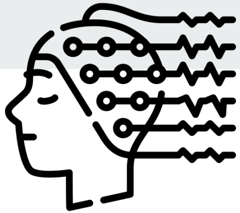


Brainathon 25 Official Submission

Soham Yedgaonkar

Result Highlight

15+ Model Architectures experimented

A 95.7% Accuracy was obtained with a outstanding precision of 0.95 and recall of 0..96 F1 Score :0.95

Brainathon Submission

Data Understanding

1) Brain- Area Position Analysis
2) EEG Data Analysis

Data Visualization

1) Power-Band Analysis
2) Skewness , Kurtosis

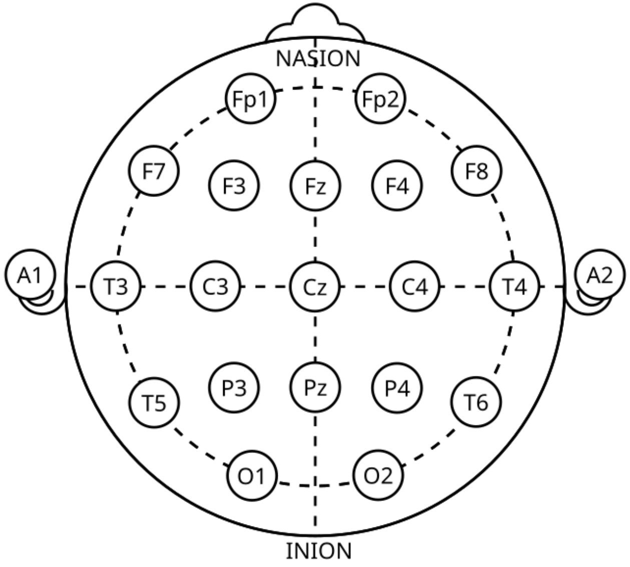
Data Preprocessing

1) Scaling wrt mean , std
2) Fourier Transform
3) Feature Extraction

Model - Training and evaluating

1) Experimenting 20 + DL models
2) Ensembling models with high accuracy

Data- Understanding

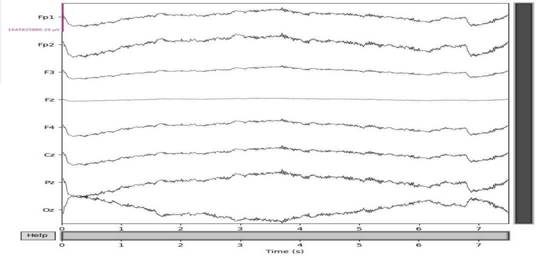


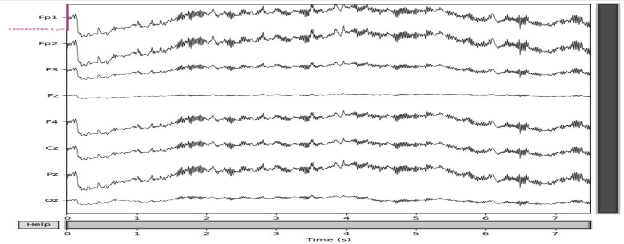
Position and Association:

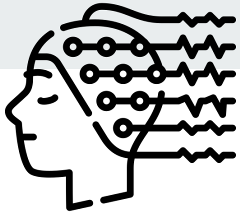
On researching about the data columns provided these insights were highlighted

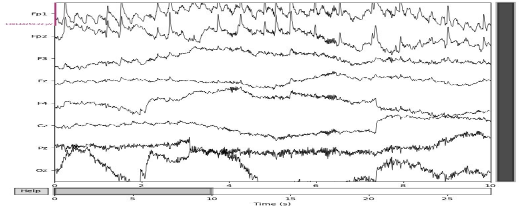
- **Fp1**: Fp1 is associated with verbal retrieval, visual working memory, and verbal analytical and approach behaviors
- **Fp2**: Fp2 is associated with face and object processing, gestalt and context, and episodic memory
- **F3**: F3 is associated with logical, detailed attention, and the organization of responses
- **Fz**: , Fz is associated with frontal eye fields, motor, focus, and action observation
- **F4**: F4 is associated with emotional/contextual attention

