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Report on

'SSVEP detection and classification for EEG based Brain Computer Interface'

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under the guidance of

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PROGRAM B. TECH

CERTIFICATE

This is to certify that the Report entitled

‘SSVEP detection and classification for EEG based Brain Computer Interface’

is a Bonafide work carried out by

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In partial fulfillment for the completion of 7th semester course work in the Program of Study B. Tech in Electronics and Communication Engineering under rules and regulations of PES University, Bengaluru during the period Jan – Dec 2024. It is certified that all corrections/suggestions indicated for internal assessment have been incorporated in the report. The report has been approved as it satisfies the academic requirements in respect of project work.

Signature with date	*Signature with date & Seal*	*Signature with date & Seal*
Shwetha G	*Dr. Shikha Tripathi*	*Dr. B. K. Keshavan*
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Name and Signature of the Examiners:

DECLARATION

We, **Ankit Agarwal, Ankur Pandey, Ashlesh Dubey, Dhanush D**, hereby declare that the report entitled, **'SSVEP detection and classification for EEG based Brain Computer Interface',** is an original work done by us under the guidance of **Prof. Shwetha G, Associate Professor, Department of ECE,** is being submitted in partial fulfillment of the requirements for completion of project work in the Program of Study B. Tech in Electronics and Communication Engineering.

PLACE: Bangalore
DATE: 03/12/2024

NAME AND SIGNATURE OF THE CANDIDATES

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ABSTRACT

This research presents a novel approach for SSVEP-based BCI systems, combining Fast-ICA preprocessing with CCA and CWT-based feature extraction, followed by CNN classification optimized via K-Fold Cross-Validation. Using EEG signals from channels O1, O2, and Oz, recorded from 35 healthy subjects, our method achieves five-fold classification accuracies of 70.48% to 85% and strong F1-scores for SSVEP frequencies between 8 Hz and 15 Hz. Comparative analyses show competitive performance, with Filter-Bank CNN achieving 90.47% and transfer learning models like DeepConvNet and EEGNet scoring 89.80% and 84.76%, respectively. This efficient pipeline supports real-time neurorehabilitation and assistive applications with robust human-machine interaction.

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1. INTRODUCTION

The feature enhancement approach in this paper combines approaches like CCA with deep neural network architectures like CNN to enhance the performance of EEG-based BCI models. The EEG-based BCIs, especially those dependent on SSVEPs, hold immense promise for applications requiring accuracy and real-time performance. These include the communication systems for physically disabled, adaptive neuroprosthetics, and immersive gaming environments. In this paper, we apply enhancements to improve SSVEP-based BCI systems that crucially depend on the accurate classification of EEG signals evoked by the visual stimuli flickering at certain frequencies.

The approach focuses on taking advantage of the distinctive advantages of both CCA and CNNs in collaboration, while addressing challenges in the development of EEG-based BCI. CCA is particularly powerful in exploiting the external frequency correlations in SSVEP signals. CCA identifies the frequency-specific components by correlating the input EEG signals with the reference signals, which are generated from the known flickering frequencies, thereby enhancing the signal quality for further processing. Besides enhancing signal clarity, the model is empowered to bring in more accurate and rich contextual classifications without adding extra computation. Unlike traditional methods, CCA offers a robust mechanism that would maintain signal integrity, balancing between simplicity and effectiveness.

Besides that, the proposed model brings CNNs into the processes of feature extraction for the EEG signals. It was particularly interested in the spatial and temporal patterns in the time-frequency plane, especially the highly represented features over the occipital part together with a generated SSVEP signal. This multilayer feature learning of EEG data will capture not only the local but also global structures across different patterns of crucial channels through the CNN, for finding subtle changes in neural activity. This lays a foundation for the frequency-specific responses corresponding to different classes of visual stimuli to be effectively captured by the model in order to improve accuracy in classification. The proposed combination of CNNs with CCA will further reinforce the strengths of the model in handling complex EEG data and allow for the finding of the robust patterns that could be difficult for standalone algorithms to capture.

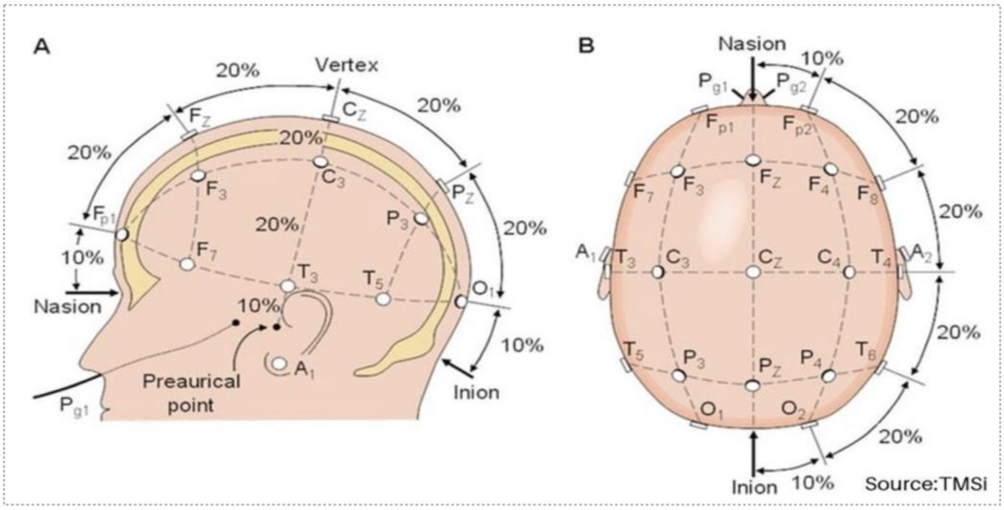


Figure 1.1 Electrode placement on scalp [1]

While these features-which are rich in contextual accuracy and signal fidelity-lay the bedrock of the proposed model, they inherently pose a challenge to maintaining them. EEG data are also very noisy and quite regularly include such artifacts as a result of muscle movements, eye blinking, and other physiological interferences. Such an artifact easily masks the important neural signals, which cannot make even sophisticated models provide good performances. On the other side, CCA is also not an exception under this noisy environment of input EEG signals, since such noisy situations weaken the correlation between the input EEG signal and reference signals, thereby leading to suboptimal feature enhancement. While CNNs require well-processed input data to avoid over-fitting on irrelevant patterns, proper preprocessing and noise reduction make them work.

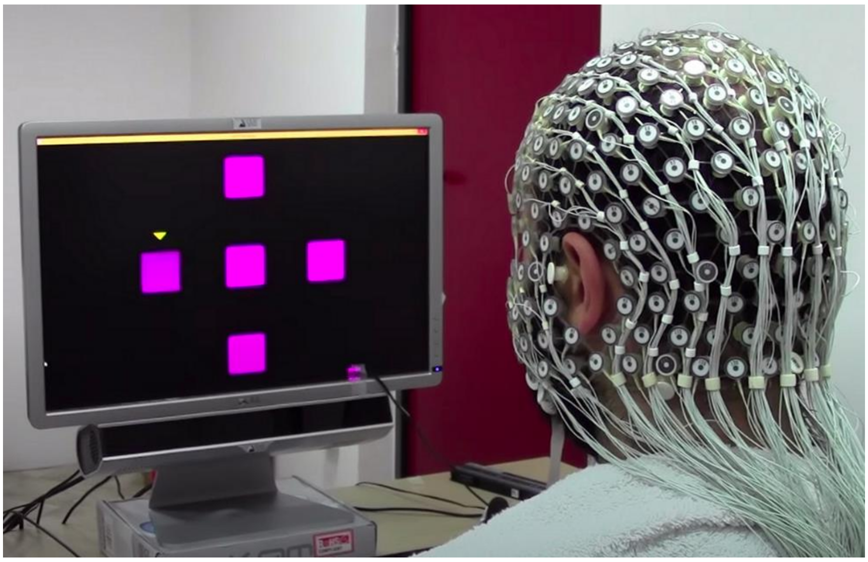


Figure 1.2 Image showing participant using high-density EEG and SSVEP stimuli [11]

2. LITERATURE SURVEY

2.1. A Benchmark Dataset for SSVEP-Based Brain Computer Interfaces, in IEEE Transactions on Neural Systems and Rehabilitation Engineering, 2017

This work introduces a comprehensive benchmark dataset for SSVEP-based BCIs, focusing on a 40-target speller system that may enable extensive testing and cross-method comparisons. The dataset included 35 participants, comprising 64-channel EEG recordings designed to facilitate offline simulations in order to improve system diagrams of stimulus coding and target identification in SSVEP-based BCIs.

