SSVEP Detection and Classification for EEG-Based Brain-Computer Interfaces

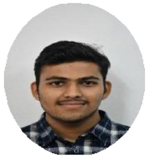
Capstone Project Phase 2
(6 Credits)

Project ID : S27

ESA Evaluation

Department of Electronics and Communication Engineering

Team Composition

Sl No	Name	SRN	Photo
1	Ankit Agarwal	PES1UG21EC046	
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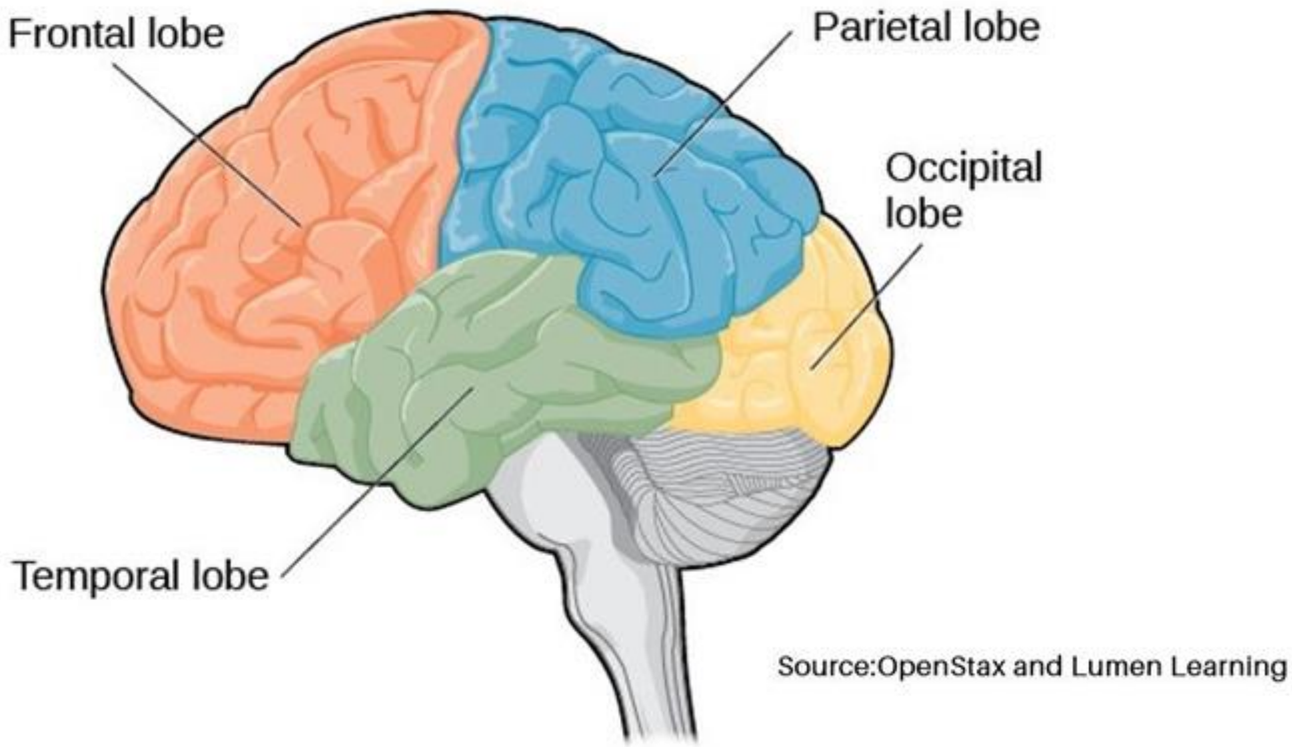
Contents

Introduction

What is BCI?

A brain-computer interface (BCI) is a computer-based system that acquires brain signals, analyzes them, and translates them into commands that are relayed to an output device to carry out a desired action.

Parts of Brain

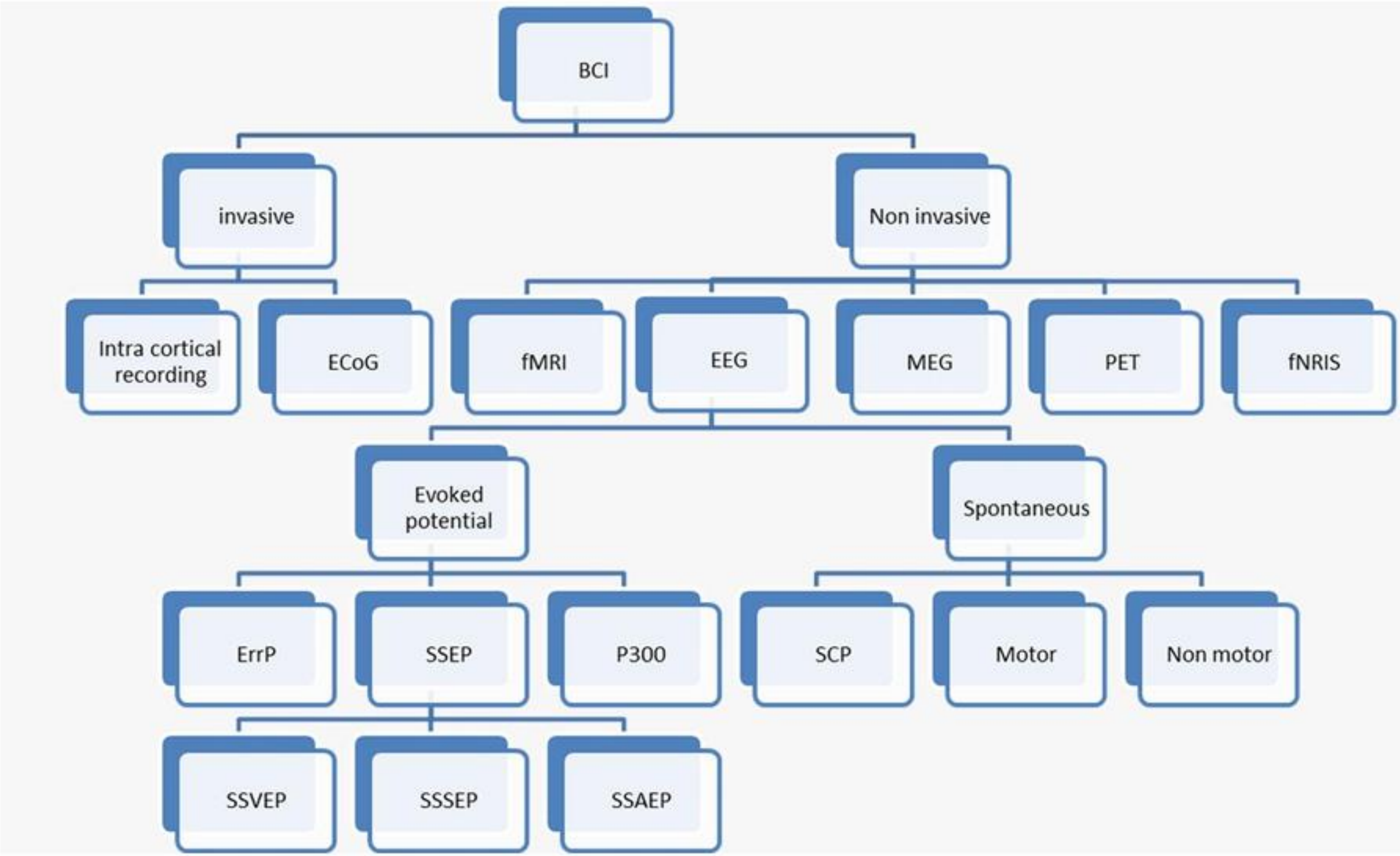


Types of Brain Waves

Brainwave Type	Frequency range	Mental states and conditions
Delta	0.1 Hz – 3 Hz	Deep, dreamless sleep, non-rapid-eye-movement sleep, unconscious
Theta	4 Hz – 7 Hz	Intuitive, creative, recall, fantasy, imaginary, dream
Alpha	8 Hz – 12 Hz	Relaxed, but not drowsy, calm, conscious
Low beta	12 Hz – 15 Hz	Relaxed yet focused, integrated
Midrange beta	16 Hz – 20 Hz	Thinking, aware of self and surroundings
High Beta	21 Hz – 30 Hz	Alertness, agitation
Gamma	30 Hz – 100 Hz	Cognition, information processing

Source:researchgate.net

Classification of BCI



SSVEP based BCI:

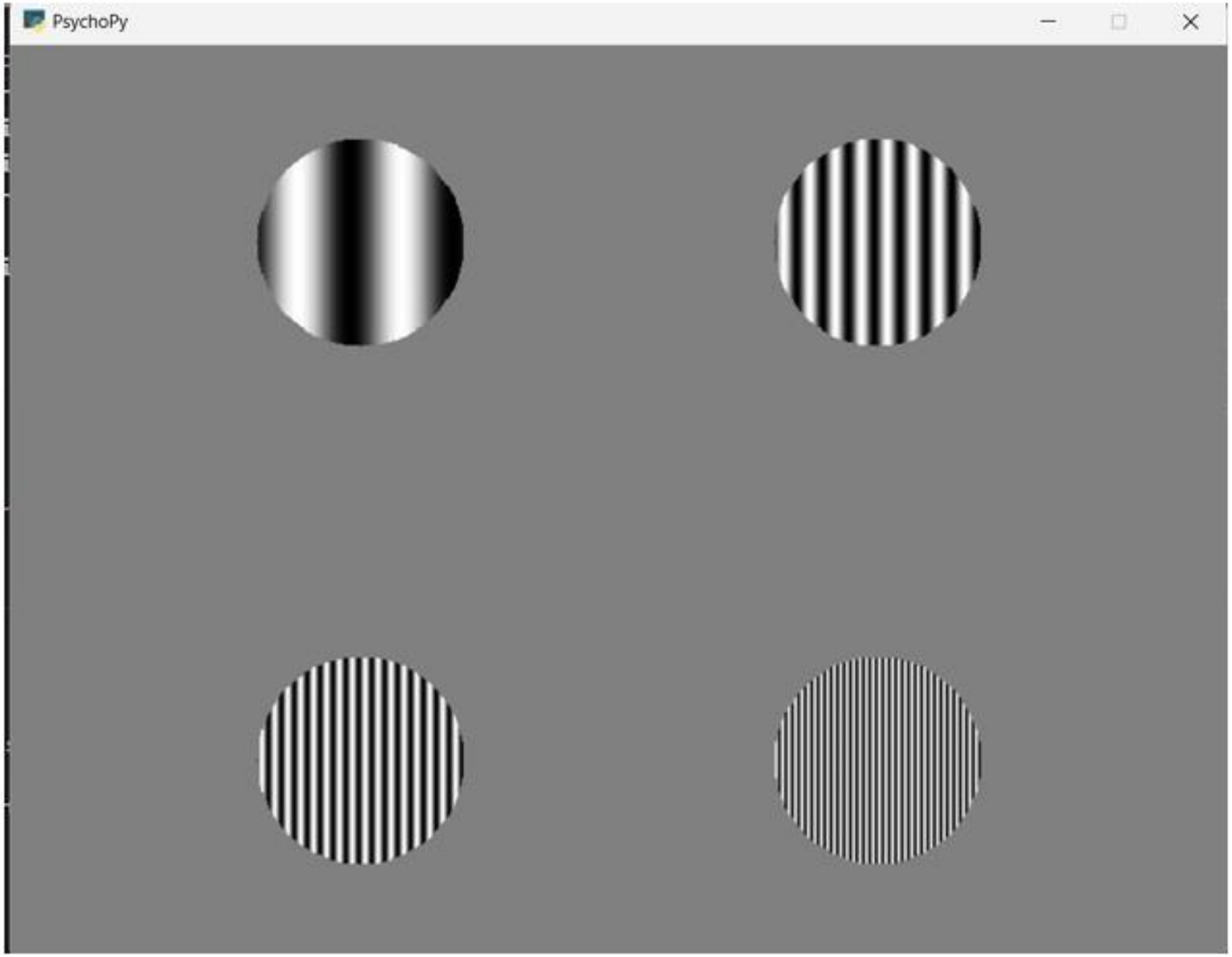
A steady state visual evoked potential based BCI (SSVEP BCI) relies on the psychophysiological properties of brain signals which occur in the occipital lobe with response to visual stimulation of specific frequency.

Advantages of SSVEP:

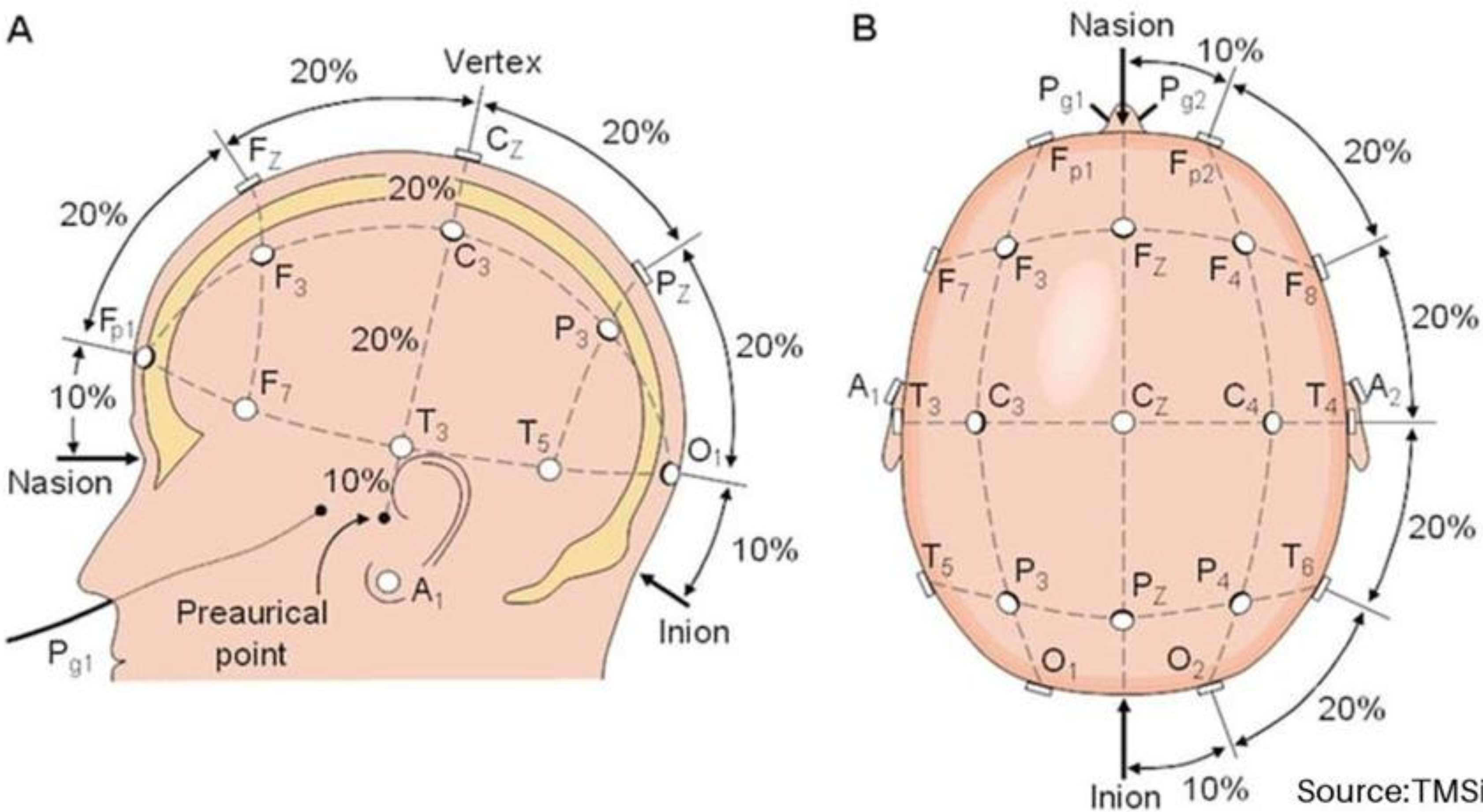
- Easy system configuration & convenient data acquisition
- Less user training
- Relatively high ITR & SNR

In SSVEP BCI system, the users are asked to make a selection to one of the multiple visual stimuli at different frequencies on the interface, and the system recognizes which frequency they are focusing on.

SSVEP - Stimuli Example Demonstration



The 10-20 system of placement of electrodes



Motivation

- Developing an SSVEP-based BCI system to provide accessible communication and control solutions for paralyzed, elderly, and motor-impaired individuals.

- Aiming to enhance independence, quality of life, and accessibility through innovative, non-invasive technologies.

Summary of Literature Survey in Phase 1 & Phase 2

[1] S.N.Aghili, S.Kilani, E.Rouhani and A.Akhavan, "A Novel Fast ICA-FBCCA Algorithm and Convolutional Neural Network for Single-Flicker SSVEP-Based BCIs," in IEEE Access, vol.12 2024.

Techniques proposed	• Dataset 1 : Recording data from 6 subjects participating in the rapid serial visual presentation (RSVP) with a sampling rate of 512Hz. • Dataset 2 : 12 participants in SSVEP experiments with a 15 Hz flickering square with a sampling rate of 2048Hz. • Pre-Processing : **Fast ICA** and Bandpass Filter • Feature Extraction : **FBCCA** , TRCA • Dimensionality Reduction : **DWT** • Classification : **CNN** , LDA , KNN and SVM
Results	• Performance evaluation through 3-fold and 5-fold cross-validation. • The (Fast ICA + FBCCA + DWT) + CNN method demonstrated average target recognition accuracy and standard deviation values of Dataset 1 : **97 ± 3.1%** and Dataset 2 : **82.12 ± 10.7%**

[2] Y. Wang, X. Chen, X. Gao and S. Gao, "A Benchmark Dataset for SSVEP-Based Brain Computer Interfaces," inIEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 25, no. 10, pp. 1746-1752, Oct. 2017

Techniques proposed	• SSVEP dataset acquired with a 40- target (BCI) speller. • The dataset consists of 64-channel Electroencephalogram (EEG) data. • **35** healthy subjects (8 experienced and 27 naïve) • **40** visual flickers, ranged from **8 to 15.8 Hz** with an interval of 0.2 Hz and phase difference **0.5π.** • For each subject, the data included six blocks of 40 trials corresponding to all 40 flickers of 5s trial duration of stimulus. • Bandpass filter : 7 Hz and 70 Hz and Notch filter at 50 Hz • Classification Techniques : FBCCA and CCA • Signal quality analysis through SNR and Amplitude spectrum.
Results	• Classification accuracy & ITR increased as the data length increased. • FBCCA outperformed over CCA.

[3] S. P. Karunasena, D. C. Ariyarathna, R. Ranaweera, J. Wijayakulasooriya, K. Kim and T. Dassanayake, "Single-Channel EEG SSVEP-based BCI for Robot Arm Control,"2021 IEEE Sensors Applications Symposium (SAS), Sweden, 2021

Techniques proposed	SSVEP signals were recorded from **Oz** with **Cz** & **Fpz** as ground and reference, using 4 white LEDs flickering at (6.5, 7.5, 8.2, 9.3)Hz for specific motor tasks classified by Euclidean Distance approach.
Results	High probability of accurate detection was observed when the buffered window length was increased (2-5s).