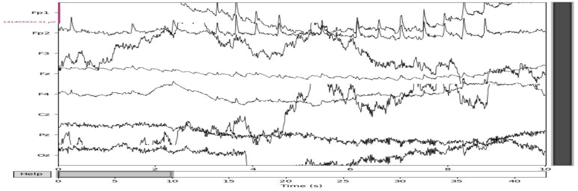
These insights were proved through waves visualization

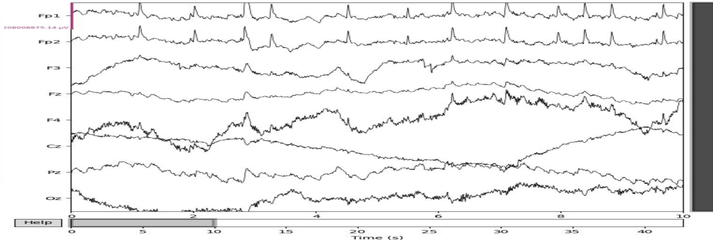












Images of EEG visualization

Insights :

1)Odd_ball :

Spikes in f1 and f2 are synchronous which means visual working , action observation and object processing are done in order to identify when to press SPACE The spikes represent the visual Decisions made.

2) Stroop_task :

Some major deviations in F1 and F2 as verbal attention and visual attention are opposite to each other .

For every spike F3 also has a sike which indicates relation in color and word (Logical thinking)

3) Task-Shifting :

High Fluctuations in F4 depicts contextual adjustments during task switches.

Spikes in f1 and f2 are synchronous which means visual working , action observation and object processing are done

4)Dual-Task:

Fp1, Fp2, Fz, and Cz, which highlight shifts in attention and motor coordination. These variations reveal how the brain reallocates resources, delays responses, and prioritizes one task over the other when managing competing demands

Data Visualisation

ParaMetric Analysis

Hjorth Activity: Measures the signal variance, reflecting overall brain activity.
Hjorth Mobility: Indicates the frequency content or changes in the signal.
Hjorth Complexity: Measures the signal's shape complexity.

1) Analyzing Different Central Tendency measures for active information-gain
2) Designing a one-pass, zero-phase, non-causal bandstop filter
3) Changes in the Hjroth Parameters represent the significant changes in the wave

	Bandpower_Delta	Bandpower_Theta	Bandpower_Alpha	Bandpower_Beta
timestamp	5.043671e-20	4.390945e-20	2.838193e-20	2.492568e-19
Fp1	1.895878e-01	1.817756e-02	1.019667e-02	5.570996e-03
Fp2	9.093149e-02	1.249466e-02	6.366267e-03	3.146285e-03
F3	1.699380e+00	3.795065e-01	4.864305e-01	3.372163e-01
Fz	1.262847e+00	7.953750e-02	7.239122e-02	4.286329e-02
F4	2.269583e-01	5.495413e-02	5.230404e-02	5.556964e-02
Cz	9.028163e-01	2.286852e-01	5.853464e-01	2.022469e-01
Pz	3.511789e-01	9.782069e-02	5.187941e-01	6.053192e-02
Oz	6.952978e-03	2.150618e-03	6.264776e-03	1.221133e-03

