model, while the others are used to train it in the first iteration. The second iteration uses the second fold as the testing set and the rest as the training set. This procedure is repeated until each of the five folds has been utilised as a test set.[10]

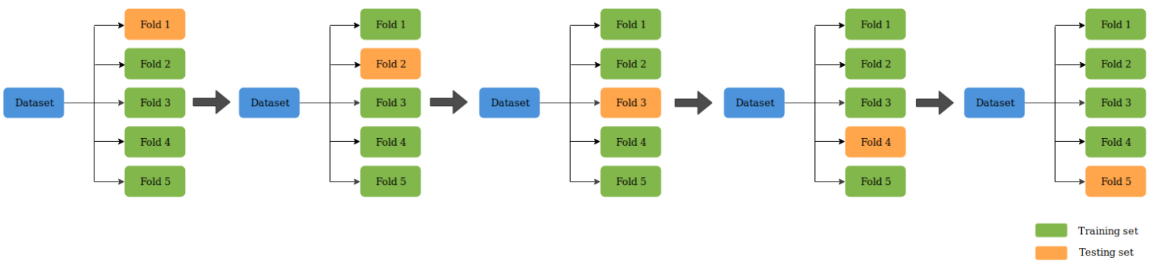
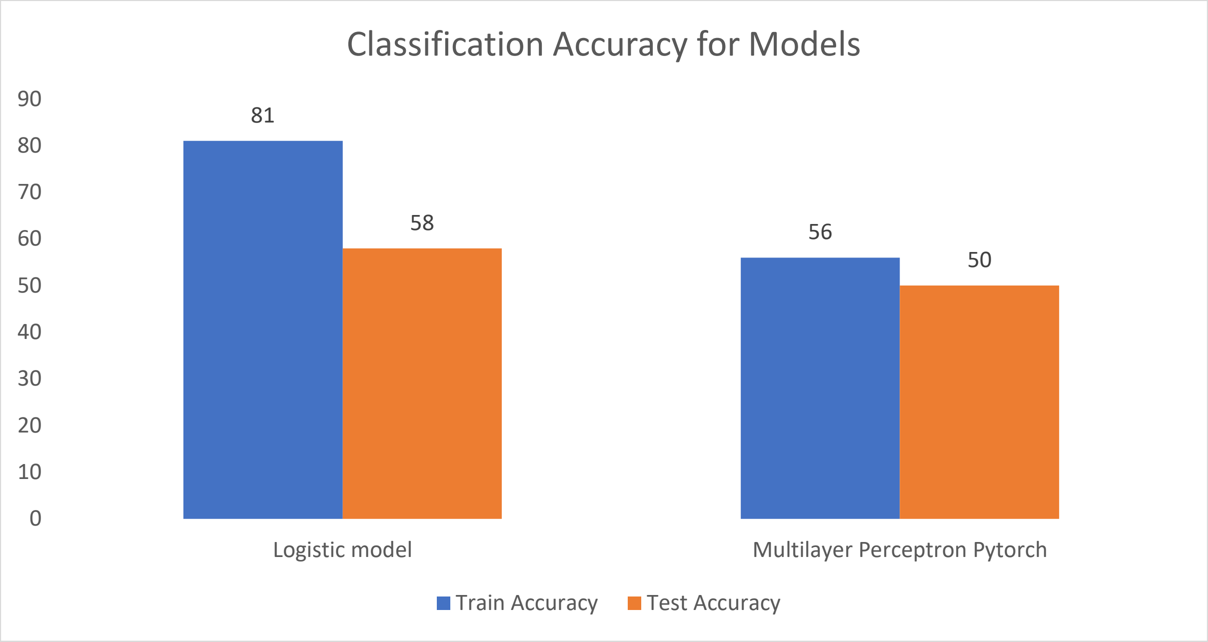


Fig 3.1.c K fold Cross validation

Results:

Following are the results after evaluating the model:

	Logistic model	Multilayer Perceptron Pytorch
Train Accuracy	81	56
Test Accuracy	58	50



Conclusion:

In Summary, we have extracted Power features and developed 2 models to classify Low Workload and Medium Workload. The Classification score we obtained was better for Logistic Model compared to the ANN model. In this study we have only extracted power features, we can also extract the connection features and combination of power and connection features will give better results.

Reflection

The process of this research has helped me understand logistic model and deep learning model better. For feature extraction I have used Power features , extracting connection features would have improved the accuracy and also evaluation was performed using 5 fold cross validation.

References

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