Confusion Level Detection Using EEG Brainwave Data Analysis

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Introduction

- Electroencephalography(EEG) is a kind of measurement that indicates the electrical activity of the human brain.

- EEG is widely used to study brain functions and to diagnose neurological disorders.

- EEG is used to study how the brain works as well as to diagnose neurological conditions like epilepsy, brain tumors, head injuries, sleep disorders, dementia, etc.

[1]

- They are useful in the treatment of anomalies, behavioral issues (such as autism), attention disorders, learning difficulties, and delayed language.

- The right and left hemispheres of the cerebrum make up the brain. The frontal, parietal, occipital, and temporal lobes make up the four divisions of each hemisphere.

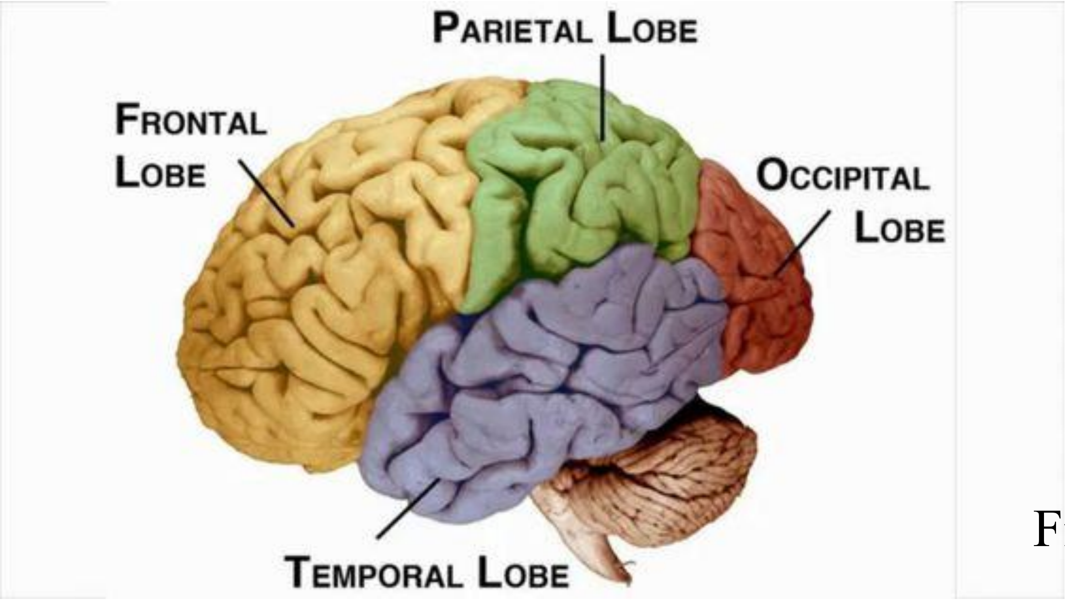


Figure 1: Different Lobes

The EEG System

- The components of an EEG system can be listed as a set of electrodes, amplifiers with filters, and a digital oscilloscope.

- With the help of temporary glues, a number of tiny discs called electrodes are positioned throughout the scalp's surface during the EEG exam.

- The electrodes are able to pick up on minute electrical charges generated by the activity of brain cells. A computer screen displays a graph of the increased charges. [1]