	Bandpower_Gamma	Hjorth_Activity	Hjorth_Mobility	\
timestamp	2.238963e-19	1.134935e-20	0.836766	
Fp1	2.581146e-03	2.255217e-03	0.162978	
Fp2	1.259639e-03	1.175969e-03	0.193114	
F3	1.309874e-01	3.842167e-02	0.619354	
Fz	1.863662e-02	1.502319e-02	0.344563	
F4	3.485543e-02	4.712786e-03	0.501239	
Cz	5.849427e-02	2.120675e-02	0.452014	
Pz	1.079002e-02	1.021992e-02	0.246257	
Oz	2.595175e-04	1.657448e-04	0.269075	

orth_Complexity	Mean	Variance	Skewness	Kurtosis	\
1.485767	4.263239e-10	1.134935e-20	0.000000	0.000000	
5.390410	1.125653e-04	2.255217e-03	0.934164	4.458388	
4.926878	9.224506e-05	1.175969e-03	1.467214	7.896620	
1.819560	7.335426e-04	3.842167e-02	0.173695	0.828322	
3.236381	1.441456e-04	1.502319e-02	-0.015950	1.070642	
2.136329	8.345506e-04	4.712786e-03	0.124135	0.936320	
2.330890	-1.495577e-04	2.120675e-02	-0.104329	0.283207	
2.490140	1.474711e-04	1.021992e-02	0.354972	4.049105	
2.896543	-5.057125e-05	1.657448e-04	-0.292721	1.691748	

ro_Crossings
0
1536
2270
6306
2834
4906
4382
2336
2546

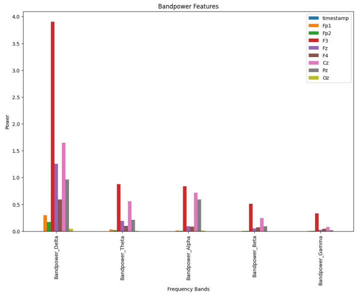
BandPower Visualization

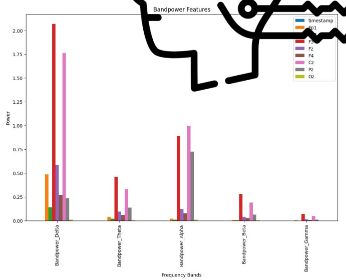
Minimal activity in **Beta and Gamma bands** in Stroop Task indicates the absence of tasks requiring intense cognitive or sensory engagement.

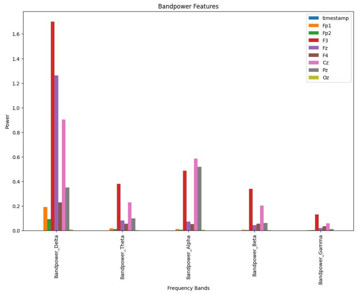
Increased Activity in the Alpha Band for OddBall resemble its low activity state

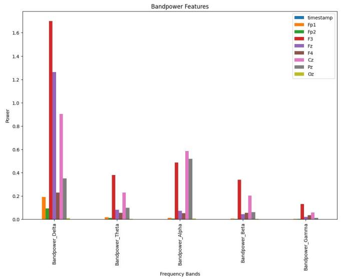
F3 and Cz proved to have greatest Power in all challenges

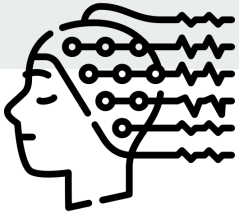
Changes in the band power in different actions specify the the changes in the electric signals from the brain of Subjects











Data Preprocessing

Data Scaling

Normalizing each subjects data with the regulazied data from the eyes-closed and eyes-open data
Calculating Cumulative-Mean and STD from the data

```
eeg_columns = [col for col in baseline_eyes_open.columns if col != 'timestamp']
baseline_mean = (baseline_eyes_open.mean() + baseline_eyes_closed.mean()) / 2
baseline_mean=baseline_mean[eeg_columns]
baseline_std = (baseline_eyes_open.std() + baseline_eyes_closed.std()) / 2
baseline_std=baseline_std[eeg_columns]
```

Regularzing

```
normalized_data[eeg_columns] =
(normalized_data[eeg_columns] - baseline_mean) /
baseline_std
```

```
This helped to reduce variation in subjects and eventually
boosting the model accuracy
```

Feature extraction

Each record just being the intensity of the signal at the particular moment No specific Information can be achieved from a single row .