[4] M. Kołodziej, A. Majkowski, L. Oskwarek and R. J. Rak, "Comparison of EEG signal preprocessing methods for SSVEP recognition," 2016 39th International Conference on Telecommunications and Signal Processing (TSP), Vienna, Austria, 2021

Techniques proposed	Green stimuli (5, 6, 7, 8)Hz are processed using a Butterworth bandpass filter (0.1–100 Hz), notch filter (48–52 Hz), CAR, and ICA, with classification via LDA and k-NN (k=10).
Results	Best results were obtained for 4s window width, for 3-harmonics and LDA classifier when the ICA method was used.

[5] D. Zhao, T. Wang, Y. Tian and X. Jiang, "Filter Bank Convolutional Neural Network for SSVEP Classification," in IEEE Access, vol. 9, 2021

Techniques proposed	• Data preprocessing : Bandpass Filter and ICA • Method used are filter bank techniques, CNN, Correlation Analysis to optimize SSVEP classification.
Results	**FBCNN** achieves the best performance compared to CNN & CCA, with the highest accuracy of **93**% on dataset 1 and **79**% on dataset 2 (BM).

[6] D. Lei, C. Dong, P. Ma, R. Lin, H. Liu and X. Chen, "An SSVEP Classification Method Based on a Convolutional Neural Network,"2023 35th Chinese Control and Decision Conference (CCDC), Yichang, China, 2023

Techniques proposed	IMUT dataset (32 channels, 1500 samples, 40 trials, 4 classes, fs = 500 Hz) is preprocessed with a 6–30 Hz BPF and **ICA**, features are extracted using **CCA** and **FBCCA**, and classified using **CNN**.
Results	CNN achieved classification accuracy of **95.86**% with 3 seconds of data and an ITR of 183.05 bit/min

[7] A. Apicella et al., "Employment of Domain Adaptation Techniques in SSVEP-Based Brain–Computer Interfaces," in IEEE Access, vol. 11, pp. 36147-36157, 2023

Techniques proposed	Employment of a DA technique on 3 different neural network classifiers : **ShallowConvNet, DeepConvNet and EEGNet** over BM dataset.
Results	The classification accuracy increased with the DA technique-adapted classifier as a function of the time window (0.5, 1, 1.5 seconds).

[8] Pengfei Ma, Chaoyi Dong, Ruijing Lin, Shuang Ma, Tingting Jia, Xiaoyan Chen, Zhiyun Xiao," A classification algorithm of an SSVEP brain-Computer interface based on CCA fusion wavelet coefficients", Journal of Neuroscience Methods, Volume 371, 2022

Techniques proposed	The data, with 4 classes and channels P3, P4, O1, O2, Pz, P7, and P8, was preprocessed using a 6–30 Hz BPF & ICA, features were extracted using a **CCA-CWT** fusion algorithm, and classified using **SVM**.
Results	The classification accuracy, averaged over k=10 folds, was 91.76% and 89.1% for the BETA dataset in a time window of 2 seconds.

Literature Gaps/Challenges

- High-quality brain signal datasets can be challenging and costly.
- Smaller datasets can limit the model's effectiveness across different subjects, and the authors highlight the need for large datasets to improve model robustness and generalization.
- Managing the 4D SSVEP dataset was challenging, requiring complex preprocessing and reshaping for effective classification and analysis.
- Single-flicker frequency limits target selection in BCI applications.
- Training deep learning models requires a lot of data and suffer from overfitting problems.
- Lack of comparison with DL techniques such as CNN, transformers, etc.

Objectives

Design of hybrid BCI based on SSVEP :

1. Implementation of a filter in Pre-Processing stage to remove artifacts efficiently from the raw EEG data.

2. Comparative analysis of Feature Extraction technique on the filtered EEG data.

3. Implementation of a classifier to classify the features extracted.

4. The SSVEP-based BCI system is applied to a text display application, enabling hands-free communication.

Problem Statement

Addressing the lack of accessible communication and control solutions for paralyzed, elderly, and motor-impaired individuals by developing a non-invasive SSVEP-based BCI system to improve independence and quality of life.

Proposed Methodology

SSVEP – EEG Data
(Dataset obtained from Tsinghua Lab)

Pre-Processing EEG Data

Feature Extraction from Filtered EEG Data

Classification of Features Extracted

Analysis of Results Obtained

Implementation Details

Implementation Language:

- Python

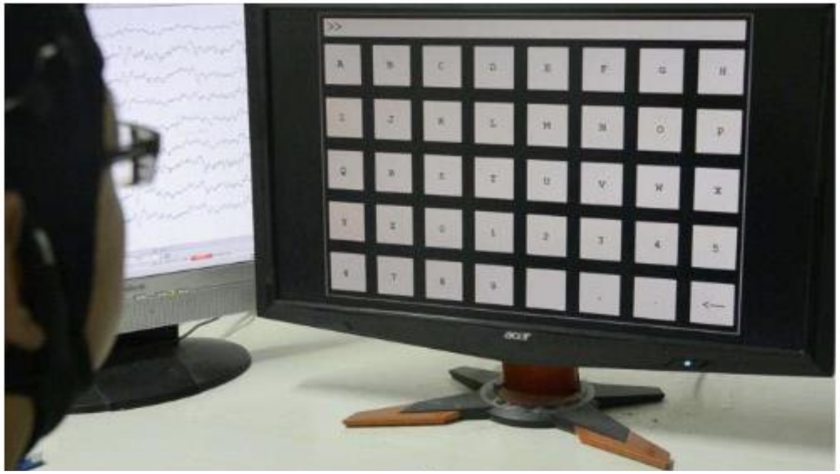
Frameworks Used:

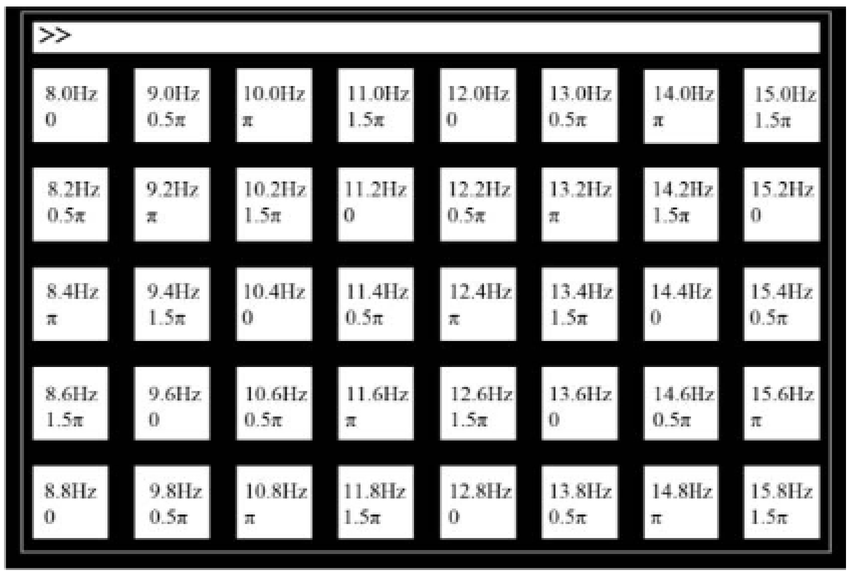
- MNE: EEG-specific data processing and analysis.
- Keras (TensorFlow backend): Deep learning model implementation and training.
- Scikit-learn: Cross-validation and evaluation metrics.
- Matplotlib & Seaborn: Data visualization.
- NumPy: General numerical operations.

Dataset Used :

- SSVEP Benchmark Dataset from Tsinghua BCI Lab. https://bci.med.tsinghua.edu.cn/

Dataset Details





General	
Filename(s)	benchmark_all_subjects-epo.fif
MNE object type	EpochsFIF
Measurement date	Unknown
Participant	Unknown
Experimenter	Unknown
Acquisition	
Total number of events	1050
Events counts	Freq_10: 210 Freq_11: 210 Freq_12: 210 Freq_8: 210 Freq_9: 210
Time range	0.000 – 5.996 s
Baseline	0.000 – 0.000 s
Sampling frequency	250.00 Hz
Time points	1,500
Metadata	No metadata set
Channels	
EEG	64
Head & sensor digitization	67 points
Filters	
Highpass	6.00 Hz
Lowpass	64.00 Hz

Source : [2] A Benchmark Dataset for SSVEP-Based Brain Computer Interfaces

Dataset Details

Subjects: 35 healthy participants (17 females), aged 17–34 years (mean age: 22).
Groups : 8 experienced (S01–S08), 27 naive (S09–S35).
Stimuli : 40 characters flickering at 8–15.8 Hz (0.2 Hz intervals).
Blocks: 6 blocks per subject.
Trials: 6 trials/subject (one per character in random order).

Trial Sequence:
Visual cue (red square): 0.5 s.
Flicker period (all stimuli): 5 s.
Blank screen: 0.5 s.
Total trial duration: 6 s.
Red triangle shown below target during stimulation to aid fixation.
Rest periods between blocks to reduce visual fatigue.

Data Segmentation:
Epochs: 6 s (500 ms pre-stimulus, 5.5 s post-stimulus).
Matrix Dimensions: [64, 1500, 40, 6]
64 electrodes, 1500 time points, 40 targets, 6 blocks.

Technologies Used

Fast Independent Component Analysis (Fast-ICA):
A statistical method used to separate mixed signals into independent sources. Fast-ICA is applied to preprocess EEG data by isolating relevant neural components and reducing noise or artifacts.

Canonical Correlation Analysis (CCA):
A multivariate statistical method that identifies correlations between two sets of variables. It is commonly used to extract and classify frequency-specific features by matching EEG signals with pre-defined reference templates.

Filter Bank Canonical Correlation Analysis (FBCCA):
An advanced version of CCA that utilizes multiple frequency bands through filter banks to enhance SSVEP detection by capturing more harmonic and sub-band frequency information, making it robust to individual differences.

Continuous Wavelet Transform (CWT):
A time-frequency analysis method that decomposes signals into wavelets to capture both frequency and temporal characteristics.