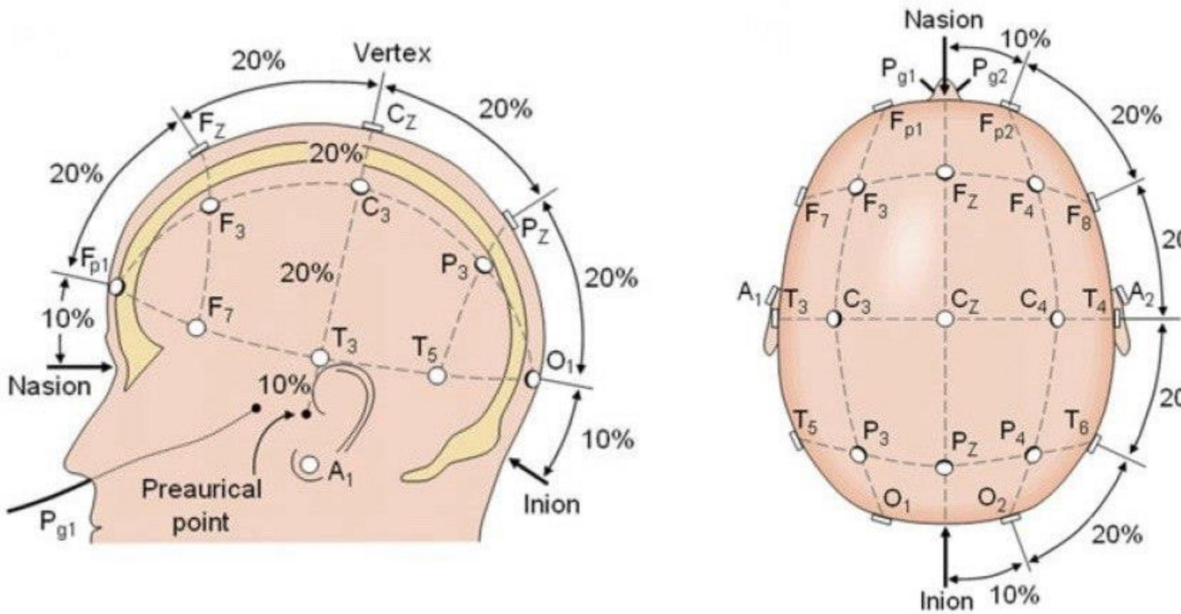


Figure 2: The international 10–20 electrode placement system

1-256 Electrodes

Ranges from 1 to 100V

Frequency Range	Features
0.5 – 4 Hz (delta, d)	the awake state, deep sleep, and severe brain problems
4 – 8 Hz (theta, h)	emotional stress, particularly anger or sadness, as well as unconscious material, inspiration for new ideas, and profound concentration
8 – 13 Hz (alpha, a)	high levels of stress, anxiety, and mental activity
13 – 30 Hz (beta, b)	doing things actively, paying attention actively, and concentrating on the outer world or addressing immediate issues.
> 30 Hz (gamma, c)	various cognitive and motor activities

Table 1 : Different Components of EEG Signals

What have we done?

- In this study, we majorly focused on the task of detecting the confusion level of a group of students using EEG data samples collected while watching educational video clips.

- For the particular task of detecting whether the student is confused or not, some Machine Learning and Deep Learning techniques have been implemented on the EEG data set to classify the state of the mind.

Objective

- To study the techniques that have been used to infer the state of confusion of the human brain using the information extracted from EEG signals by researchers.

- To perform some techniques on the same confused student brainwave data.

Techniques Used?

- 1D CNN, ANN, and a 1D CNN along with a Decision Tree and a Logistic Regression Classifiers.

Motivation

- **Massive Open Online Courses (MOOCs)** - Primary issue is the absence of feedback between students and teachers.

- **Accidents** - Can be applied to public transportation to track the health of drivers to take preventive action if the drivers are drowsy or confused.

- **Re-design AR/VR tools** - To provide more interactive experience with AR/VR headsets.

Literature Review

Year	Authors	Methodology Proposed
2013 [2]	Wang, H., Li, Y., Hu, X., Yang, Y., Meng, Z., and Chang, K.	Introduced the confused student brainwave dataset. Gaussian Naïve Bayes classifier was used to classify the confusion level of the students. For detecting pre-defined confusion states : 64% accuracy for student independent classifiers and 57% for student-independent classifiers. For detecting user-defined confusion states, average accuracies were 56% and 51% accordingly.
2017 [3]	Ni, Z., Yuksel, A. C., Ni, X., Mandel, M. I., and Xie, L.	The same data set was trained with RNN-LSTM and Bidirectional LSTM models along with SVM, K-Nearest Neighbors, Convolutional Neural Network, Deep Belief Network and RNN-LSTM as baseline approaches. The accuracies gained were as below. • SVM with a linear kernel - 67.2% (5-fold cross-validation) • SVM with RBF kernel and SVM with sigmoid kernel - 51.3% and 51.0% accordingly.

		• KNN – 51.9% • CNN – 64.0% • Deep Belief Network - 52.2% • RNN-LSTM model : 69% • Bidirectional LSTM architecture - 73.3%.
2021 [4]	Ibtehaz, N., and Naznin, M.	They have used the same data set, confused student brainwave data, and some Machine Learning classifiers were used for the comparison. A CNN architecture was used to extract features from the training data before experimenting with the classifiers. According to their findings, the KNN algorithm outperforms every other classifier with an accuracy of **82.92%**.

