CE889 Course Work

EEG Classification

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Abstract

One of the most important features of a mental state monitoring tool is the efficacy of workload identification. The workload in this subject is typically recognized in terms of binary classes. Studies on multi-class workload identification are rare because, despite the addition of a new workload class, workload identification remains a very difficult task. Furthermore, most of the research that has already been done has only used individual channel spectral power measures, neglecting a wealth of inter-channel data that show how different brain areas interact. In this study, we classified binary workload classes based on EEG by using characteristics that represent intra-channel and inter-channel information. Firstly, the logistic regression model showed an unconvincing classification accuracy of **~45%.** Due to this low accuracy, after feature extraction technique, the accuracy has significantly increased to **~87%** which is on par with the Convolution Neural Network, which also achieved an accuracy of **~87%.**

Background

The techniques used for EEG classification in this study, spanning from conventional techniques like logistic regression to deep learning structures like CNN. For binary classification applications, logistic regression offers a baseline model that is both straightforward and efficient. Its linear structure, however, might make it less effective in identifying intricate patterns in EEG data. By taking use of their capacity to extract hierarchical features from unprocessed input, CNNs have demonstrated a good performance in a range of image and signal processing tasks.

Methods

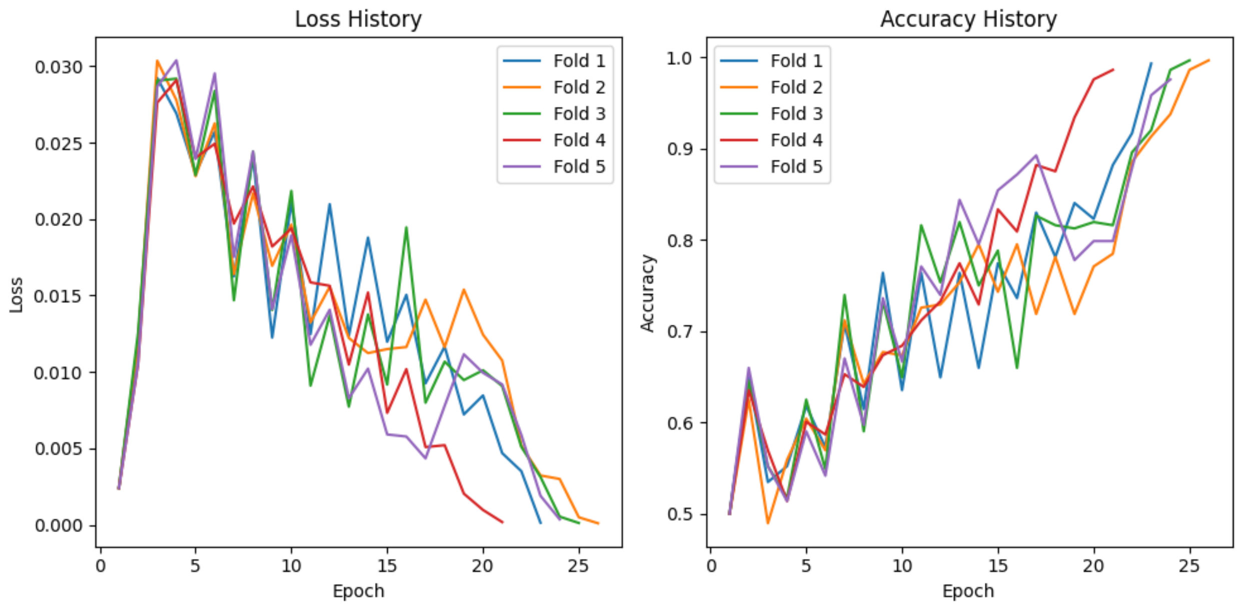
To classify the EEG signals, 2 models were used to train the dataset.

1. Logistic Regression (from scratch without use of any libraries, except NumPy)
    - with the raw data
    - with the feature extracted data.
2. CNN (Convolution Neural Network)

Logistic Regression with the raw data from scratch (without use of any libraries, except NumPy).

The output displays the progress of training with each epoch. It shows the epoch number along with the corresponding loss. This indicates that the model is training successfully, and the loss is decreasing, which is a positive sign. After training for each fold, the test set **Accuracy, Confusion matrix, Classification report (precision, recall, f1-score)** are calculated. Finally, the average accuracy achieved across all folds using the logistic regression model is ~45%. The below picture shows the graphical representation of the losses and accuracies.

Accuracy and loss metrics graph:



Logistic Regression with the feature extracted data.