The visual stimulation was a 5×8 matrix of flickering targets with unique frequency-phase encoding provided by JFPM. The stimuli were presented on a 23.6-inch LCD monitor. The EEG signals were measured by a Synamps2 EEG system with great precision at an acquisition rate of 1000 Hz, later down-sampled to 250 Hz for optimization of storage and processing efficiency. Data were carefully preprocessed by extracting epochs and filtering out noise to get the best quality of the signal.

The experimental results indicated that the signals had a robust character, with well-defined harmonic peaks, while the signal-to-noise ratio was constant across frequencies. These data were further verified for their efficacy using advanced algorithms such as Filter Bank Canonical Correlation Analysis and JFPM by demonstrating very high classification accuracy and ITR, especially for experienced users.

This dataset provides data from the same subjects in different configurations. All data is provided in open format to support access to these data in MATLAB, extensively documented, and electrode position merits. Further, all the above can guarantee the reproducibility of findings for great value in developing sophisticated BCI systems or providing proper cross-study validation in the domain of SSVEP-based BCIs

Limitations:

While the discussed dataset has many strengths, certain limitations should be taken into consideration. The data recording is offline; thus, actual testing cannot be performed simultaneously, which diminishes the purpose of this database in usability studies of BCIs from a practical perspective. In general, future developments may relate to online data acquisition and let one directly compare the obtained results for both simulated and real BCIs. The dataset deals with gaze-dependent BCPs, and hence controlled gaze is required.

This constraint makes the system unsuitable for people who cannot control their gaze due to certain ailments, such as locked-in syndrome. For these challenges, gaze-independent BCI datasets and algorithms probably need to be developed in independent efforts.

The dataset can also be extended by a larger pool of subjects for stronger cross-subject analyses that increase the generalizability of the conclusions. Collecting multi-session data from the same participants will further facilitate research on session-to-session transfer learning, a very important aspect of BCI development. Finally, standardized benchmarks across different studies based on datasets like this can help develop cross-study comparability, accelerating advancements in the SSVEP-based BCI technologies.

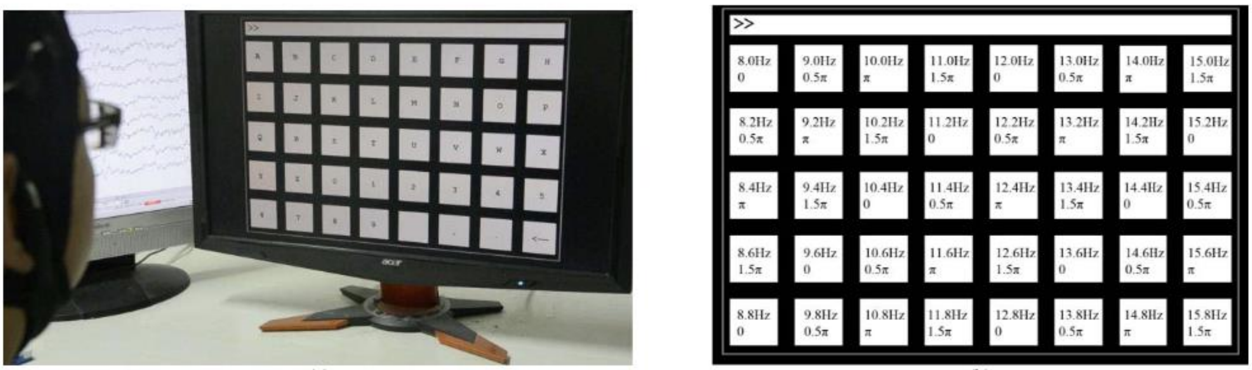


Figure 2.1 Stimulation interface of the 40-target BCI speller [8]

2.2. A Novel Fast ICA-FBCCA Algorithm and Convolutional Neural Network for Single-Flicker SSVEP-Based BCIs, in IEEE Access, 2024

This proposes a new machine-learning algorithm that will help in increasing the accuracy and reliability in single-flicker SSVEP-based BCIs. It uses the combination of fast ICA, Filter Bank Canonical Correlation Analysis, and DWT for feature extraction. It improves classification accuracy using advanced techniques, along with a low-parameter CNN. It clearly depicts from the results an overall increased performance of up to 97% in Dataset 1 and 82.12% on Dataset 2, and outperformed the conventional approaches while proving its potential toward practical applications.

Methodologically, two different data sets are used to evaluate the performance of the proposed BCI system. The first dataset consists of six subjects, each with a BCI speller system exposed to a 15 Hz flickering stimulus; the second dataset consists of twelve subjects with 32-channel EEG recordings with regard to SSVEP responses elicited by a centrally flickering square. In preprocessing, the recorded EEG signals are band-pass filtered and segmented into epochs; then, key channels in the occipital and parietal regions are selected. Herein, feature extraction involves the use of noise-reduced Fast ICA, followed by the extraction of SSVEP harmonics with FBCCA combined for enhanced frequency resolution.

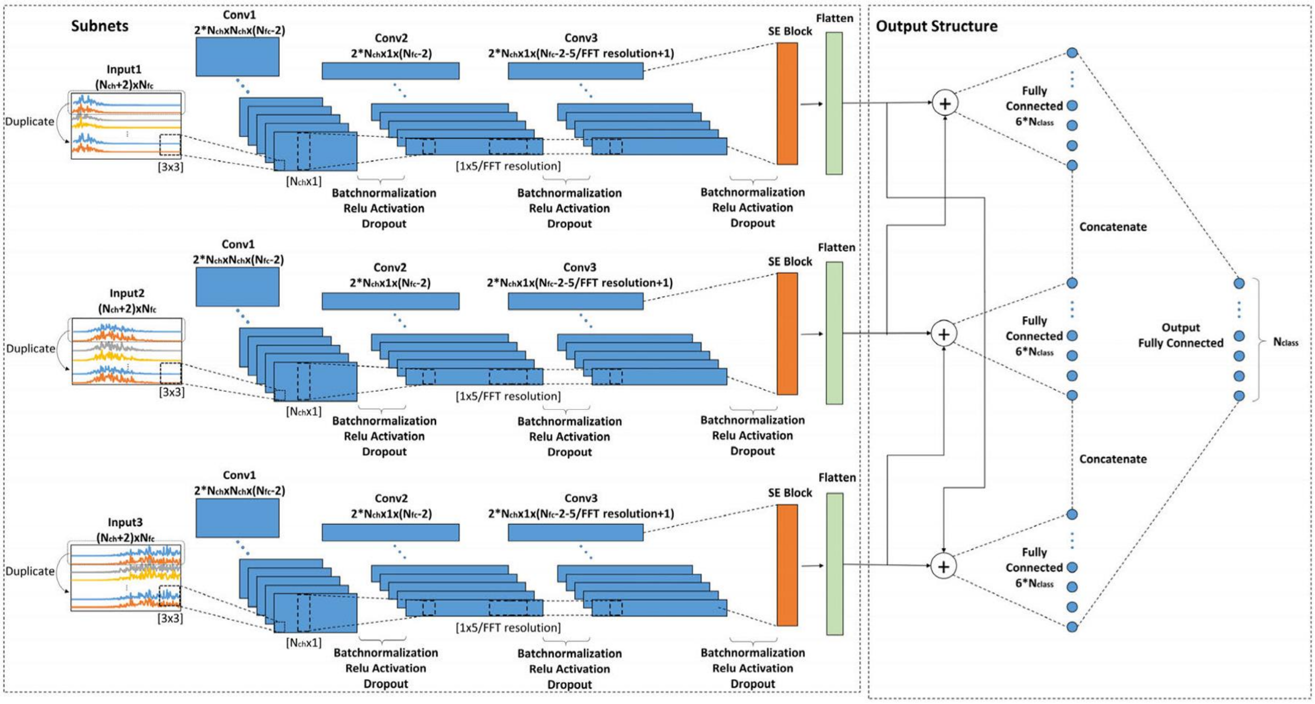


Figure 2.2 FBCNN network architecture including the subnets and the output structure[2]

The batch normalization and temporal convolution involved in the proposed CNN architecture for classification ensure that the parameters used are efficient for real-time implementation. The performance and effectiveness of the architecture are confirmed by cross-validation and testing on both datasets. The results indicate great improvements in accuracy, including the integration of Fast ICA, FBCCA, and DWT, in comparison with traditional methods. The attained accuracy is 97% and 82.12% from Dataset 1 and Dataset 2, respectively. Moreover, this approach reduces eye fatigue because it can improve the accuracy with fewer repetitions. T-SNE visualization confirms that the feature extraction process effectively distinguishes between classes and hence shows the robustness of the proposed technique in SSVEP-based BCIs.