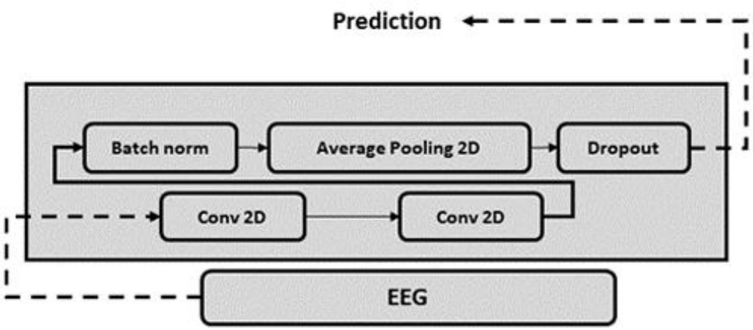
Technologies Used

EEGNet:
A compact deep learning architecture specifically designed for EEG data analysis. EEGNet is lightweight, computationally efficient, and well-suited for BCI tasks, including SSVEP classification.

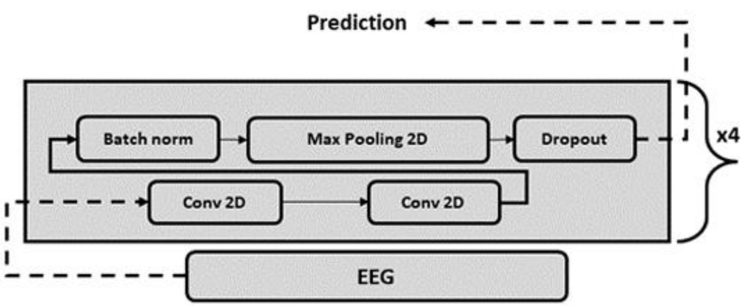
Deep Convolutional Net:
A deeper variant of CNNs with multiple convolutional layers. In SSVEP BCI, deep convolutional nets capture complex spatial-temporal features in EEG data, improving classification accuracy for high-dimensional inputs.

Shallow Convolutional Net:
A simpler CNN architecture focusing on fewer layers to capture low-level features. Particularly useful for SSVEP BCI when the dataset is small, as it reduces overfitting while still leveraging spatial-temporal patterns.

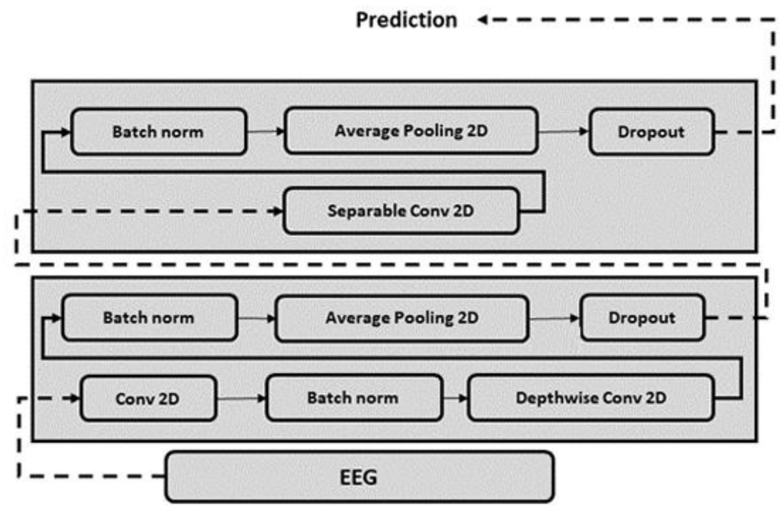
Architecture



ShallowConvNet



DeepConvNet



EEGNet

Source : [7] Employment of Domain Adaptation Techniques in SSVEP-Based Brain–Computer Interfaces

Convolutional Neural Network (CNN):

A deep learning model designed for image and grid-like data analysis. In SSVEP-based BCI, CNNs are used to learn spatial and temporal patterns in EEG signals automatically, enabling effective classification.

CNN Model Architecture used :

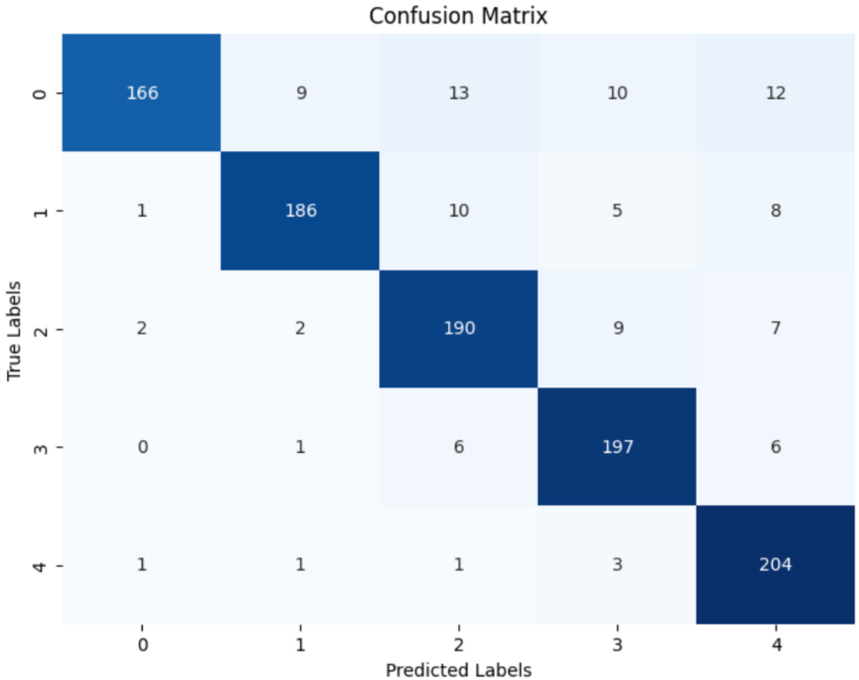
Model: "sequential_31"

Layer (type)	Output Shape	Param #
conv2d_62 (Conv2D)	(None, 14, 1246, 32)	4,032
max_pooling2d_62 (MaxPooling2D)	(None, 14, 249, 32)	0
conv2d_63 (Conv2D)	(None, 12, 247, 64)	18,496
max_pooling2d_63 (MaxPooling2D)	(None, 6, 49, 64)	0
flatten_31 (Flatten)	(None, 18816)	0
dense_62 (Dense)	(None, 256)	4,817,152
dense_63 (Dense)	(None, 5)	1,285

Total params: 14,522,897 (55.40 MB)
Trainable params: 4,840,965 (18.47 MB)
Non-trainable params: 0 (0.00 B)
Optimizer params: 9,681,932 (36.93 MB)

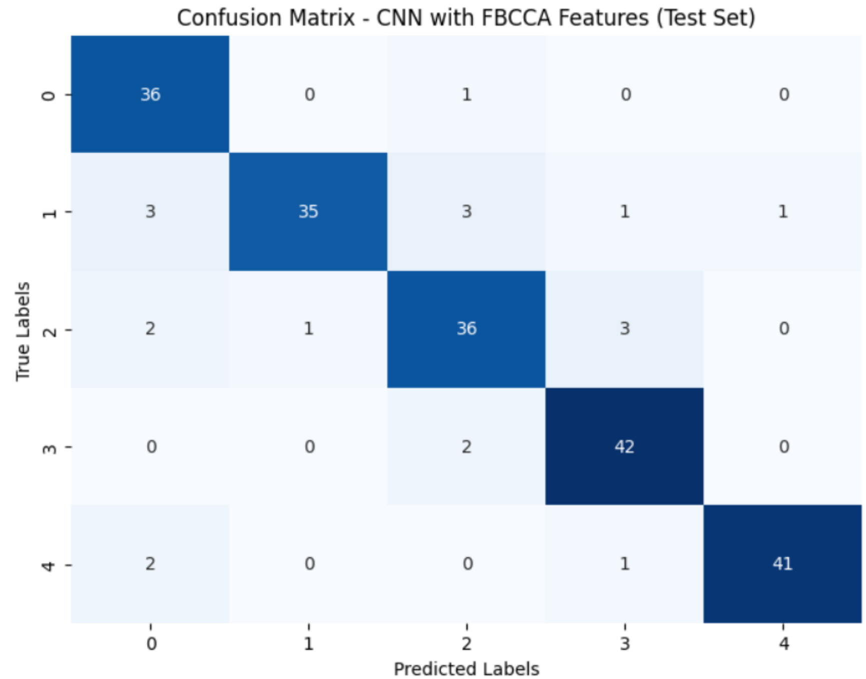
optimizer : Adam   loss: Categorical Cross Entropy