Table 2 : Literature Review

About the Data Set..

- EEG data were collected from 10 students while watching lecture video clips.

- 20 videos were shown to an individual student which consisted of a mixture of confusing and non-confusing lectures.

- After each video clip, the student rated the confusion level on a scale of 1-7.

- Later these labels were further quantized into two states confused(1) or not confused(0). [5]

- The data have been sampled every 0.5 seconds and the **statistical features** were used to represent the values of each feature. There are total of 12811 samples.

Feature	Description	Sampling Rate	Statistic
Attention	Proprietary measure of mental focus	1 Hz	Mean
Meditation	Proprietary measure of calmness	1 Hz	Mean
Raw	Raw EEG Signal	512 Hz	Mean
Delta	1 – 3 Hz	8 Hz	Mean
Theta	4 – 7 Hz	8 Hz	Mean
Alpha1	Lower 8 – 11 Hz	8 Hz	Mean
Alpha2	Higher 8–11 Hz	8 Hz	Mean
Beta1	Lower 12 – 29 Hz	8 Hz	Mean
Beta2	Higher 12 – 29 Hz	8 Hz	Mean
Gamma1	Lower 30 – 100 Hz	8 Hz	Mean
Gamma 2	Higher 30 – 100 Hz	8 Hz	Mean

Project Work

- The approaches followed in this study to classify the mental state of the student are the simple **ANN** model, **1D CNN** model and 1D CNN feature extractor for two classifiers **Decision Tree** and **Logistic Regression**.

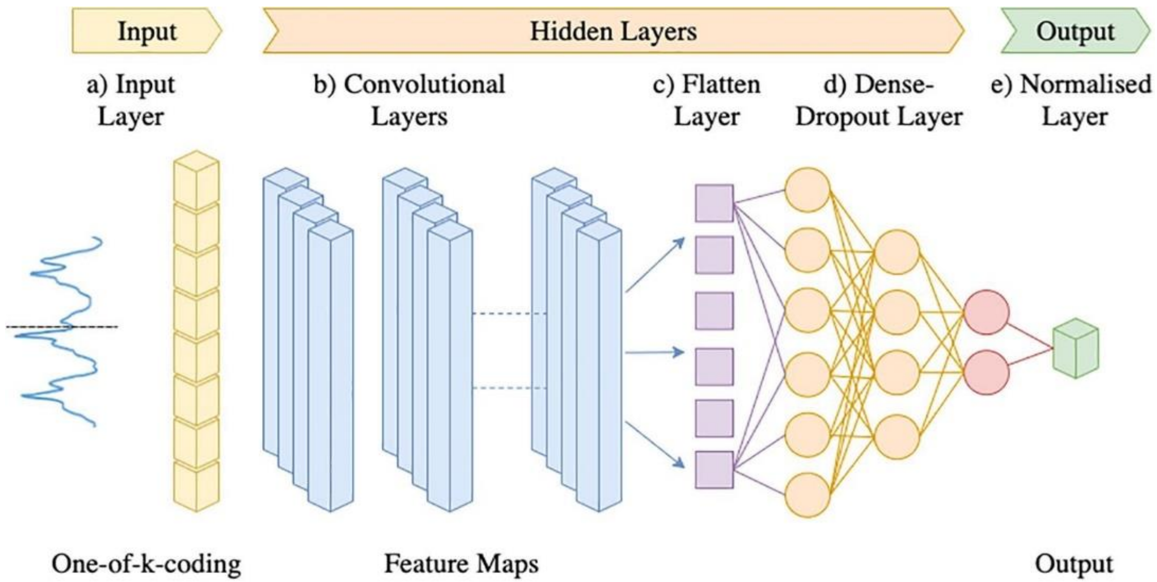
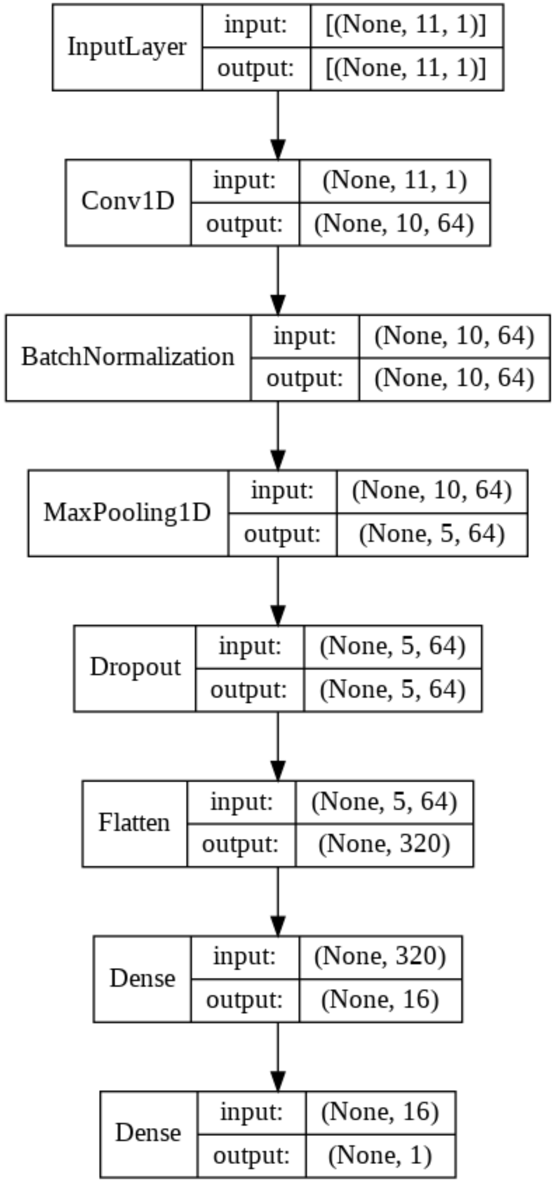