Limitations:

The system has a few limitations that could impact its wider applicability. These would include limitations to reliance on a single flicker frequency, which allows only limited target number selection. Development of methods for using increased numbers of flicker frequencies or the inclusion of hybrid paradigms would therefore offer more choice. There is also limited generalizability because few state-of-the-art datasets pertain to single-flicker SSVEP analysis. Further studies may focus on the creation or collaboration in developing more comprehensive datasets. The system is also susceptible to noise and artifacts from eye movements and muscle activity; therefore, further improvement of denoising techniques is needed. The last one refers to the optimization of the computational cost of FBCCA that is using multiple filters. The proposed approach could further reduce this by optimizing the number of subbands while keeping the performance and improving efficiency.

2.3. Single-Channel EEG SSVEP-based BCI for Robot Arm Control, IEEE Sensors Applications Symposium (SAS), Sweden, 2021

SSVEP signals were recorded from one Oz electrode, with Cz and Fpz as ground and reference, respectively. The experiment had been carried out with four flickering white LEDs at frequencies 6.5, 7.5, 8.2, and 9.3 Hz corresponding to a particular motor task. These flashing stimuli would finally elicit SSVEP responses in the subjects, which, using the Euclidean Distance approach, would then classify. Among the different classification methods of SSVEP signals, the Euclidean Distance approach has been one of the most popular because of its simplicity and effectiveness for determining the similarity of measured and preset reference patterns.

The study recorded a high likelihood of rightly detecting the target SSVEP signals, especially when the length of the buffered window was extended. More specifically, when the window length was increased from 2 to 5 seconds, it provided results that were most reliable. This result also agrees with the previous literature that suggested a longer time window will include a more stable signal, which is very necessary for enhancing the classification accuracy in BCI systems. A longer window captures more information from the EEG signals, hence it reduces the noise and enhances the signal-to-noise ratio. This will help the classifier do a better identification between the different flicker frequencies.

Contributing further to the robustness of signal detection, several flicker frequencies were used during the experiment. The system utilized frequency-dependent characteristics of the SSVEP responses by using four different flicker frequencies at 6.5, 7.5, 8.2, and 9.3 Hz. This is important because SSVEP signals are frequency-dependent, and using several flickering frequencies helps pinpoint the target correctly according to the responding frequency from the subject's brain activity. Further, the use of these frequencies with a buffer window could facilitate handling the temporal dynamics of SSVEP responses in that system.

The classification based on the Euclidean Distance method worked quite well in this paper. This technique determines the separation in feature space between the observed SSVEP signal and a predetermined reference signal. The closer the distance, the more likely it is that the target signal frequency will match the observed signal. Despite its simplicity, Euclidean Distance has demonstrated satisfactory performance for real-time BCI systems due to its ease of implementation and low computing cost. Longer buffering windows were used to further improve classification accuracy, resulting in more constant and dependable feature extraction.

Limitations:

There was a fixed set of flicker frequencies-6.5, 7.5, 8.2, and 9.3 Hz-which may limit the target selection and flexibility in practical uses. Also, the method for classification using Euclidean Distance, while effective herein, is not guaranteed to scale for more complex patterns in the signals or larger datasets. A fixed buffered window length may not be optimal for all subjects or conditions and hence might affect the accuracy in real-time BCI applications.

2.4. Comparison of EEG signal preprocessing methods for SSVEP recognition, 39th International Conference on Telecommunications and Signal Processing (TSP), Vienna, Austria, 2021

In the present work, the analysis of green stimuli for a frequency of 5, 6, 7, and 8 Hz with SSVEP-based BCI systems is studied. The obtained signals will go through different pre-processing processes: Butterworth band-pass filtration in a range of 0.1-100 Hz for canceling the unwanted frequency components; notch filtering between 48-52 Hz, power-line interference removal. Common Average Reference (CAR) is applied to the EEG signals to improve spatial resolution, followed by Independent Component Analysis (ICA) to further enhance signal quality by separating out artifacts such as eye movements and muscle activity. For classification, Linear Discriminant Analysis (LDA) and k-Nearest Neighbors (k-NN) classifiers are used, with k set to 10.

The best classification results were achieved with the usage of a 4-second window width, which offered an optimal balance between time resolution and signal quality. The highest accuracy in ICA usage for artifact removal was reached with the use of three harmonics for feature extraction and the application of the LDA classifier. This underlines that both preprocessing techniques and classifier choice are of great importance in achieving high accuracy of classification. The results indicate that ICA does a great job in cleaning the data, hence providing better features for the LDA method to classify more accurately.

In this regard, the current study using green flicker stimuli with the following parameters-5, 6, 7, and 8 Hz-requires advanced pre-processing approaches in relation to SSVEP-based BCIs. An optimum system configuration using a window of 4 seconds, three harmonics for feature extraction, and LDA classifier gives considerably improved performance of the system. These methods can then be used reliably for real-time applications of BCI. These results highlight the importance of a careful choice of preprocessing and classification techniques in order to achieve the best possible detection accuracy for SSVEP-based BCIs.

Limitations:

The use of fixed green flicker frequencies of 5, 6, 7, 8 Hz, which may constrain the flexibility of target choice. The reliance on the use of a 4-second window may not be optimal for all users or conditions and may affect real-time performance. Also, the ability of ICA to remove artifacts depends on the quality of the original signal. Selection of LDA and k-NN classifiers may be too limited to generalize.

2.5. Filter Bank Convolutional Neural Network for SSVEP Classification, in IEEE Access, 2021

The following study will be focusing on the optimization of SSVEP classification by applying different techniques, including bandpass filtering, ICA, filter bank methods, CNN, and CCA. The preprocessing includes bandpass filtering in order to remove the noise and other unwanted artifacts, followed by ICA in order to separate and remove the components of the signal related to eye movements or muscle activity. An integration method optimized in CNN known as Filter Bank CNN/FBCNN, with both filter bank techniques, together performed the task of feature extraction with ultimate classification on the SSVEP signal.

The results reflect that the application of FBCNN improves in classification accuracy compared to some more traditional methods like CNN and CCA. In particular, FBCNN obtains very remarkable accuracy of 93% for Dataset 1 and 79% for Dataset 2 (BM), which shows that FBCNN is capable of handling the complexity in SSVEP signals. Due to the filter bank approach combined with CNN, there is better feature extraction possible by capturing frequency-specific patterns in the SSVEP signal, while the correlation analysis further improves the model's ability to identify distinct features of the signal. It therefore presents a very promising candidate to meet real-time performance improvement for an FBCNN approach in Brain-Computer Interface-BCI systems.

Despite these promising results, a number of limitations still remain for this study. First, pre-processing was performed in this study by using a fixed bandpass filter, which might not be optimal in each and every dataset or in the individual variations in brain activity. Moreover, ICA is effective in removing these artifacts and depends on the quality of the signal; hence, it is not always capable of completely removing all types of noise, especially when the signal-to-noise ratio is low. Besides, while FBCNN has shown a good performance for two datasets, its generalization for other datasets or for more complex SSVEP tasks is not certain. Further, filter bank approaches and CNNs involved here introduce higher computational complexity that could easily challenge real-time implementation in resource-constrained devices.

Limitations:

This can be seen in the relatively low accuracy of 79% achieved on Dataset 2 (BM), which is indicative of the fact that the method may not give consistent performance across different datasets or experimental setups. This performance difference shows that more optimization and fine-tuning are needed to adapt to different conditions, such as the number of subjects, recording quality, or parameters used in the filter bank. Finally, although FBCNN outperforms CNN and CCA, it is still worth exploring other deep learning and signal processing techniques that may provide better performance or computational efficiency for real-time BCI applications.

2.6. An SSVEP Classification Method Based on a Convolutional Neural Network, 35th Chinese Control and Decision Conference (CCDC), Yichang, China, 2023

The aim of this study is to optimize SSVEP-based BCI systems using the IMUT dataset. In this dataset, there are 32 EEG channels, each containing 1500 samples, 40 trials, and 4 classes, sampled at 500 Hz. To preprocess the data, a 6–30 Hz bandpass filter was applied to eliminate noise outside the target frequency range and further Independent Component Analysis was applied to separate the brain activity from artifacts like eye movements or muscle interference.

CCA and FBCCA are used in this work to extract features. These techniques were put out to break down SSVEP signals into sub-bands in order to capture their frequency-specific properties. By using various frequency bands, FBCCA improves the capacity to differentiate SSVEP responses, increasing classification accuracy overall.

The classification task is carried out with the use of a Convolutional Neural Network, one of the most prominent deep learning models capable of capturing spatial and temporal patterns in complex data. The results are very promising: a CNN can achieve 95.86% classification accuracy using only 3 seconds of data. Moreover, the system provides an ITR of 183.05 bits per minute-a key indicator of the potential of this system for real-time applications.