Implementation – 1 :
Fast ICA + FBCCA



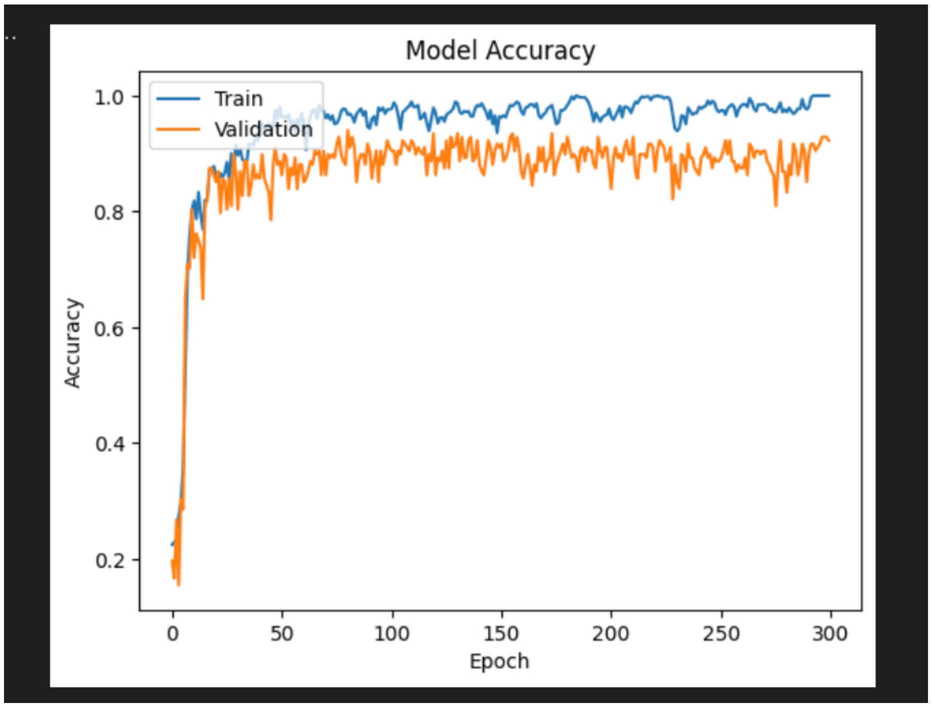
Classification Accuracy : 89.80%

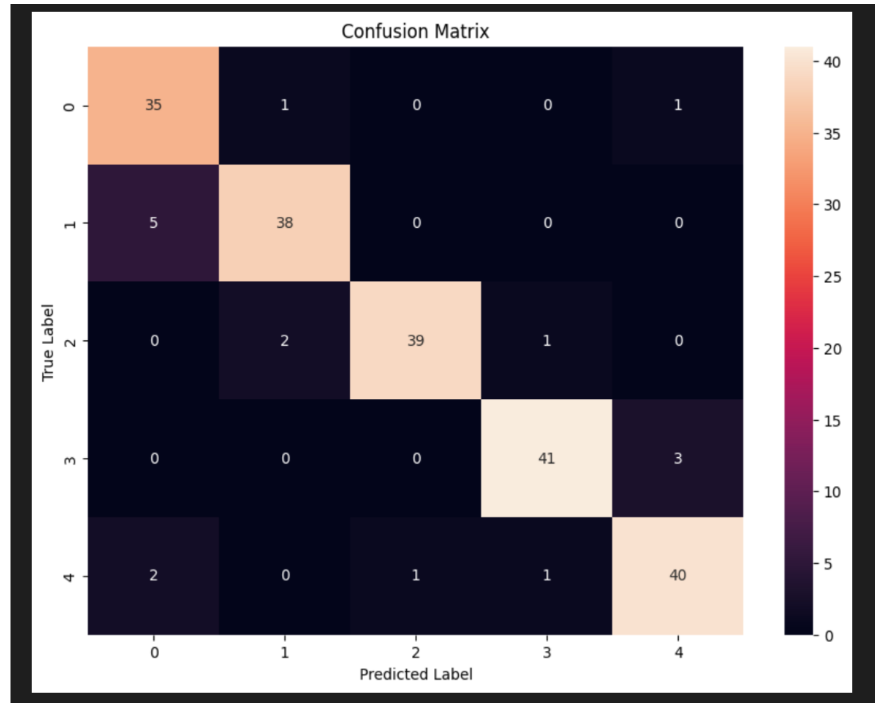
Implementation – 2 :
Fast ICA + FBCCA + CNN



Classification Accuracy : 90.47%

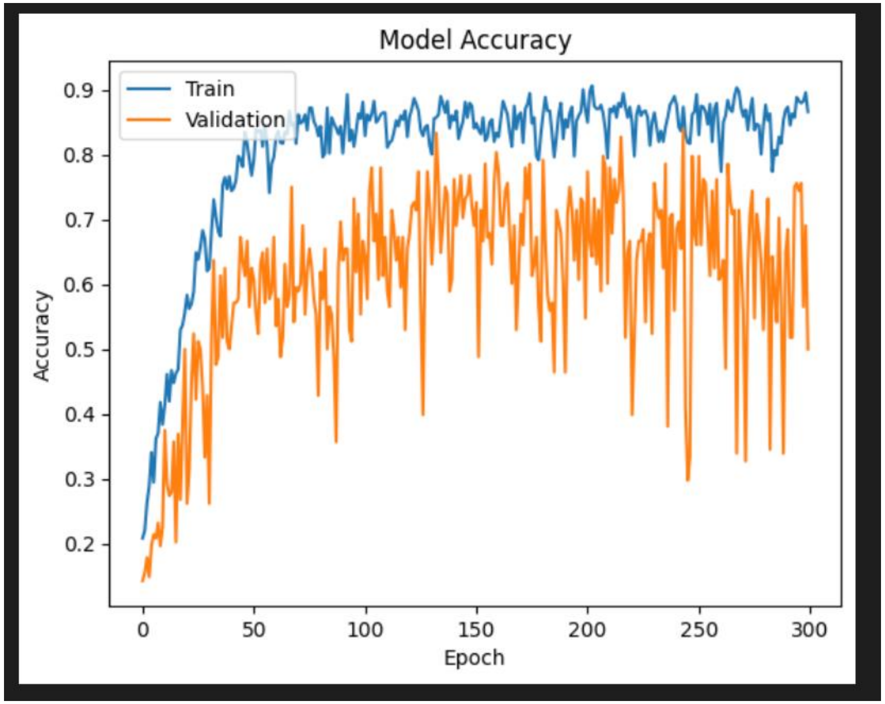
Implementation – 3 :
Fast ICA + DeepConvNet