Figure 3 : 1D CNN Architecture

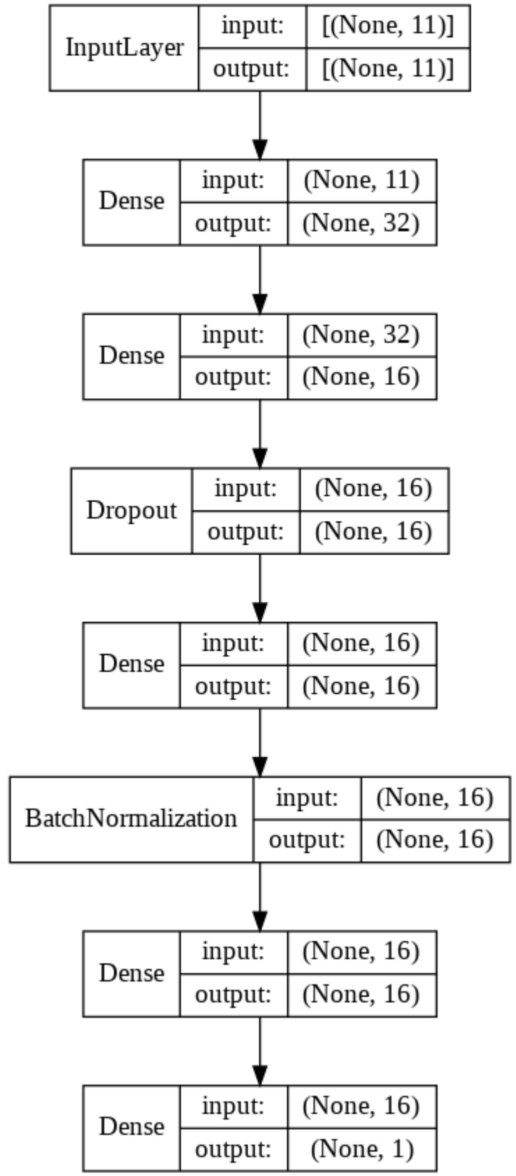
- A typical CNN model can have multiple number of layers including Convolution Layer, Pooling Layer and as per the requirement, Batch Normalization layer, Dropout Layer etc. can be included. [8]

Model	Specification
1D-CNN	1 1D Convolution Layer, Batch Normalization Layer Max Pooling Layer, Dropout Layer with a rate of 0.25 Flatten, Dense Layer and Output Layer with sigmoid activation function.
ANN	4 Dense layers, Batch Normalization Layer and Output Layer with sigmoid activation function.
1D CNN - Decision Tree	2 1D Convolution Layers, 2 Batch Normalization Layers, Max Pooling Layer and Flatten which creates a feature map for the classifier Decision Tree with Entropy criterion
1D CNN - Logistic Regression	Same CNN architecture as above