Therefore merging a data from some adjacent rows seems promising . Calibrating sampling rate and time window . Data for that specific time will be considered

```
    # Extract windows of data
    for i in range(num_windows):
        start_idx = i * samples_per_window
        end_idx = start_idx + samples_per_window
        window = eeg_data.iloc[start_idx:end_idx].values
        X.append(window)
        y.append(activity_label)

# Convert to numpy arrays
X = np.array(X)
y = np.array(y)
```

DEEP-Learning Models

FULL-CNN
RESIDUAL CNN
RNN-LSTM
RNN-GRU
ATTENTION-CNN
HYBRID CNN LSTM
TRANSFORMER
EEG-TCNET
SCCNET
FBCNET
GRAPH-CNN
INCEPTION
EEGNEX
NEURO-GPT
EEG-TRANSFORMER
EEG-GPT
INTERWINED NN
GNN4EEG

Some models fail to learn effectively, possibly due to , insufficient data preprocessing, or unsuitable architecture.

Validation and test performance for the Inception model suggest possible overfitting; the training accuracy does not correlate well with test accuracy.

```
Epoch 1/8
164/164 ━━━━━━━━━━━━━━━━━━━━ 5s 29ms/step - accuracy: 0.8827 - loss: 0.2878 - val_accuracy: 0.8992 - val_loss: 0.2518
Epoch 2/8
164/164 ━━━━━━━━━━━━━━━━━━━━ 5s 30ms/step - accuracy: 0.8777 - loss: 0.2948 - val_accuracy: 0.8527 - val_loss: 0.3272
Epoch 3/8
164/164 ━━━━━━━━━━━━━━━━━━━━ 4s 25ms/step - accuracy: 0.8713 - loss: 0.2993 - val_accuracy: 0.8893 - val_loss: 0.2593
Epoch 4/8
164/164 ━━━━━━━━━━━━━━━━━━━━ 4s 26ms/step - accuracy: 0.8943 - loss: 0.2666 - val_accuracy: 0.8397 - val_loss: 0.3849
Epoch 5/8
164/164 ━━━━━━━━━━━━━━━━━━━━ 5s 26ms/step - accuracy: 0.8951 - loss: 0.2493 - val_accuracy: 0.8527 - val_loss: 0.3457
Epoch 6/8
164/164 ━━━━━━━━━━━━━━━━━━━━ 4s 25ms/step - accuracy: 0.8972 - loss: 0.2464 - val_accuracy: 0.9382 - val_loss: 0.1869
Epoch 7/8
164/164 ━━━━━━━━━━━━━━━━━━━━ 5s 26ms/step - accuracy: 0.9012 - loss: 0.2416 - val_accuracy: 0.9420 - val_loss: 0.1673
Epoch 8/8
164/164 ━━━━━━━━━━━━━━━━━━━━ 5s 26ms/step - accuracy: 0.9090 - loss: 0.2442 - val_accuracy: 0.8733 - val_loss: 0.2809
```