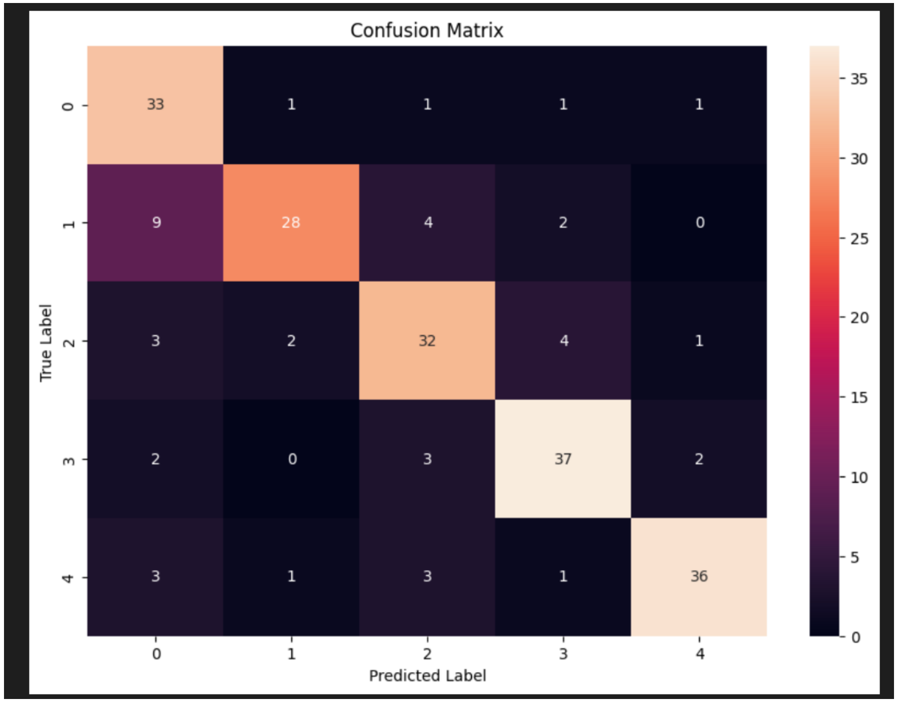




Classification Accuracy : 91.90%

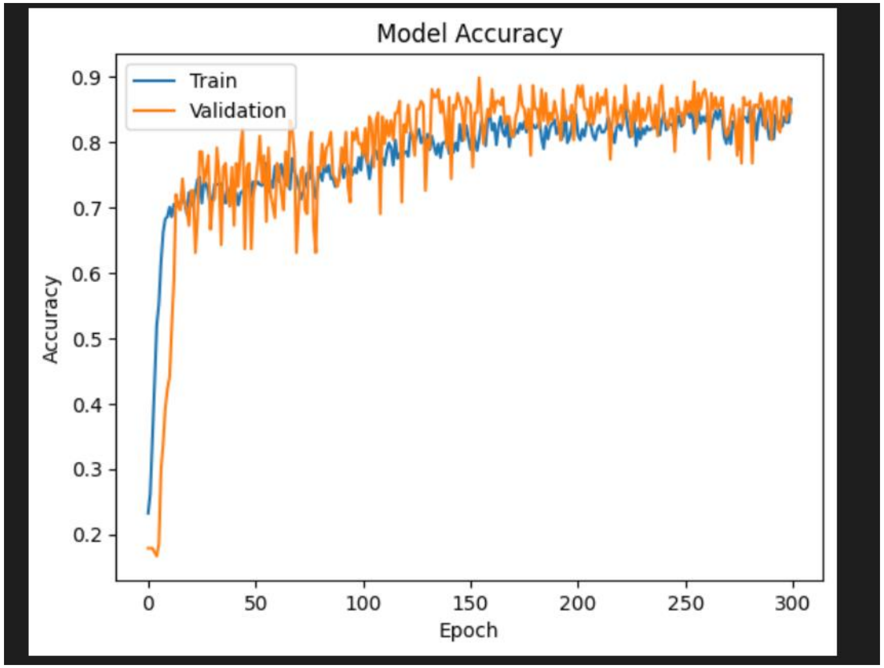
Fast ICA + ShallowConvNet

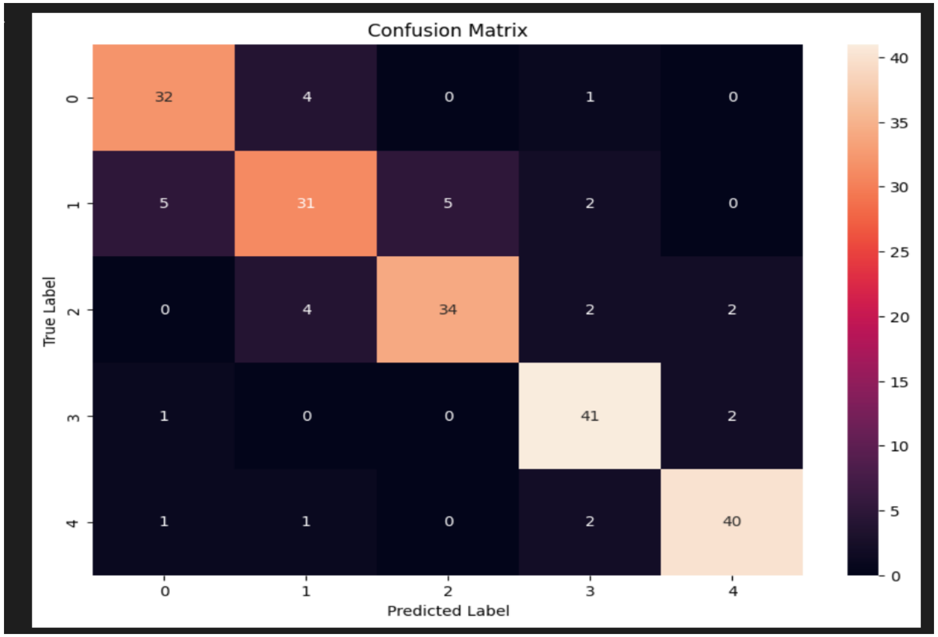




Classification Accuracy : 79.04%

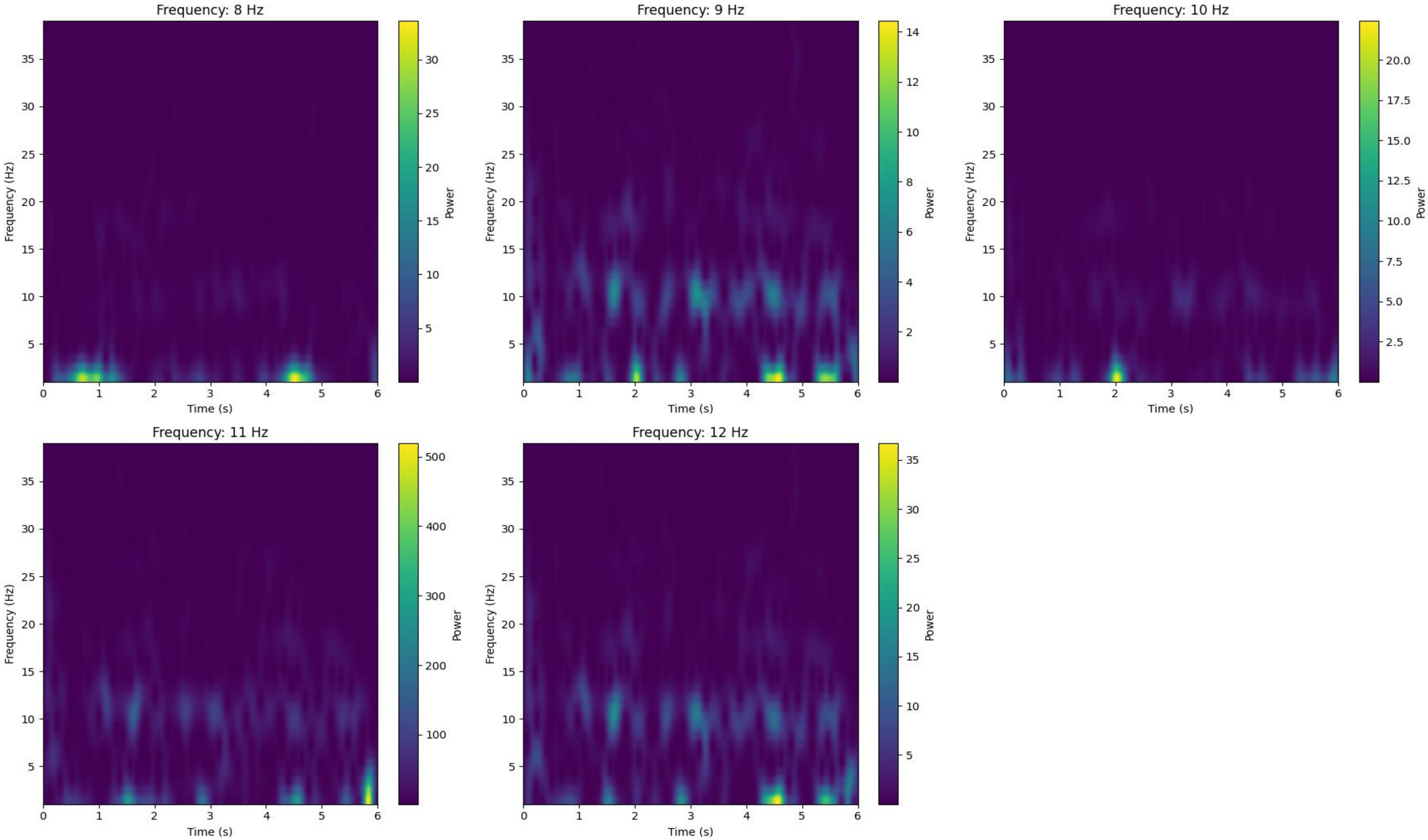
Fast ICA + EEGNet:



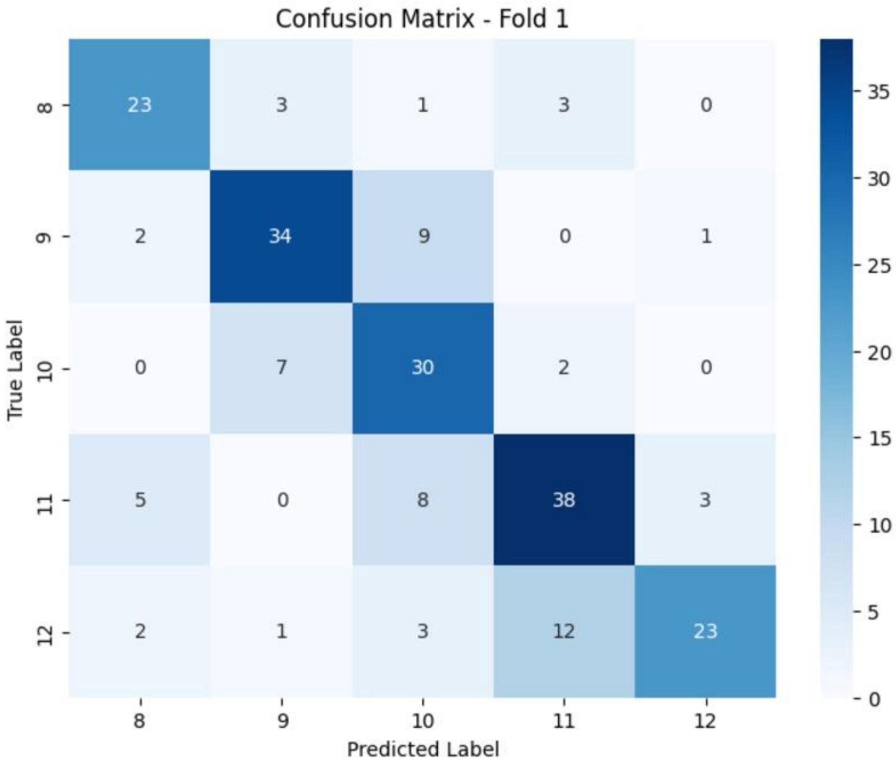


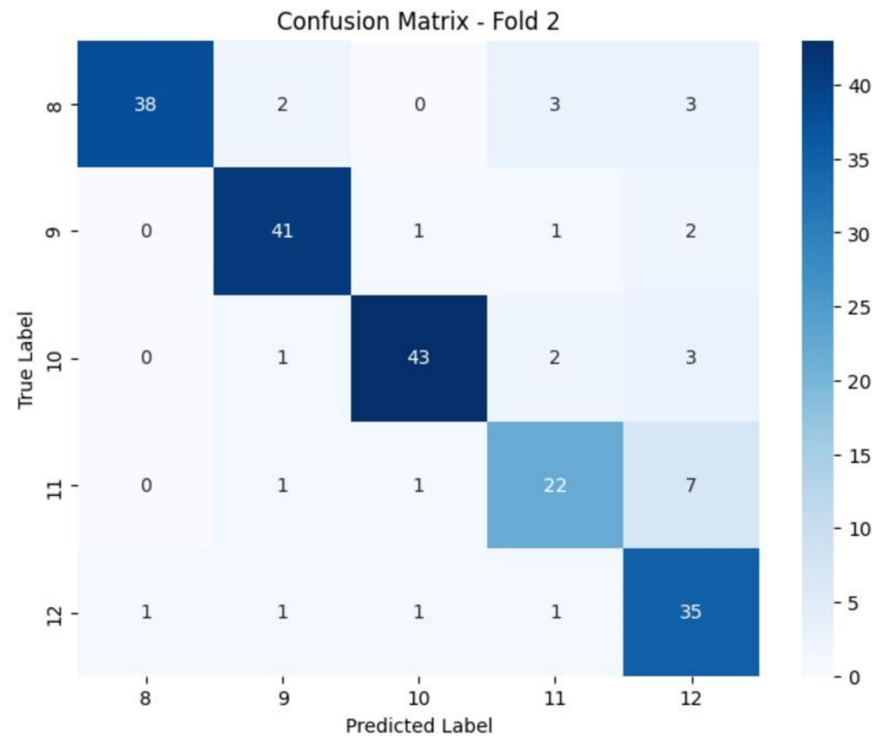
Classification Accuracy : 84.76%

Implementation – 4 : Fast ICA + CCA + CWT + CNN



Time Frequency Representations (CWT) for Different Frequencies



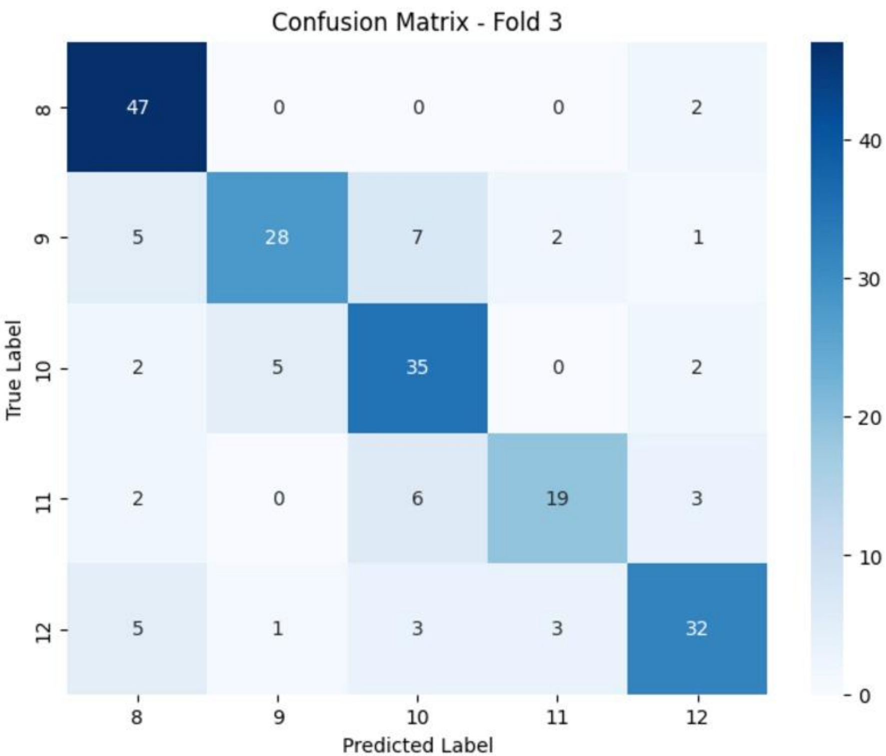


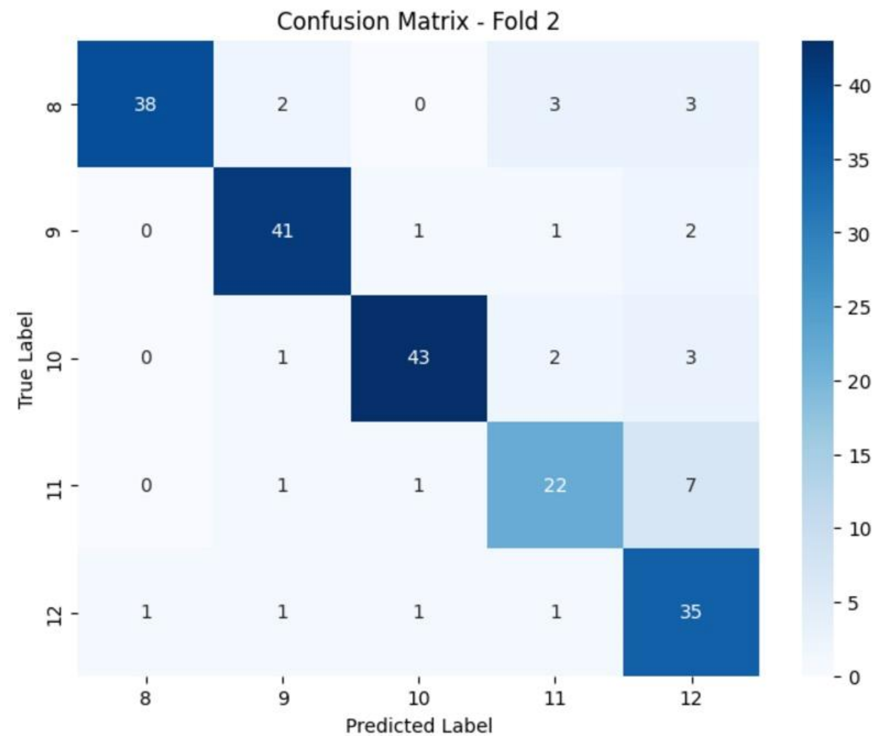
Fold 1: Accuracy: 70.48%

Frequency	Precision	Recall	F1-Score
8Hz	0.72	0.77	0.74
9Hz	0.76	0.74	0.75
10Hz	0.59	0.77	0.67
11Hz	0.69	0.70	0.70
12Hz	0.85	0.56	0.68

Fold 2: Accuracy: 85%

Frequency	Precision	Recall	F1-Score
8Hz	0.97	0.83	0.89
9Hz	0.89	0.91	0.90
10Hz	0.93	0.88	0.91
11Hz	0.76	0.71	0.73
12Hz	0.70	0.90	0.79



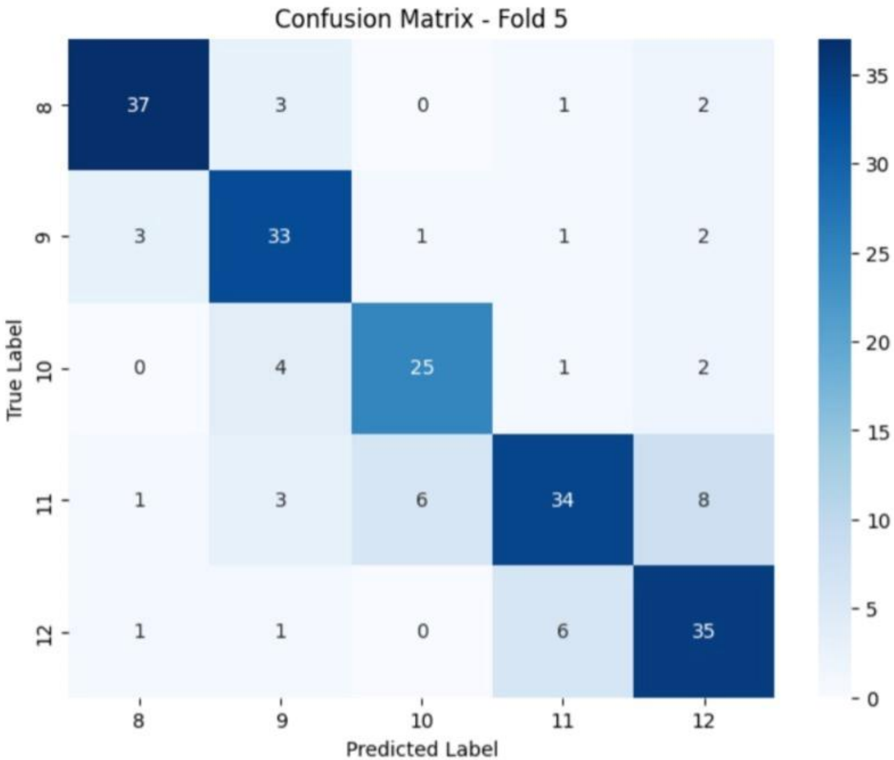


Fold 3: Accuracy : 77%

Frequency	Precision	Recall	F1-Score
8Hz	0.72	0.77	0.74
9Hz	0.76	0.74	0.75
10Hz	0.59	0.77	0.67
11Hz	0.69	0.70	0.70
12Hz	0.85	0.56	0.68

Fold 4: Accuracy 76%

Frequency	Precision	Recall	F1-Score
8Hz	0.82	0.79	0.80
9Hz	0.85	0.64	0.73
10Hz	0.73	0.96	0.83
11Hz	0.70	0.65	0.67
12Hz	0.72	0.72	0.72



Fold 5: Accuracy 78%

Frequency	Precision	Recall	F1-Score
8Hz	0.88	0.86	0.87
9Hz	0.75	0.82	0.79
10Hz	0.78	0.78	0.78
11Hz	0.79	0.65	0.72
12Hz	0.71	0.81	0.76

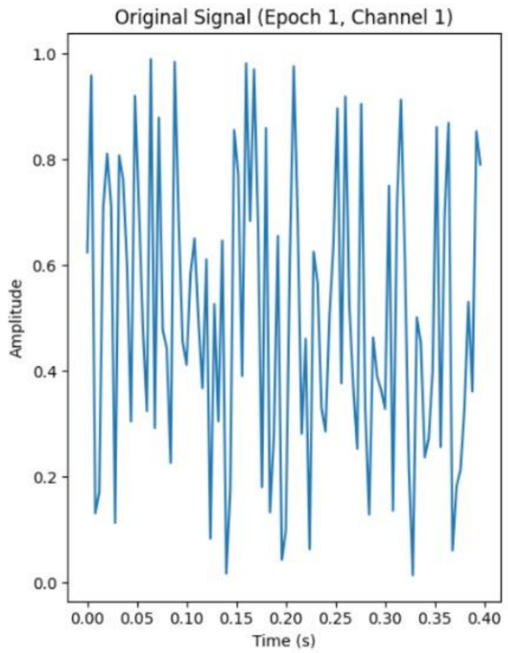
```
Average accuracy: 77.24%
Standard deviation: 4.76%
```

Results and Analysis

Preprocessing	Feature Extraction	Classification Technique	Classification Accuracy
Bandpass Butterworth Filter + Fast-ICA	Filter Bank Canonical Correlation Analysis	Filter Bank Canonical Correlation Analysis	89.80%
Bandpass Butterworth Filter + Fast-ICA	Filter Bank Canonical Correlation Analysis	Convolution Neural Network	90.47%
Bandpass Butterworth Filter + Fast-ICA	-	EEGNET Deep Conv Net Shallow Conv Net	84.76% 91.90% 79.04%
Bandpass Butterworth Filter + Fast-ICA	Canonical Correlation Analysis + Continuous Wavelet Transform	Convolution Neural Network	77.24%