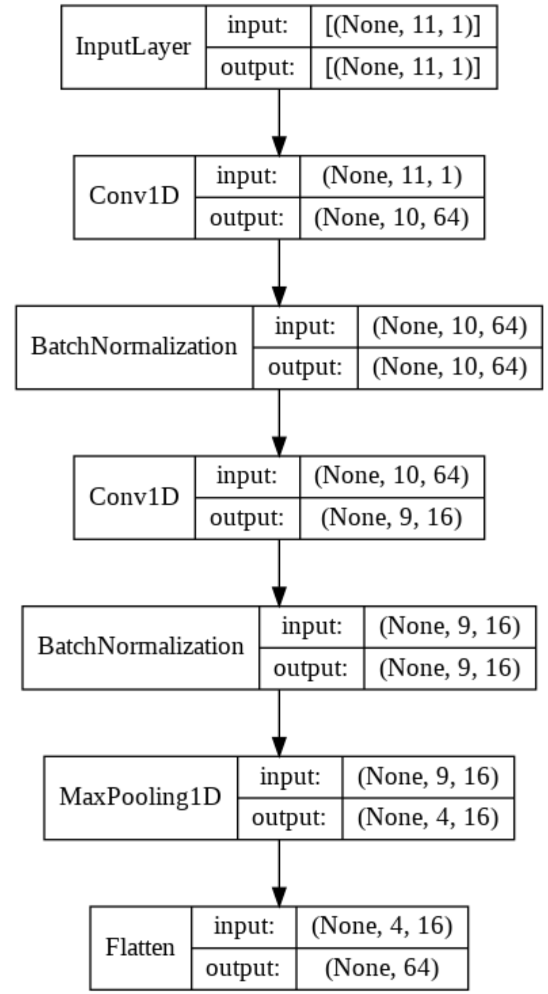
Table 4 : Model Specifications



1D CNN Architecture



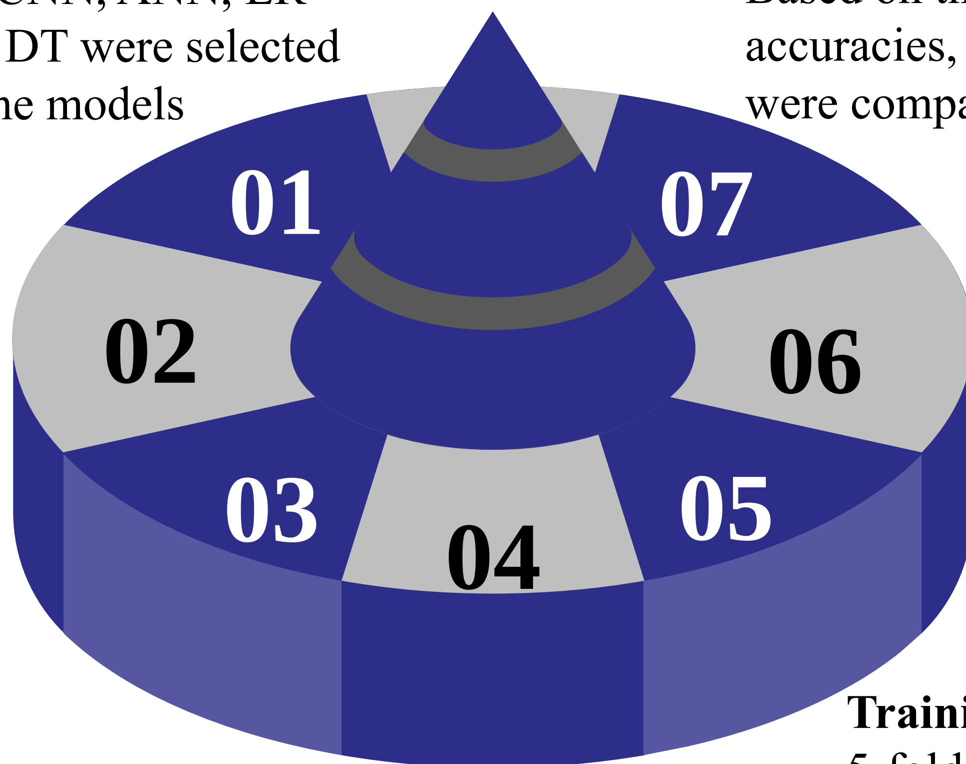
ANN Architecture



1D CNN FE Architecture

Loss Function - Binary cross-entropy
Epochs - 100
Optimizer - Adam

Methodology Used



Model Selection
1D CNN, ANN, LR and DT were selected as the models

Data preprocessing
Removed "predefinedlabel" feature.