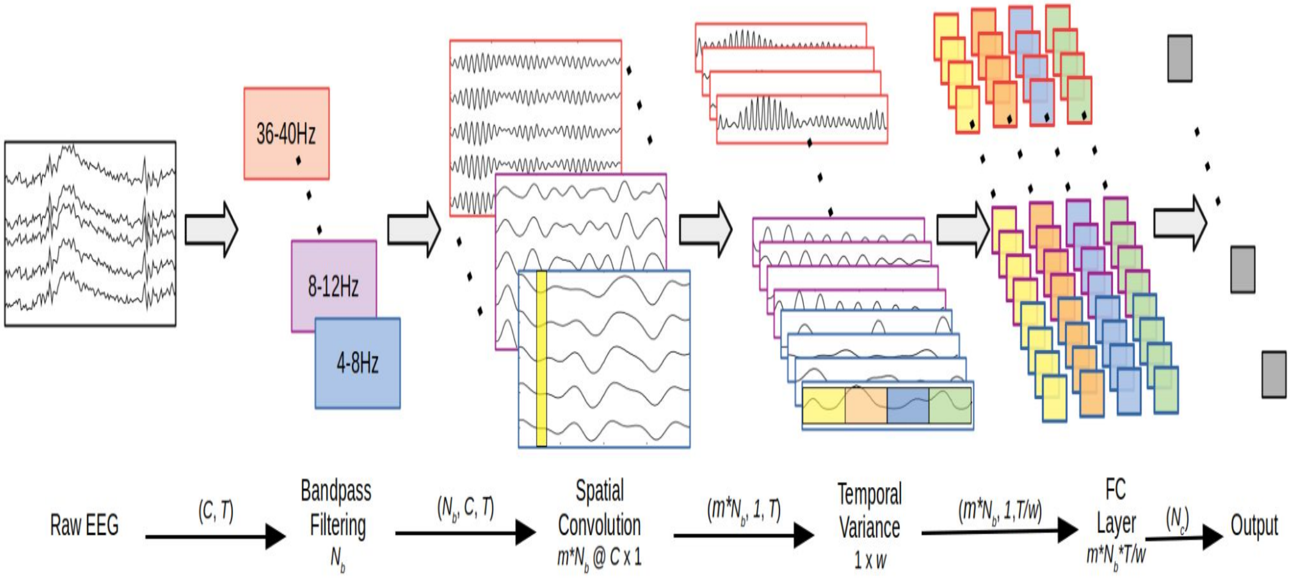
FBC-NET

FBC-NET :Consistent improvement in accuracy and loss shows its architecture is better suited for the dataset.

–) EEG signals are divided into multiple frequency bands

–) Unlike traditional methods that require extensive manual feature extraction, FBCNet integrates preprocessing, feature extraction, and classification into a single pipeline.

–) Accuracy : 0.9305



Ensemble model

```
41/41 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step
0.8732824427480916
41/41 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step
0.9465648854961832
41/41 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
0.4076335877862595
41/41 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step
0.8664122137404581
41/41 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step
0.9
41/41 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
0.49694656488549616
41/41 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
0.3015267175572519
41/41 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
0.9198473282442748
41/41 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step
41/41 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step
41/41 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step
41/41 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step
✓ 1s   completed at 11:45 AM
```

Advantages :

Improved predictive performance

Increased robustness

Increased Model Flexibility

Ensembling Models with higher accuracy for better results :

Models :