These results have demonstrated that for SSVEP-based BCI, ICA pre-processing with removal of artifacts supported by the two CCA extensions, such as CCA and FBCCA for filtering and extracting features, besides the state-of-the-art deep CNN network, gives overall better performances in this kind of BCI classification problem. Besides the classification performance, compared to those from some competitive works in recent studies, this investigation has realized the promise of using high-classification-accuracy CNNs on an ITR-enhanced system to boost real-time and effective employment in many practical applications regarding assistive devices or communications on behalf of paralyzed individuals. A number of questions on dealing with variations within data, adequacy in preprocessing steps involved, and computer requirements would hence be resolved with future attempts.

Limitations:

This study includes that ICA preprocessing techniques may not always be able to completely eliminate noise or artifacts, especially when the signal-to-noise ratio is very low. The fixed window size is 3 seconds, which may limit optimum performance and needs flexibility, as different users may need it. The high computational demands of CNN are problematic in real-time applications, particularly for resource-constrained devices. Finally, reliance on the IMUT dataset raises concerns about the generalization of this system under various real-world conditions or using other datasets**.**

2.7. Employment of Domain Adaptation Techniques in SSVEP-Based Brain–Computer Interfaces, in IEEE Access, 2023

This work will introduce the application of the DA approach in improving three different neural network classifiers, namely ShallowConvNet, DeepConvNet, and EEGNet, for classifying EEG signals from the benchmark dataset, BM. It is one of the most used datasets in BCI experiments, especially those involving the use of Steady-State Visual Evoked Potentials, SSVEPs-a kind of brain wave generated by a certain frequency flickering visual stimulus. The investigation shall, therefore, focus mainly on how the DA technique improves classification accuracy while adapting neural network models more effectively to the characteristics of the EEG data.

The DA technique proposed herein can help in reducing the domain shift, which is one of the major challenges in BCI systems for different subjects or recording environments.

The problem of poor generalization is more relevant for traditional BCI systems, where classifiers are normally trained on data from certain subjects and may not generalize well for other users or datasets. Domain adaptation has helped solve this problem by transferring knowledge learned from one domain, thus enhancing the classifier's generalization capability across different subjects or conditions. In this work, the DA technique will be applied to three neural network classifiers: ShallowConvNet, DeepConvNet, and EEGNet, which are normally used for EEG signal classification tasks. ShallowConvNet is light in model structure with fewer layers and, therefore, more computationally efficient, whereas DeepConvNet is deeper and more complex, hence it can learn intricate patterns in the data.

EEGNet has been designed for EEG signal classification with a specialized architecture that optimally processes the EEG data. This study will therefore assess the effectiveness of the DA technique by comparing the classification accuracy across these models. Results are presented to show that the DA technique significantly enhances the classification performance of all three classifiers and is a function of the time window (0.5, 1, 1.5

seconds). That would mean longer time windows carry more information for the classifier to process, hence enhancing the classifier's ability to distinguish between the different brain states associated with SSVEPs.

Improvement in the classification accuracy in this manner demonstrates the efficacy of DA for adapting those classifiers to the BM dataset and rendering them robust and accurate enough to work in realistic BCI applications.

The key takeaway of this paper is to underline the effectiveness of Domain Adaptation for improving performance in neural network classifiers operating on the EEG signal processing task. The work presented within this thesis adapts the classifier to domain shifts and reports the model that achieves higher accuracy, mainly when longer time windows are used. These findings thus emphasize that domain adaptation provides a more generalizable means of implementing BC systems and one that is practically feasible for real-world applications.

Limitations:

This study includes reliance on the BM dataset, which itself is not fully representative of varieties of EEG signals one may experience in real-world applications of BCI. Generalization of the DA technique to other datasets with greater variation or subjects is considered uncertain. While the DA technique promotes better classification accuracy, its results might still be vulnerable due to variations in individual brain activities and thus may not generalize well through all users or conditions. Moreover, the experiments restrict themselves to a small set of time windows (0.5, 1, 1.5 sec) and may not imply other time window settings and dynamic environments. Finally, the computational complexity of deep neural networks, such as DeepConvNet and EEGNet, can be challenging in real-time applications, especially on low-power devices, which may make them unsuitable for practical applications.

2.8. A classification algorithm of an SSVEP brain-Computer interface based on CCA fusion wavelet coefficients, Journal of Neuroscience Methods, 2022

The approach outlined in this study for the classification of EEG signals using the BETA dataset classifies brain activities into four classes. Data from seven very relevant EEG channels are recorded: P3, P4, O1, O2, Pz, P7, and P8, because these channels are expected to reflect important brainwave patterns related to visual stimuli and cognitive tasks. EEG data was preprocessed by passing the signals through a 6–30 Hz BPF to remove the noise outside the target frequency range and then ICA for the removal of eye movements, muscle activity, and other unwanted sources of interference. This needs to be done in order to isolate the true neural signals, which would improve the accuracy of the classification model.

The feature extraction includes a fusion algorithm from the CCA with Continuous Wavelet Transform -CWT. The latter provides CCA with the feature extracted, showing better relations between different EEG channels and the most discriminant for distinguishing states of the human brain. CWT is a time-frequency technique that can represent temporal and frequency information of EEG signals more comprehensively. Hence, CCA combined with CWT will not only fuse the feature set through spatial and spectral but enhance it, classifying the brain activities effectively.

These are then used as input to a Support Vector Machine classifier, which is a fairly established model in machine learning known to usually perform well on high dimensional data like EEG signals. The overall classification performance for the BETA dataset after averaging 10-fold cross validation (k = 10), which ensures that the model performs well on different subsets of the dataset, was 91.76%.

These results confirm that the proposed combination of CCA-CWT fusion with SVM classification is highly effective to carry out SSVEP-based EEG classification tasks with solid performance on accuracy.

This study should be robust in showing the classifying method for EEG signals based on improved feature extracting methods such as CCA-CWT fusion and powerful classifiers like SVM.

Limitations:

This study includes the fact that the dataset is relatively small, which may result in overfitting, and the fixed 2-second time window may not be optimal for all types of EEG signals or conditions. The preprocessing methods, though effective, might not completely remove all types of artifacts in more complex or noisy environments. Furthermore, the performance of the method may vary across different subjects, limiting its generalizability. Another challenge for real-time BCI applications may be the high computational demand of the SVM classifier and feature extraction techniques.

2.9. SSVEP Brain-Computer Interface Decoding Based on Spatio-temporal TRCA Filtering and Least Squares Data Migration, 2023.

It talks about the developments in decoding with respect to steady-state visual evoked potential-based Brain-Computer Interface-SSVEP. The SSVEP reflects electrical impulses appearing in the cerebral response when an individual looks at certain light stimuli with frequencies such as 6 Hz-80 Hz and above and are very reliable with regards to their information transfer rate because they have a greater amount of stability. However, one of the challenges in the SSVEP-based BCI system is inter-subject variability. It requires extensive calibration with large amounts of training data from each user. An enhanced decoding method, combining spatial-temporal filtering and transfer learning, was put forward to improve the performances of SSVEP BCI systems.

The proposed method integrates temporal and spatial filters into the Task-Related Component Analysis (TRCA) algorithm. Conventional TRCA has worked well to date for the extraction of task-related brain signal components; it still has a number of disadvantages in terms of its performance on noise and non-task-related components, especially under conditions where only limited training data are available. The newly proposed TRCA algorithm further modified to be suitable for both spatial and temporal information allows the creation of a more stable template that enhances the accuracy of the signal classification. This adaptive integration of spatial and temporal data serves to reduce the effect of noise on decoding.

Besides, the study is applied with transfer learning through a least squares transformation approach. Indeed, transfer learning allows previous data from other subjects that represent the source domain to fit into the training of newer subjects that represent the target domain; this helps nullify the need for excessive data.

LST aligns the features between source and target domain data by minimizing the distance, which allows the model to apply knowledge learned from one subject to another. This integration reduces the number of calibration efforts a new user has to go through, hence making the practicality and adaptability of the BCI system much easier.

The performance of the novel stTRCA-LST is based on the Wang2016 dataset, which comprises high-density SSVEP recording from 35 subjects. Numerical results demonstrate that integrating spatiotemporal filtering and transfer learning methods substantially improves the classification accuracy based on the conventional TRC by 8.73%. The proposed algorithm still outperforms the multiple variations of TRCA using LST together with spatiotemporal filtering in separate formats. Eventually, this provided an effective approach for the performance enhancement of SSVEP-based BCIs. In the following, an improved version called the stTRCA-LST algorithm is proposed; this ensures higher recognition accuracy with reduced calibration burden, better subject adaptability; thus, opening a wider route toward enhanced, effective, and accessible BCIs.

Limitations:

The stTRCA-LST method is that it is bound by the availability of a sufficiently large and variant dataset for transfer learning to be effective. While improving the classification accuracy, this method may still be influenced by the quality and variability of data across different subjects. Besides, the complexity of the algorithm probably raises the computational cost, which restricts real-time applications in some scenarios.