Data Normalization

Train Test Split
30 : 70 ratio

Training Models
5-fold cross validation was used

Testing Models
Used testing data to check accuracy of each model using evaluation metrics, precision, recall and f1-score.

Model Comparison
Based on the testing accuracies, models were compared.

Evaluation Metrics

- Precision: A measure of confidence that can be imposed on the predictions.

$$\text{Precision} = \frac{TP}{TP + FP}$$

- Recall: Measures how correctly the model predicts the class of the sample.

$$\text{Recall} = \frac{TP}{TP + FN}$$

- F1-Score: It is the harmonic mean of Precision and Recall.

$$\text{F1-Score} = 2 \text{ x } \frac{\textit{Precision x Rexall}}{\textit{Precision} + \textit{Recall}}$$

- Accuracy: Ratio of correct predictions with all samples.

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + TN + FN}$$

Results and Discussion

- **Cross Validation results** : We have experimented with Decision Tree and Logistic Regression classifiers other than simple an 1D CNN model and an ANN model.

Model	Accuracy(%)
1D CNN	62.65
ANN	56.96
1D CNN - DT	61.20
1D CNN - LR	62.20

Table 5 : Average Accuracies for 5-fold cross validation

- The results convey that 1D CNN performs better that other models for validation data in each fold.
- The models which use a CNN architecture as a feature extractor show better consistency over ANN.