residual_cnn_model: ,

Fully_cnn_model,

Hybrid_cnn_lstm_model

graph_cnn_model

inception_model

fbcnet_model

Calculating Mode of all the model predictions and getting the final prediction

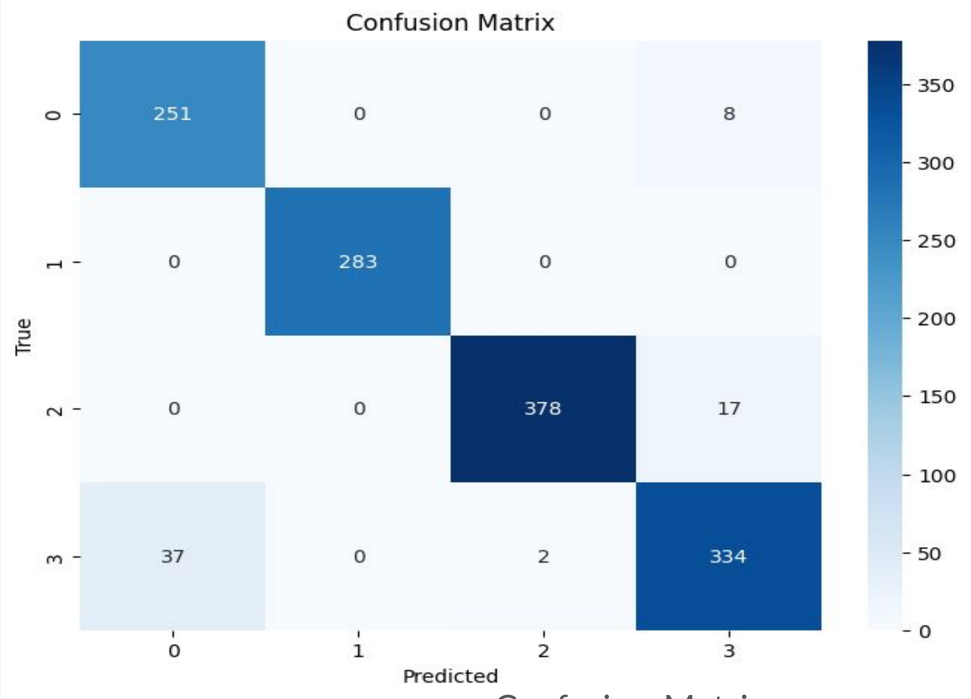
Result

Classification Report:

	precision	recall	f1-score	support
0	0.87	0.97	0.92	259
1	1.00	1.00	1.00	283
2	0.99	0.96	0.98	395
3	0.93	0.90	0.91	373
accuracy			0.95	1310
macro avg	0.95	0.96	0.95	1310
weighted avg	0.95	0.95	0.95	1310

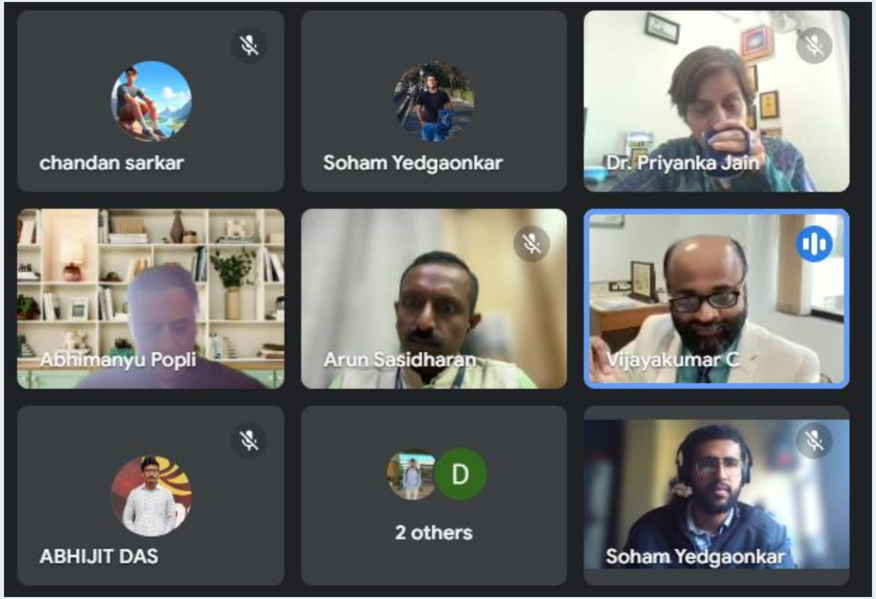
Classification_Report

```
41/41 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step
41/41 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step
41/41 ━━━━━━━━━━━━━━━━━━━━ 0s 8ms/step
41/41 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step
41/41 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step
41/41 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step
Final Ensemble Accuracy: 0.9572519083969465
Ensemble Predictions: [2 3 3 ... 1 0 3]
```



Confusion_Matrix

A 95.7% Accuracy was obtained with a outstanding precision of 0.95 and recall of 0..96 F1 Score :0.95


chandan sarkar
Soham Yedgaonkar
Dr. Priyanka Jain
Abhimanyu Popli
Arun Sasidharan
Vijayakumar C
ABHIJIT DAS
D
2 others
Soham Yedgaonkar