3. PROPOSED METHODOLOGY

This work focuses on the enhancement of SSVEPs classification based on novel signal processing and deep learning approaches. Recordings for the dataset are from 35 healthy subjects, which include 17 females ranging in age from 17 to 34 years. During the experiment, subjects were supposed to pay attention to 40 different characters flickering at frequencies ranging from 8 to 15.8 Hz, with a 0.2 Hz interval between each target frequency. Data collection consisted of 6 blocks, each block containing 40 trials, where the stimuli were presented in a random order. Each trial was initiated by a visual cue to direct attention to a target character followed by the 5-second flickering stimulus. EEG was recorded with the Synamps2 system on the scalp and was placed according to the international 10-20 system. A sampling rate of 1000 Hz was used, and amplifier frequency passband was within a range of 0.15-200 Hz. Following the experiment, the continuous EEG was divided into continuous 6-second epochs, and data were down sampled to 250 Hz for further processing.

In the preprocessing, a band-pass filter that retains frequencies from 6 to 40 Hz was used as a filter to filter the signals in order to retain the frequency that will contain the significant SSVEP. Consequently, Fast-ICA was performed to decompose the EEG signals, separating the relevant SSVEP components from the artifacts related to eye blinks and muscle activity. This decomposition helped in isolating the true neural responses to the flickering stimuli. After decomposing the signals, O1, O2, and Oz channels were selected for further analysis because these channels are on the visual cortex, where SSVEPs normally show their maximal effects. This channel selection was important to perform because the visual cortex is one of the major brain regions responsible for the processing of visual stimuli, including those involved in SSVEP responses.

The relevant data having been extracted, feature extraction was further enhanced using CCA. CCA is a statistical method applied to enhance the SSVEP signals by maximizing the correlation between the EEG data and the target flicker frequencies. This greatly enhances the signal-to-noise ratio and makes the detection of SSVEP responses relatively much easier from the raw EEG data. We performed the Continuous Wavelet Transform to extract features; hence, with this transform, both frequency and temporal dynamics of SSVEP responses are obtainable. This transform usually works well on nonstationary signals such as EEG because it reflects a time-frequency view of the given signal, depicting

how variations in the spectral content vary over time. Obtained features from CCA and CWT were then fed into a Convolutional Neural Network, as it is one of those deep learning models that efficiently solve complex spatial and temporal dependencies in data.
Then the CNN was trained using k-fold cross-validation, which allowed an objective estimation of the performance across different subsets of the given dataset. Results on the classification varied in terms of accuracy over the five folds; the best-performing was Fold 2, with an accuracy of 85%. It had a macro average precision and recall of 0.85 and 0.84, respectively, an indicator of its strong performance in the identification of the different target frequencies.

Comparing our results with those from traditional methods and transfer learning models, our approach has outperformed FBCCA with an accuracy of 86% and CCA with an accuracy of 68%. CNN was also better compared to the transfer learning models: DeepConvNet was 91%, ShallowConvNet was 66%, and EEGNet was 88%, further validating our methodology. In summary, the proposed methodology that combines ICA on signal decomposition, CCA on signal enhancement, and CWT on feature extraction coupled with the powerful CNN as a classifier has achieved supremacy in classifying SSVEP signals. It not only outperforms traditional methods but also transfers learning models enormously, indicating great potential to real-time BCI application. The deepened results evidenced that complex patterns can be captured by CNN, maybe in concert with advanced signal processing, which represents one of the most compelling pipelines for the SSVEP classification so far. Powerful advanced versions like RNN are time-consuming, new model developments, or those using some intricate temporal and spatial characteristics. This might be further improved by the integration of multi-modal data, including eye-tracking or other bio signals, not only to increase the classification performance but also to extend the range of applications of the methodology to a wider spectrum of BCI uses.

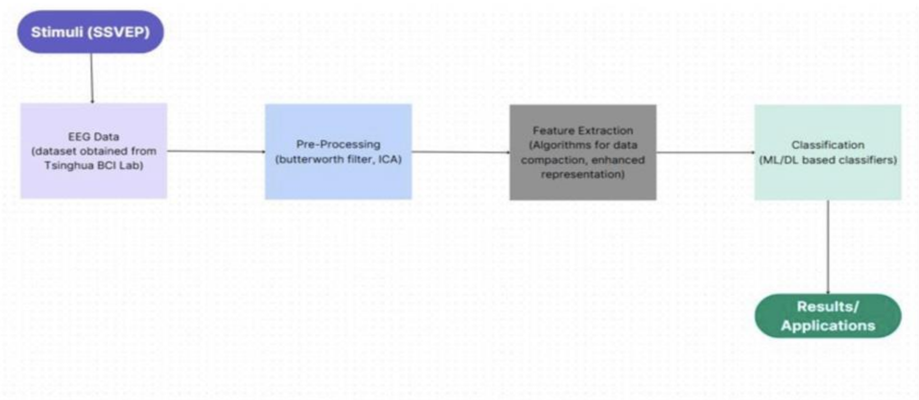


Figure 3.1 Methodology for SSVEP Detection and Classification

4. IMPLEMENTATION

4.1. Brief Implementation Overview

In our project, an EEG-based BCI system will be implemented for classifying SSVEP by recording the EEG signals from healthy subjects with their focus on flickering visual stimuli. The aim is to classify the target stimulus based on the SSVEP responses captured through the EEG signals. The first step of the implementation was to obtain an open-source SSVEP dataset that included recordings from 35 healthy subjects, each participating in a series of trials corresponding to 40 visual stimuli flickering at different frequencies, ranging from 8 Hz to 15.8 Hz. EEG data was recorded using a Synamps2 system, with 64 channels distributed over the scalp, capturing brain activity with a sampling rate of 1000 Hz.

Afterwards, the EEG data were preprocessed by filtering around the frequency range of 6 Hz to 40 Hz, which is typical for SSVEP signals.

After filtering, Fast-ICA was applied for signal decomposition, by which noise and artifacts in EEG data could be removed. Selection of three channels was based on the fact that visually evoked potentials are most prominent along the visual cortex. In particular, O1, O2, Oz form the major channels recording these potentials.

In this regard, we used the CCA for feature extraction to enhance the signal by correlating EEG data with known stimulus frequencies. Then, Continuous Wavelet Transform was applied in extracting time-frequency features representing both the temporal and frequency dynamics of the SSVEP signals. In the classification stage, the performance was estimated in terms of accuracy and robustness of the model on unseen data. We employed k-fold cross-validation for this purpose and implemented a ConvNet model for SSVEP responses. Then we did some investigation of other methods of classification, including DeepConvNet, ShallowConvNet, and EEGNet. These models have been further tuned with the use of transfer learning to improve the model performances. DeepConvNet gives the best performance, as much as 91% while for CNN it was less and variant.

4.2. Preprocessing Stage and Techniques

4.2.1. About

The most important factor for the success of an EEG-based classification system is its preprocessing stage, especially in dealing with Steady-State Visual Evoked Potentials (SSVEPs). This step is critical to prepare and enhance the data quality before further processing and classification. Raw EEG signals recorded from the brain include a wide range of different noises and artifacts that can potentially degrade the detection performance of the SSVEP features. Such unwanted components may emerge from muscular activity, blinking, or power-line interface, to name a few. Pre-processing, therefore, is such a step without which cleaning and amplification of the raw EEG signal, wherein the relevant brain activity is available with very little unwanted noise, is a must.

One of the main purposes of preprocessing is to increase the SNR of the EEG data. Preprocessing cleans the data to filter out irrelevant components and reduce noise, such that the successive feature extraction and classification stages can work with cleaner and more accurate data. This holds true in the case of SSVEP classification, where the evoked potentials are often very minute and may get masked by the background noise. It will serve to enhance the signal quality using different preprocessing techniques, such as bandpass filtering, artifact removal, and noise reduction. A bandpass filter, for instance, limits the frequency range to only the frequencies where the SSVEPs are most pronounced, such as 8-15 Hz, depending on the specific experimental setup.

4.2.2. Types of Filters Used

- **High-Pass Filter (HPF):**

  The high-pass filter in this project seeks to eliminate low-frequency noise, mainly baseline drift and slow eye movements, among other physiological signals that can cause distortion to the SSVEP signal. It only allows higher frequencies to pass through by allowing the setting of the cutoff frequency, say 6 Hz. Such a filter ensures that slow artifacts not relating to the SSVEP signal are removed effectively, hence enhancing the general clarity of the signal for further analysis.

- **LPF: Low-Pass Filter:**

  It tends to get rid of high-frequency noise due to muscle activity or/and electronic interference in the EEG data. Setting a cutoff frequency, for instance, to 40 Hz, this filter ensures that only frequencies that constitute the SSVEP range are retained. It cleans the data from unwanted high-frequency components which will obscure the true SSVEP signal, making it easier to become focused and cleaner toward future processing stages.