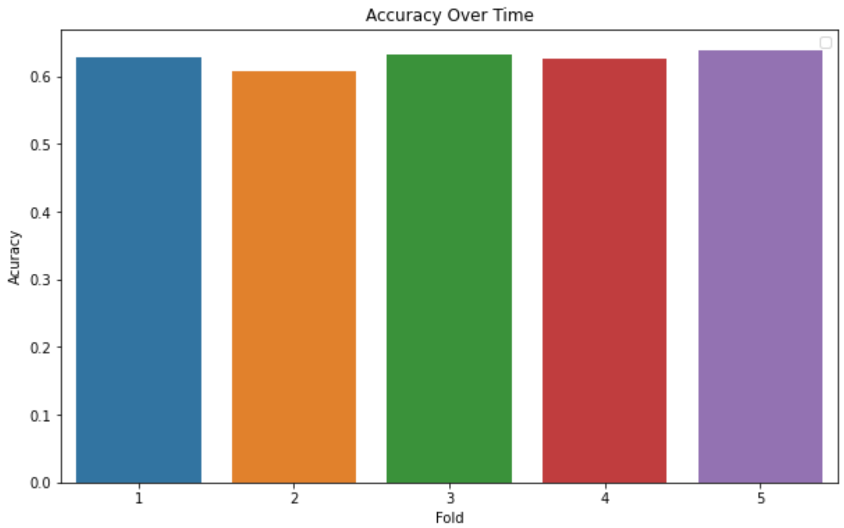


Figure 4 : 1D CNN - 5-Fold Cross Validation Accuracy

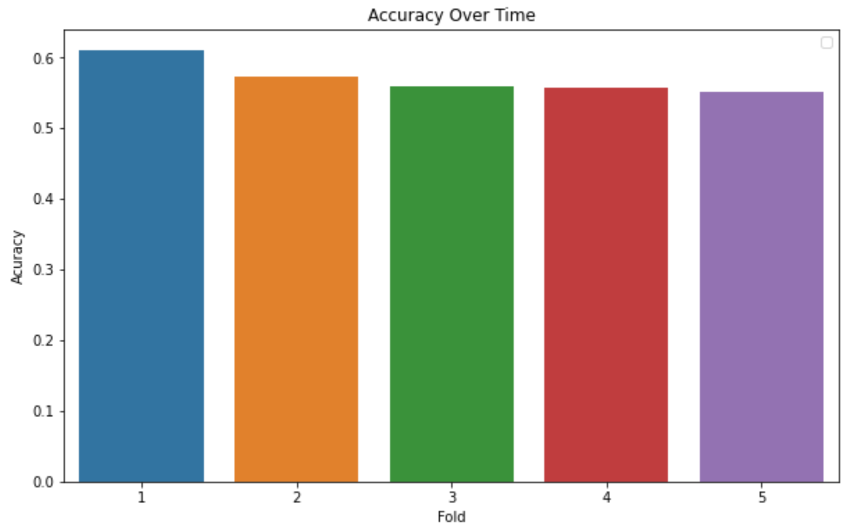


Figure 5 : ANN - 5-Fold Cross Validation Accuracy

Model	Precision	Recall	F1-Score	Accuracy (%)
1D-CNN	0.54	0.82	0.65	57.59
ANN	**0.55**	**0.71**	**0.62**	**58.61**
1D CNN - DT	0.52	0.82	0.64	54.93
1D CNN - LR	0.54	0.77	0.63	56.68

Table 6 : Testing Accuracy Comparison

- All the trained models then tested with our unseen test data.
- We calculated precision, recall and F1-score for each of the models.