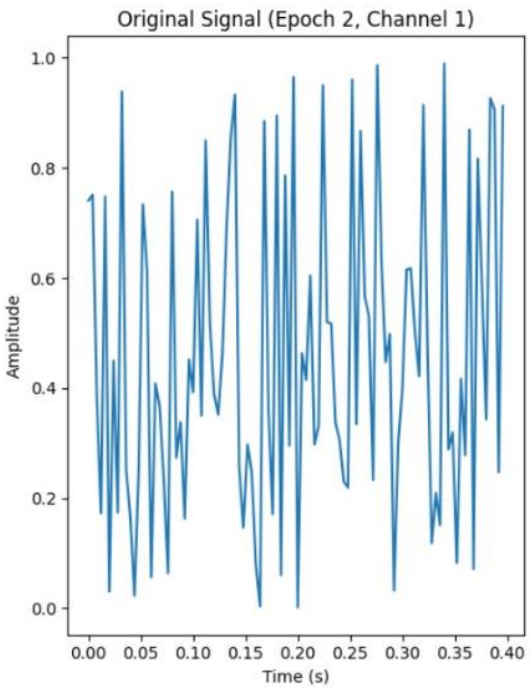
Application

Frequency	Task Label
8 Hz	Food
9 Hz	Water
10 Hz	Washroom
11 Hz	Emergency
12 Hz	TV

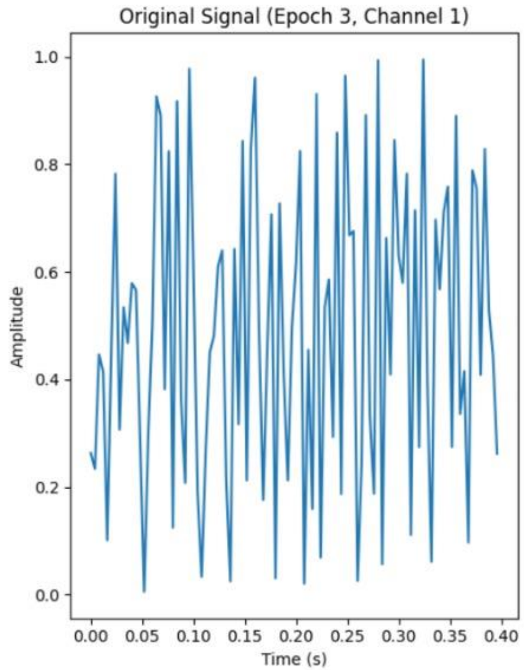


Actual Label: food

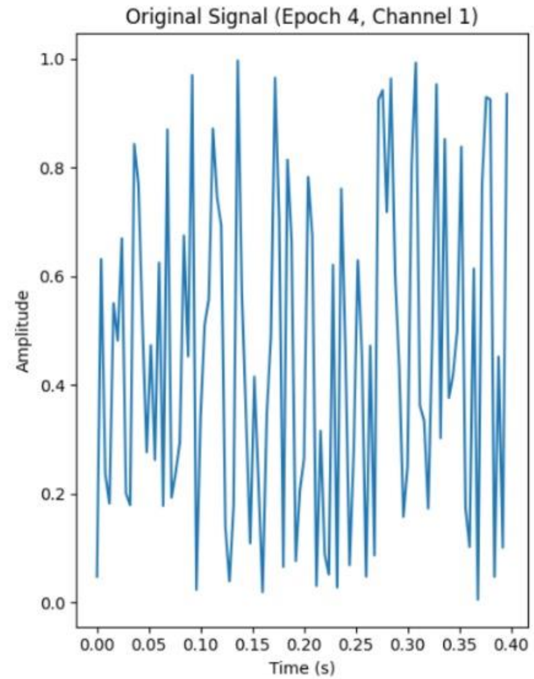
Predicted Label: food



Actual Label: water



Actual Label: washroom



Actual Label: emergency

Predicted Label: water

Predicted Label: water

Predicted Label: emergency

Conclusion

1. Advanced CNN models like DeepConvNet, ShallowConvNet, and EEGNet demonstrate high accuracy (up to 91%) for SSVEP classification in real-time BCI applications.

2. Preprocessing techniques and feature extraction methods such as FBCCA, CCA, and CWT significantly enhance classification reliability.

3. Robust validation methods like k-fold cross-validation (70%-85% accuracy) are crucial for generalization and optimizing BCI system performance.

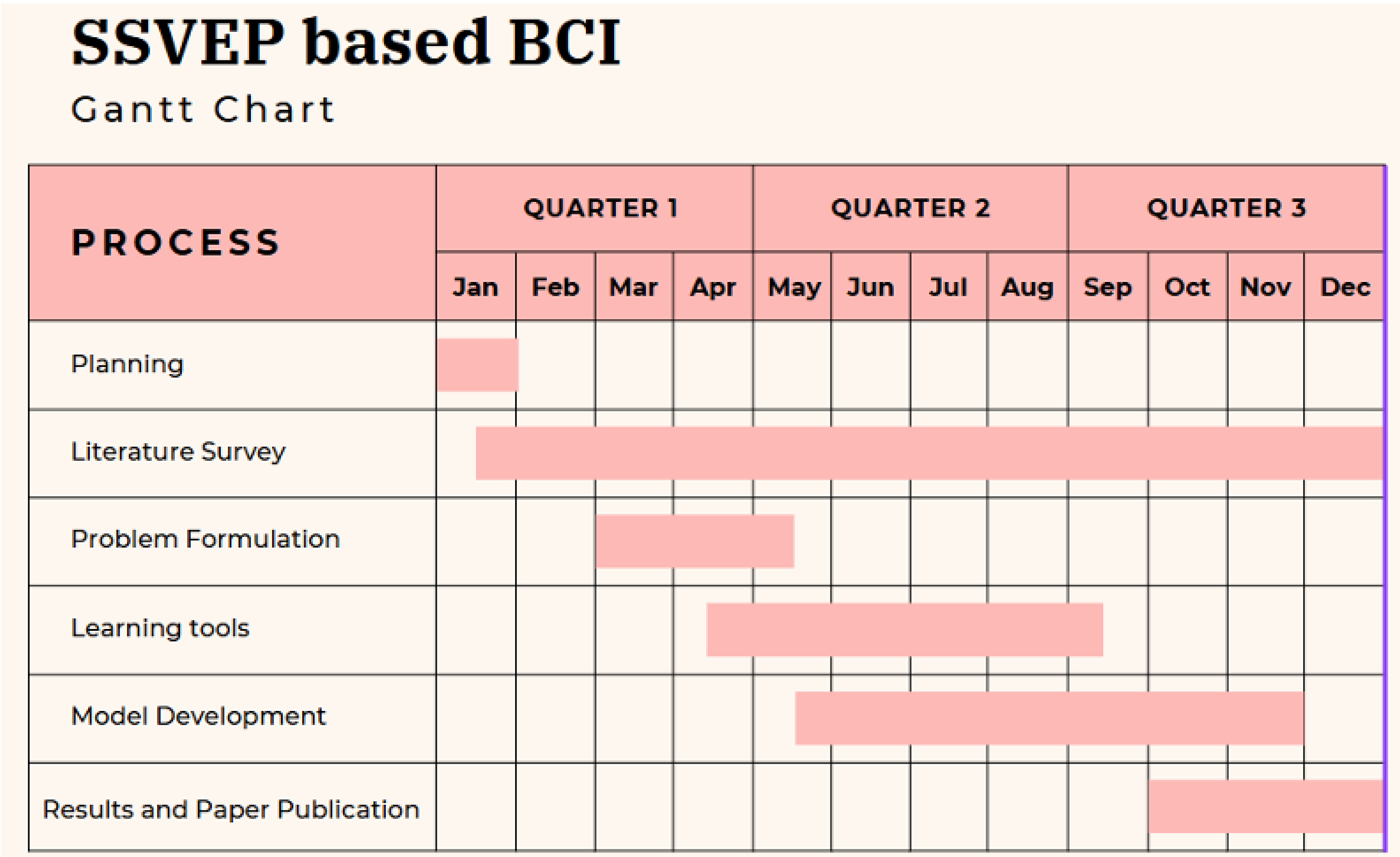
Future Works

1. Test methodologies like FBCCA, CCA, and CNN models in real-time SSVEP-based BCI systems to evaluate practicality and efficiency.

2. Enhance robustness by integrating multimodal features such as spatial metrics or data fusion into SSVEP classification models.

3. Use advanced AI techniques like GANs and VAEs for synthetic data augmentation, noise reduction, signal enhancement and addressing limited EEG data challenges.

Project Timeline



References

[1] S.N.Aghili, S.Kilani, E.Rouhani and A.Akhavan, "A Novel Fast ICA-FBCCA Algorithm and Convolutional Neural Network for Single-Flicker SSVEP-Based BCIs," in IEEE Access, vol.12 (2024)

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Individual Contributions

Ankit Agarwal (PES1UG21EC046)	Conducted a literature survey on preprocessing techniques for SSVEP-based BCI systems, identifying optimal approaches and implemented Fast ICA in the project to enhance signal quality, and drafted a research paper detailing our work and findings.
Ankur Pandey (PES1UG21EC048)	Worked on conducting a literature survey and implementing feature extraction techniques, including CCA, FBCCA and DWT, for the project. Additionally, I wrote a detailed report documenting the methodology and findings.
Ashlesh Kumar (PES1UG21EC059)	Contributed to implementing the feature extraction technique CWT and classification techniques using CNN and Transformer models. Additionally, I prepared the project poster to showcase our work and findings.
Dhanush D (PES1UG21EC082)	Performed a deep literature survey to identify research gaps in SSVEP-based BCI systems. I worked on selecting the primary EEG channel for analysis, searched for relevant SSVEP datasets, and maintained the project's presentation tasks.

Q & A

Thank You