- **BPF Band-Pass Filter**:
  Accordingly, it can be seen that the band-pass filter works in concert with both the high-pass and low-pass filters to narrow the signal down to exclusively the frequency band of interest-6-40 Hz. This filter selects only those critical frequencies that are relevant for SSVEP detection while rejecting both low and high-frequency noise. The band-pass filter focuses on the desired frequency range, where only the frequencies relevant for the accurate signal analysis are passed, and improves the SNR.

- **Notch Filter**:
  Then, the notch filter is applied with the purpose of removing specific frequency interference, particularly power-line noise that is one of the most common subject-generated artifacts in EEG recordings from electrical equipment, at 50 Hz or 60 Hz. In this project, it will be used to remove the power-line noise without affecting the relevant EEG signal. By setting the narrow frequency band around the noise frequency, the notch filter suppresses this unwanted interference and allows the rest of the frequencies, along with those related to SSVEP, to pass through. This helps in enhancing the overall quality of the EEG data to make sure that the signal used for further analysis does not include such a kind of contamination.

4.2.3. EEG Signal Decomposition by Using Fast-ICA:

After filtering, the Fast Independent Component Analysis-Fast-ICA algorithm is performed on 64 channels to decompose the pre-filtered EEG signal into independent components. Fast-ICA is an efficient scheme for separating the mixed signal into independent sources. This gives, separately, the brain activity of the SSVEP signal from other noises, such as that generated by eye blinks or muscle movement; hence, it will prevent incorrect classifications. With Fast-ICA applied, it removes the artifacts from the EEG data effectively, which in return makes the signal cleaner for further analysis.

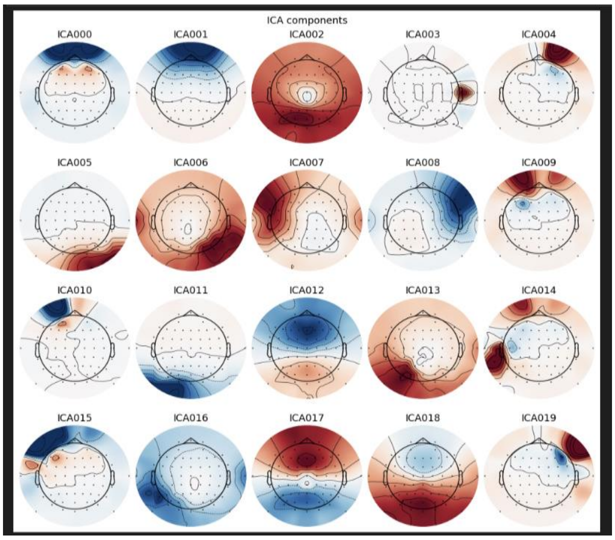


Figure 4.1 ICA Components of benchmark dataset (showing 20 of 64)

4.2.4. Channel Selection

As SSVEP responses are most prominent in the visual cortex, we will choose channels sensitive to the mentioned signals. In our application, the electrodes of interest are O1, O2, and Oz over the occipital lobe. These channels are assumed to pick up the largest SSVEP response since they are directly connected with visual processing. Focusing on these channels reduces the data complexity while being concentrated on the most informative regions for the purpose of SSVEP detection.

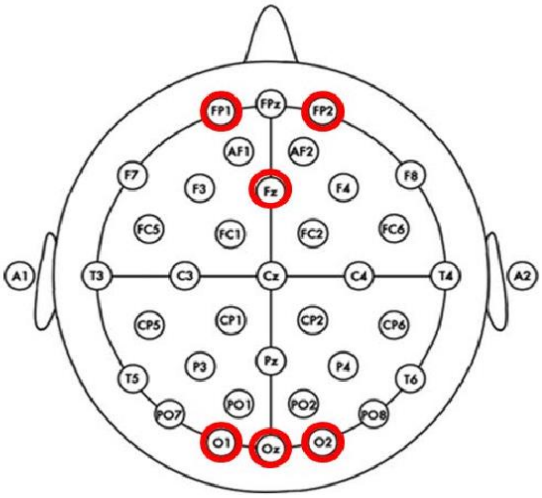


Figure 4.2 Lead placement positions on scalp [1]

4.2.5. Data Segregation

This first step in the analysis or preprocessing of raw EEG data forms a very important milestone for obtaining the relevant information on SSVEP-based BCI systems. For this work, the recorded continuous EEG data from subjects will be segmented into 6-second epochs; each will contain a 500-ms pre stimulus period and a 5.5-second post-stimulus period. This segmentation is designed to focus on time windows centered around the onsets, since that's when the brain is particularly excited due to the flickering visual stimulus. The 500ms before the stimulus starts serve to establish a baseline, which will provide some sense of the brain activity just prior to the application of the visual stimulus for further comparisons. On the other hand, the 5.5-second post-stimulus period captures the brain's oscillatory activity regarding the SSVEP response driven by the visual stimulus that flickers at a specified frequency. This will allow us to dramatically reduce irrelevant data, which is usually background brain activity, noise, or artifacts, which will also enhance the SNR, allowing any feature extraction method to be narrowly focused on the SSVEP signal. The proposed approach reduces the dimensionality of the data, because only segments that are directly related to the stimulus are analyzed; hence, the process of feature extraction becomes more effective. By narrowing down to the time windows of the instant of stimulus onset, we provide the algorithm with a cleaner and objective signal that could help in making improvements in capturing the most representative frequency and phase feature involving SSVEP. Then again, the system, focusing its attention on most of the task-relevant activities themselves, can increase the performances associated with the classification task.

4.3. Feature Extraction

4.3.1. About

Feature extraction in this work involves transforming preprocessed EEG data into an informative feature set for classification. The major goal would be toward enhancement of the SSVEP signal and, as such, the pattern identification for different frequencies, which is much easier by the model.

It starts with CCA, which maximizes the correlation between the EEG data and the target stimulus to enhance the SSVEP signal. This improves the separation between the signal and noise. Then there is CWT, which extracts the frequency-time features that are dynamic for the captured EEG over a continuous time. CWT provides a time-frequency representation that enables the model to better understand how the SSVEP signal is evolving over each trial.

These convolutional features are then inputted into a Convolutional Neural Network, which then classifies them. The steps of feature extraction ensure that the data coming into this model is clean, informative, well-structured, and will perform well in its learning of meaningful patterns to make proper predictions.

4.3.2. Basic Techniques used in Feature Extraction

- **Canonical Correlation Analysis (CCA):**

  Canonical Correlation Analysis (CCA) is performed to improve the Signal-to-Noise Ratio (SNR) of the SSVEP signal by correlating the EEG signal with the stimulus frequencies.

  CCA finds the linear relation between two sets of signals - the EEG signal from the brain and the reference stimulus frequencies - such that the correlation between the two is maximized.

  The potential frequency components relevant to the SSVEP get enhanced, while irrelevant noises get attenuated through this process. In essence, it provides a clearer isolation of the target frequencies, thereby making the brain's response to flickering stimuli easier to detect.

- **Continuous Wavelet Transform**:

  Continuous Wavelet Transform has been used to extract the frequency-time features of EEG signals to capture both frequency and temporal characteristics of the signal. The operation CWT is, therefore, done using wavelet functions in a scaling and translation manner over the signal in order to derive a time-frequency representation. It decomposes the signal into its various frequency components.

  It allows the system to explore the SSVEP signal in both time and frequency domains at the same time. It captures the dynamics of the EEG signal, therefore providing features that are sensitive both to the frequency of the stimulus and to the timing of the brain response. Subsequently, this CWT output becomes a spectrogram-like feature map that is then used for finding temporal patterns in brain activity.

- **Filter Bank Canonical Correlation Analysis (FBCCA):**

  Filter Bank Canonical Correlation Analysis (FBCCA) is an extension of CCA that utilizes multiple filters across different frequency bands to enhance the SSVEP signal.

  That is, during operation, FBCCA applies a bank of filters to the EEG data, splitting the signal onto several frequency bands. For each band, CCA is applied for correlating the EEG signal with the target stimulus. Then, results from all bands are combined into a representation from a robust signal.

This effect, where several frequency bands are utilized by FBCCA, serves to expand the range of frequency components that can be captured within an EEG signal, hence enhancing the strengths that this model has in detecting SSVEP signals at a variety of frequencies. The proposed approach is very effective in instances where the SSVEP signal spans many ranges of frequencies.

5.3.3. Feature Selection and Fusion

After feature extraction using CCA, CWT, and FBCCA, the system then needs to select the most informative features and combine them for input into a classification model.
Operation: This includes feature selection, which pinpoints which of the extracted features will contribute most to correct classification. This is usually done with statistical methods or machine learning methods that rank the features according to their relevance.
• Effect: In this way, dimensionality is reduced by the removal of features that are redundant or bear little significance regarding end models. By fusing the features from the different extraction methods, the system can leverage multiple aspects of the EEG signal to improve classification accuracy.