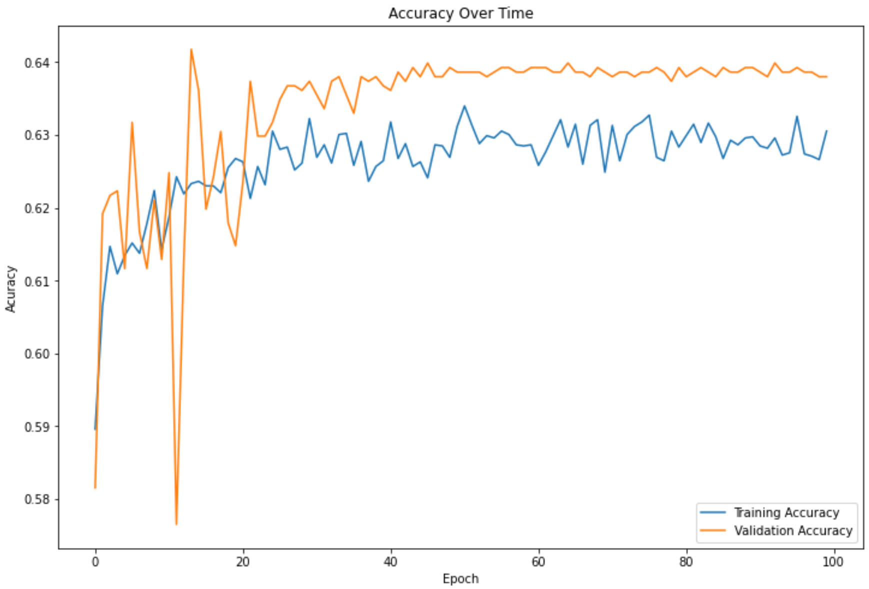


Figure 5 : 1D CNN - Testing Accuracy over epochs

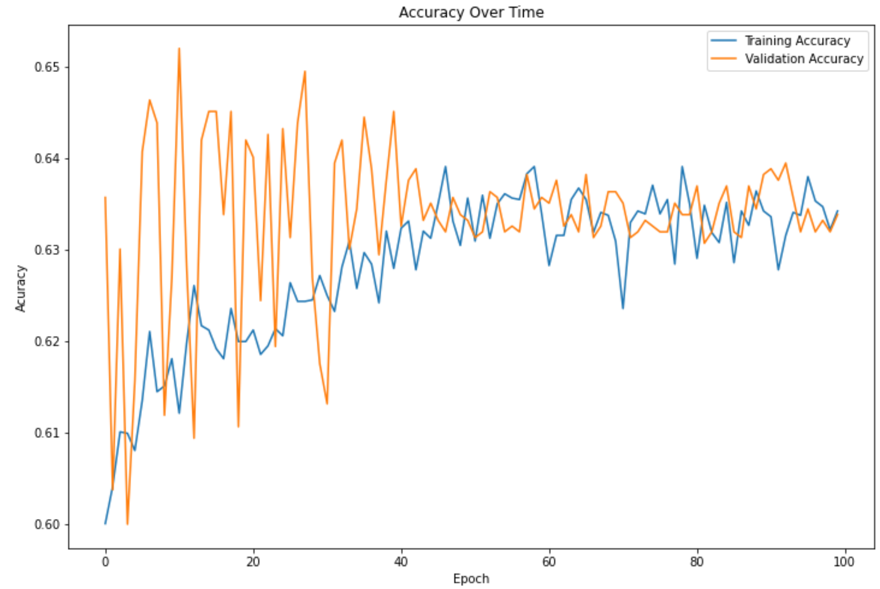


Figure 5 : KNN - Testing Accuracy over epochs

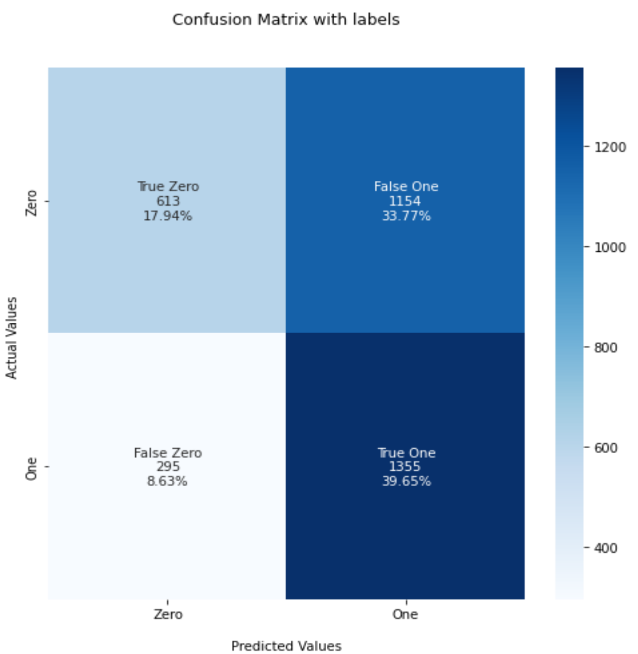


Figure 6 : 1D CNN – Confusion Matrix

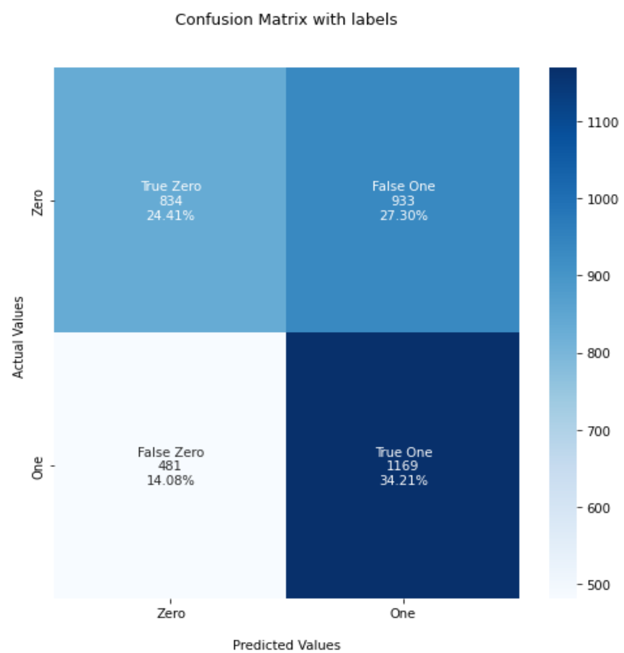


Figure 7 : ANN – Confusion Matrix

- For testing data, ANN outperforms every model with an accuracy of 58.61%.

Conclusion

- Instead of extracting features manually, we trained a CNN model to recognize the important features.
- Even though this study has not yielded a remarkable improvement over earlier findings and models, the objective of this study was achieved with success.
- The study provided a good understanding of the EEG data and their background.
- Provided a good understanding of Machine Learning and Deep Learning approaches and how to use those techniques for EEG data classification tasks.

Limitations

- The experiment had performed only with 10 students and each student has watched 20, two-minute video clips.
- Since we have limited number of samples to be considered, we couldn’t end up with a strong conclusion.
- The models experimented in this study are giving low accuracies compared to some past works due to the choice of classifiers that do not fit to the data set we use.

Scope for Further Research..

- The experiment can be further extended by using different data synthesis and data augmentation methods to expand the data set to generate a new data set from the existing data set.

- We can experiment with different Machine Learning and Deep Learning models on the new data set to explore new findings.

References

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[6] Srinivasamurthy, R. S., 2018. "Understanding 1d convolutional neural networks using multiclass time-varying signalss". PhD thesis, Clemson University.