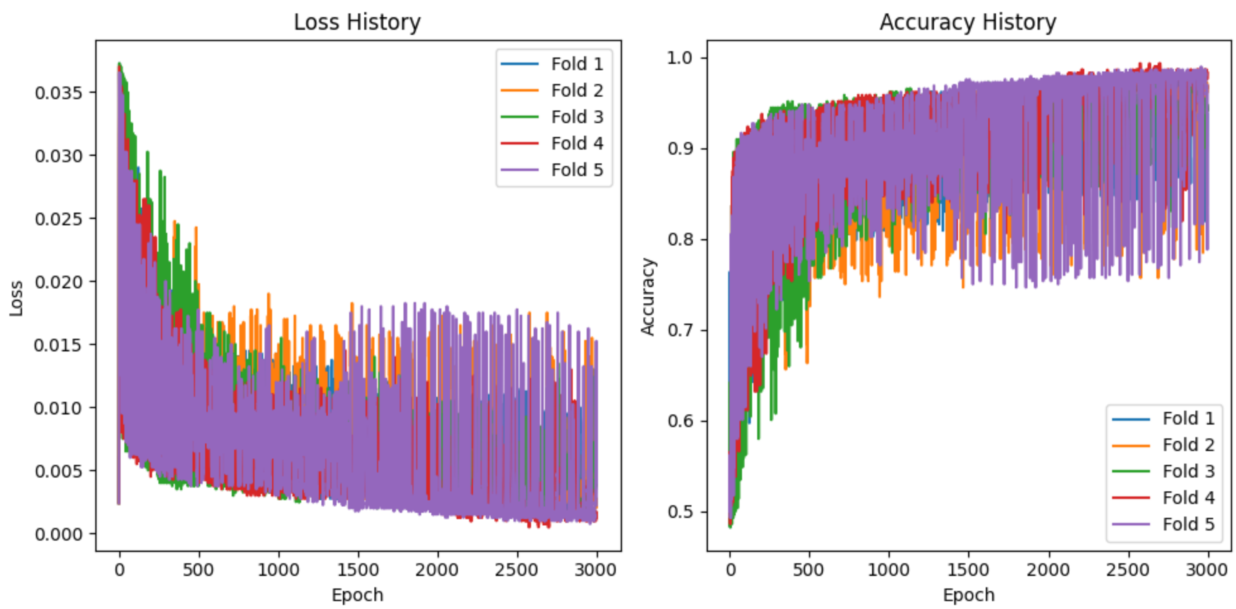
After the feature extraction process (given below), the model has improved greatly. The average accuracy achieved across all folds using the logistic regression model is ~88%. The **Classification report (precision, recall, f1-score)** has also improved significantly. These results show the significance of feature extraction.

Feature Extraction process.

This procedure breaks down the EEG data into segments and uses the FFT to calculate the power spectra of each segment. There are five predetermined frequency bands: delta, theta, alpha, beta, and gamma. For each channel, the average power within each band is determined. Then, a feature matrix is created using these averages, with each row denoting a data segment and each column a channel-band combination. This matrix makes it possible to categorize or comprehend patterns of brain activity through additional analysis or machine learning activities.

(Reference; https://ieeexplore.ieee.org/document/9178781)

Accuracy and loss metrics graph:



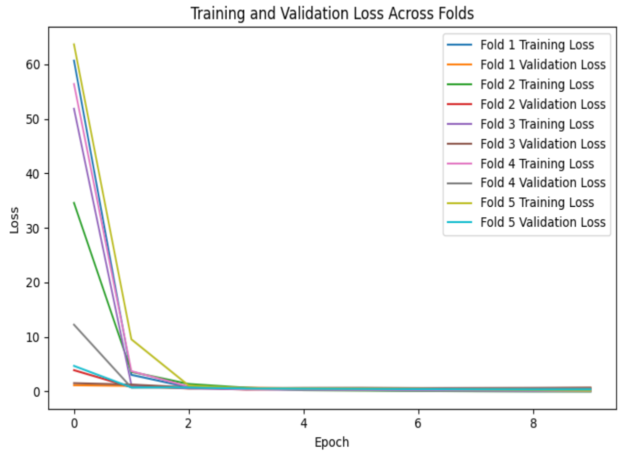
CNN (Convolution Neural Network).