•The CCA serves to increase the SSVEP signal by correlating it with the stimulus frequencies and enhances the clarity of the signal. • CWT represents the dynamic time-frequency characteristics of the EEG signal, which is richer. • FBCCA enhances signal enhancement by applying filters over a range of frequency bands to capture more detail on the SSVEP signals. • Feature selection and fusion ensure the most relevant and informative features are used for classification to optimize the performance of the model.

4.4. Classification

4.4.1. About

For classification, this project uses the extracted features of EEG signals to determine which target stimuli or character a subject is focusing on. The key goal for any classification process in this scope will be the correct labeling of each trial of the EEG data with the respective frequency or character that was being the target. Classification includes several steps that, when combined, contribute to the overall performance of the system in determining the right stimulus.

The selection of the model is the first most important step in classification; the model that is chosen to be applied to this work is a Convolutional Neural Network, CNN. CNN is more suitable for this kind of task due to its inherent nature, which allows it to learn spatial hierarchies and complex patterns in data. Time-frequency features obtained by methods like Continuous Wavelet Transform (CWT) or Frequency-Phase based Canonical Correlation Analysis (FBCCA) in the context of EEG classification could also be analyzed efficiently by CNNs. Features from these methods will represent time-varying characteristics of the EEG signals in response to the stimuli, thus being an ideal input to the CNN model owing to the network's capability for capturing complex patterns and relations across diverse time and frequency domains. The CNN learns these relationships automatically through its layers, enabling it to identify the underlying structure in the EEG data.

The CNN model then undergoes training after choosing the type of model. Later, this network is to be fed with features of EEG signals extracted that would learn the small variations within numerous target frequencies. During the training process, the network is fed with labeled datasets, where every trial's input features are matched with a known target label, such as target 8, target 9, and so on. In this supervised learning, the CNN learns to associate particular patterns of brain activity with the correct target frequencies and improves its ability to accurately classify unseen data. The model, throughout the training process, refines its weights through a minimization process of the loss function, thus becoming better with time.

K-fold cross-validation is embedded in the training to make the model robust and generalizable. It does this by splitting the available dataset into multiple subsets or "folds." Some of these folds are used to train the model, while the model is tested on the remaining ones. In other words, cross-validation means that during the training process, the performance of the model will be tested on different subsets of the data. By doing cross-validation, one checks the performance of the model for different splits and therefore gets a better estimate of the performance; overfitting to a specific set is also reduced. Cross-validation ensures that the model is not biased towards one-fold and can generalize to unseen data.

At last, after the training of the model and its evaluation, the performance of the model is measured in terms of different metrics such as accuracy, precision, recall, and F1-score. It calculates the accuracy or the portion of correctly classified trials, while precision and recall offer a deeper look at the model's ability to correctly identify certain targets and avoid false positives or false negatives. The F1-score is computed as well, representing the harmonic mean of precision and recall for the balanced evaluation of the performance of the model. These metrics jointly present how well the model is identifying the target stimuli and guide further refinements in improving the classification accuracy. The ultimate goal is to have high accuracy in labeling each EEG trial with the correct target, ensuring the effectiveness of the system for real-time brain-computer interface applications.

4.4.2. Classification Techniques Used

- **Convolutional Neural Networks:**

  CNNs are one class of deep learning algorithms which are built to handle data that comes in grid-like format, such as images, videos, or time-series data. In this project, the use of CNNs takes into consideration the classification of the extracted features from EEG signals where the extracted data have time-frequency representations.

  CNNs have the ability to learn patterns hierarchically from the input data. In classification of EEG signals, CNN intrinsically learns time-frequency patterns and spatial dependencies from features extracted using techniques like CWT and FBCCA.

- **Input Features:**

  For CNN training, the features are taken in Pure time-frequency features extracted from the EEG data. These features were extracted using the Continuous Wavelet Transform (CWT) and FBCCA (Frequency Band Common Spatial Pattern) methods to enhance the signal at frequencies regarding SSVEP, consequently improving the signal-to-noise ratio.

- **Architecture:**

  CNN typically consists of several layers:

  - Convolutional layers: These layers implement filtering, making it possible to extract patterns in the input data, such as frequency-time characteristics from the EEG signal.

- Pooling Layers: These layers of convolutional neural networks reduce the dimensionality after convolution, maintain the important information of the data, and allow better generalization of models.
- Fully connected layers: These make the final classification decision based on the learned features.

Model Training: The CNN was trained using K-fold cross-validation. In each fold, the model is exposed to a subset of the data to train on while its performance is validated on remaining data so that the model generalizes well across a variety of subsets of data and does not overfit.

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

Figure 4.3 Architecture of the CNN model used for classifying the CWT data

- **Performance Evaluation:**
  Accuracy, precision, recall, and F1-score have been computed to give an overall idea about the performance of the CNN classifier in classifying EEG signals from each SSVEP target.

4.4.3. Deep Learning Methods Used

- **ShallowConvNet**
  ShallowConvNet is a neural network architecture designed specifically for processing EEG data. It is a relatively lightweight and straightforward convolutional neural network (CNN) architecture, often used in Brain-Computer Interface (BCI) applications for tasks like EEG signal

classification. Figure Shows the architecture of the model.

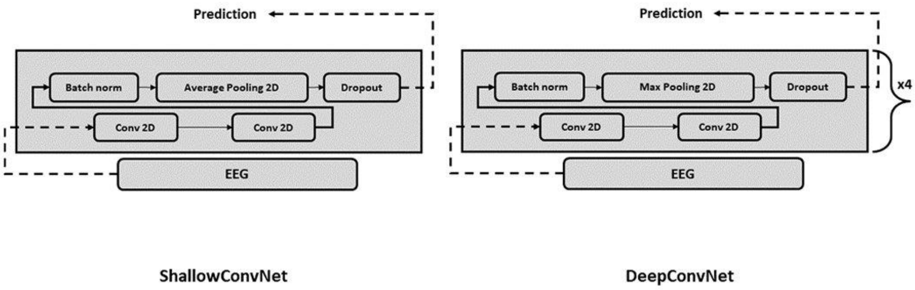


Figure 4.4 Network Architecture of ShallowConvNet and DeepConvNet [4]

- **EEGNet**

  EEGNet is lightweight and can be trained on small EEG datasets, making it suitable for real-time applications. It is versatile and has been successfully applied to tasks such as motor imagery classification, SSVEP detection, and seizure detection. Extensive use of batch normalization and dropout layers helps mitigate overfitting, which is especially important when working with limited EEG data. Architecture of the model is shown in Figure

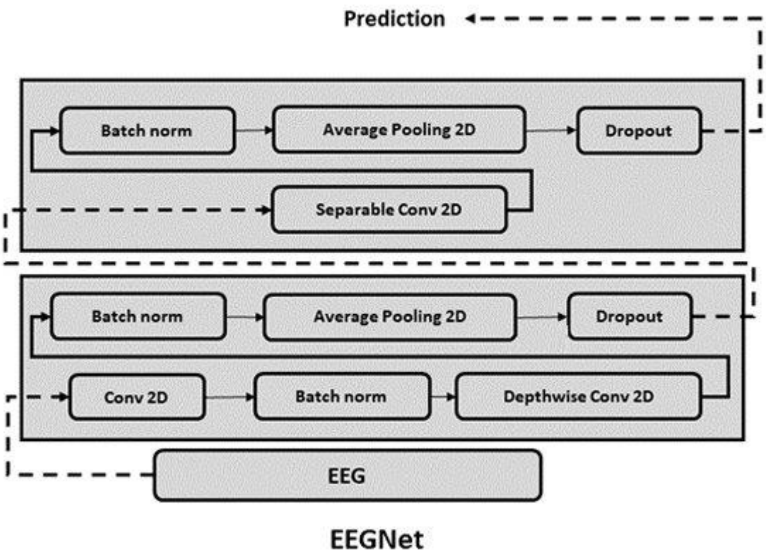


Figure 4.5 Model Architecture of EEGNet[4]

- **DeepConvNet**

  DeepConvNet is a deep neural network architecture designed for EEG signal classification. It is particularly effective for tasks requiring the extraction of complex spatial and temporal patterns from EEG data. Unlike simpler models, DeepConvNet uses multiple convolutional layers stacked sequentially, enabling it to capture higher-order features. Architecture of the model is shown in Figure

4.5. Dataset

4.5.1. About Dataset

The dataset used for the project is the publicly available SSVEP Brain-Computer Interface dataset. It consists of 35 healthy subjects (17 females, 18 males) aged between 17 and 34 years. The objective of this dataset is to use it in BCI systems since it was designed for performing a classification based on the brain activity of the subject on visual stimuli. Visual flickering stimuli at 40 different frequencies, starting from 8 Hz up to 15.8 Hz, were presented with an increment of 0.2 Hz. In this regard, attempts have been made to capture the electrical responses of the brain-EEG signals-while the subject exposed them to such stimuli are crucial for developing SSVEP-based BCIs.