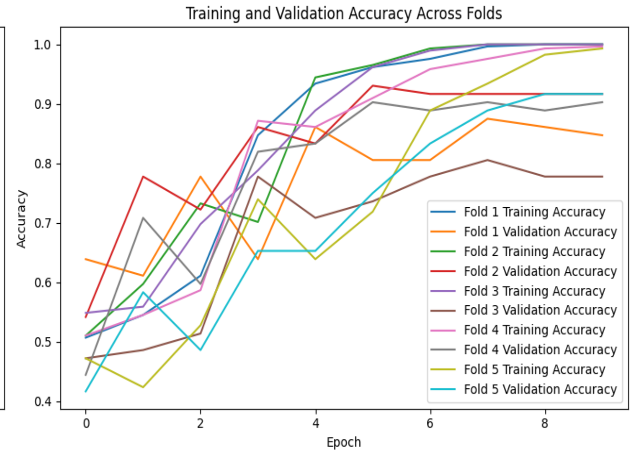
Model Architecture:

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 508, 58, 6)        156

 max_pooling2d (MaxPooling2  (None, 254, 29, 6)        0
 D)

 conv2d_1 (Conv2D)           (None, 250, 25, 16)       2416

 max_pooling2d_1 (MaxPoolin  (None, 125, 12, 16)       0
 g2D)

 flatten (Flatten)           (None, 24000)             0

 dense (Dense)               (None, 1200)              28801200

 dense_1 (Dense)             (None, 128)               153728

 dense_2 (Dense)             (None, 1)                 129

=================================================================
Total params: 28957629 (110.46 MB)
Trainable params: 28957629 (110.46 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

The reported average accuracy of **87%** suggests that the model achieves high accuracy in classifying EEG signals into binary categories. This indicates the effectiveness of the model in distinguishing between different states or conditions represented by the EEG data. Further refinement, including architectural adjustments, optimizing hyperparameters such as learning rate, batch size, or model architecture can potentially improve model performance. Like the logistic regression model, **Confusion matrix, Classification report (precision, recall, f1-score)** are also calculated.

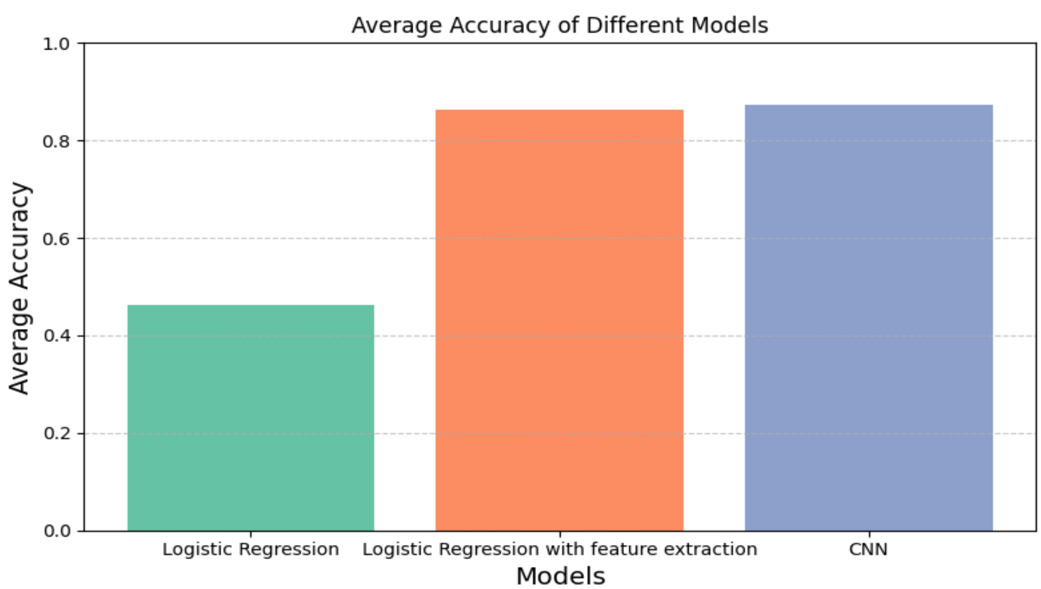
Accuracy and loss metrics graph:





Results

Model	Average Accuracy
Logistic Regression:	~45%
Feature Extraction + Logistic Regression	~87%
CNN Model	~87%



Conclusion

The findings show that in EEG classification tasks for two classes, the logistic regression model with feature extractions performs is on par with the CNN model. But there could be improvement in the CNN model by tuning the hyper parameters and adding more complex layers. This highlights the significance of deep learning approaches in identifying complex patterns in EEG data. When paired with logistic regression, feature extraction dramatically increases classification accuracy, underscoring the significance of obtaining pertinent features from unprocessed data. Additionally, this study offers possible directions for future investigation, such as investigating more complex neural network hyperparameters tuning for classification performance.

References

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- EEGNet-Pytorch. https://github.com/aliasvishnu/EEGNet/blob/master/EEGNet-PyTorch.ipynb
- NN Pytorch tutorial. https://pytorch.org/tutorials/beginner/nn_tutorial.html