Subjects participated in 6 experimental blocks, consisting of 40 trials each, presented in a random order. A red square visual cue was presented in the center of the screen for 0.5 seconds to provide a warning for the beginning of each trial that the subject should pay his or her attention to the target. Immediately after the cue disappeared, multiple flickering stimuli were presented with different frequencies for 5 seconds and the subject focused on the indicated target. After 6 seconds, the trial ended and a short pause occurred before the start of another trial. The goal was to collect high-quality EEG data while these stimuli were presented.

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

Figure 4.6 Epochs info for benchmark dataset in MNE Python

The EEG signals were recorded by the Neuroscan Synamps2 system, with a set of 64 channels placed on the scalp, according to the international 10-20 system for electrode placement. The system was operated at a sampling rate of 1000 Hz to give very broad and realistic data on the activity of the brain. The arrangement of electrodes covered the most important parts of the brain involved in processing visual information and specifically the occipital lobe, where SSVEP signals are strongest. The reference electrode was placed on the vertex while the ground electrode was at a point midway between Fz and FPz.

The common artifacts and noise were removed for pre-processing of the dataset. A notch filter of 50 Hz was used to remove the power line interference and the continuous EEG signals were divided into 6-second epochs, covering 500ms of data as pre-stimulus and 5.5 seconds of data as post-stimulus. These epochs were then down sampled to 250 Hz in order to make the data more manageable and computationally efficient. Thereafter, a "Save as" procedure was conducted and the data was saved as MATLAB files, each labeled with the name of the subject, such as S01.mat or S35.mat. Data is organized in a 4-D matrix with the following dimensions: electrode index, time points, target index, and block index. This format was structured enough to support easy access to the raw EEG data for further analysis. The electrode locations in subject-specific form are also given in a separate file, ensuring that electrode positions can be correctly referred to during analysis. Frequency and phase values for each target stimulus were recorded on a separate.

All of these files are important for carrying crucial information required in the analysis of the frequency-specific SSVEP signals used to optimize the signal processing and classification tasks. Because the design and structure of this SSVEP dataset fits with training and testing a machine learning algorithm to classify visual stimuli through EEG signals, it opens studies for algorithm evaluation that decodes SSVEP responses and translates them into meaningful output-a very important feature for real-time BCI systems. It is a very useful dataset; it gives diverse and high-quality EEG recordings that would be very helpful in the furtherance of the development of SSVEP-based BCI systems for different applications, such as assistive technologies, neurofeedback system, and brain-computer communication.

4.5.2. Pictures of Dataset Sample

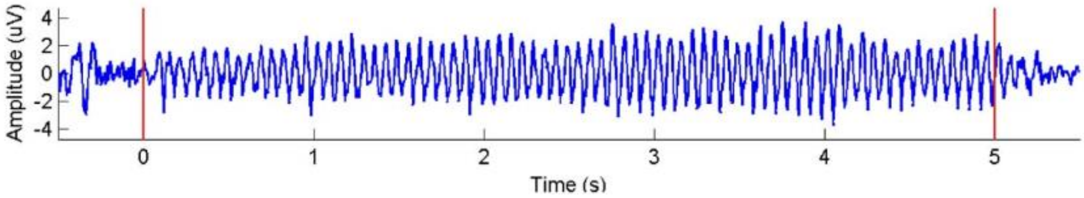


Figure 4.7 Average 15 HZ SSVEP waveforms from OZ electrode [8]

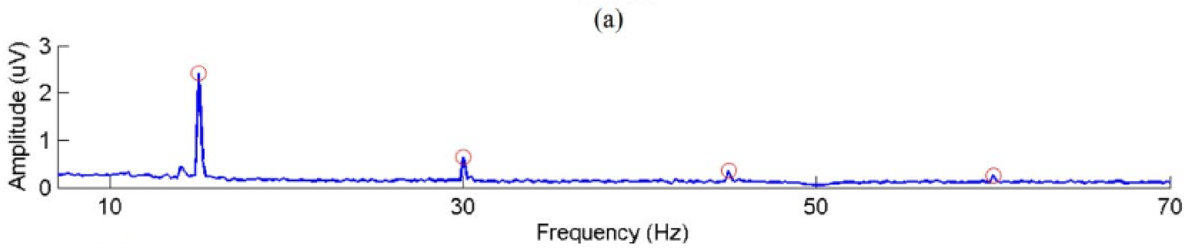


Figure 4.8 Average amplitude of 15 Hz SSVEP [6]

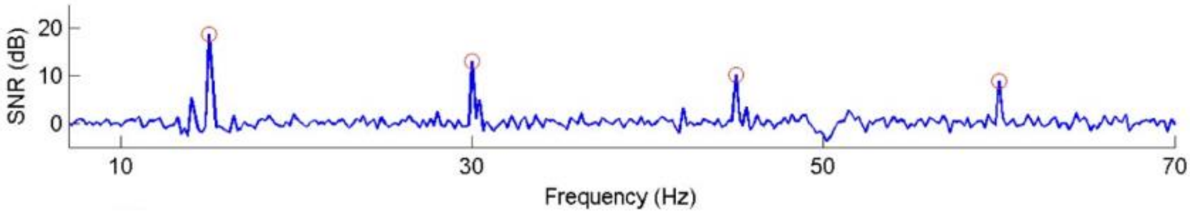


Figure 4.9 Average SNR of 15 Hz and map of scalp [8]

5. RESULT AND ANALYSIS

5.0. Performance Metrics

Accuracy

- Formula:

$$Accuracy = \frac{Number\ of\ correct\ Predictions}{Total\ Number\ of\ Predictions}$$

- Measures the percentage of correctly classified samples.

Precision

- Formula:

$$Precision = \frac{True\ Positives}{True\ Positives\ +\ False\ Positives}$$

- Indicates the proportion of positive predictions that are actually correct.
- Important when false positives are costly (e.g., spam detection).

Recall (Sensitivity/True Positive Rate)

- Formula:

$$Recall = \frac{True\ Positives}{True\ Positives\ +\ False\ Negatives}$$

- Reflects the model's ability to find all relevant instances.
- Important in scenarios where false negatives are costly (e.g., medical diagnoses).

F1 Score

- Formula:

$$F1 = 2 \times \frac{Precision\ \times\ Recall}{Precision\ +\ Recall}$$

- Harmonic mean of precision and recall.
- Useful for imbalanced datasets.

ROC-AUC (Receiver Operating Characteristic - Area Under Curve)

- Plots the True Positive Rate (Recall) vs. False Positive Rate for different thresholds.
- AUC value ranges from 0 to 1, with higher values indicating better performance.

Confusion Matrix

- A table showing True Positives, False Positives, True Negatives, and False Negatives.
- Useful for understanding model errors in multiclass problems.

Macro Average

- Formula:

$$Macro\ Average = \frac{1}{N}\sum_{i=1}^{N} Metric\ for\ Class\ i$$

  where N is the number of classes.
- Macro averaging computes the metric independently for each class and then takes the average (unweighted mean).
- Treats all classes equally, regardless of their support.
- Macro averaging is useful when you want to evaluate the model's performance across all classes equally, even if the dataset is imbalanced.

Support

- Support refers to the number of actual instances of a given class in the dataset.
- It gives context to the evaluation metrics by showing how many samples belong to each class.

Weighted Average

- Formula:

$$\frac{\sum_{i=1}^{N}(Support\ for\ Class\ i) \times (Metric\ for\ Class\ i)}{\sum_{i=1}^{N} Support\ for\ Class\ i}$$

  where N is the number of classes.
- Weighted averaging computes the metric for each class and takes a weighted mean, where the weight is the number of true instances (support) of each class.
- Accounts for the support of each class, giving more importance to classes with more instances.

- Weighted averaging is ideal when you want to evaluate overall performance, especially in imbalanced datasets where larger classes should have more influence on the metric.

5.1. FastICA + CCA + CWT + CNN

The presented research combines CCA with Continuous Wavelet Transform to present an improved feature extraction in the classification of SSVEP signals. In general, CCA aims to find the maximal coherent features between the EEG signals and target stimulation frequencies to provide higher performance in the separation of SSVEP signals from noises and artifacts. This helped to identify the specific frequency components of the stimulus, enabling the model to focus on the most relevant features of the EEG data. Following the enhancement of the SSVEP signal using CCA, the Continuous Wavelet Transform was performed to capture the time and frequency characteristics of the EEG signals. Indeed, CWT is one among the most effective time-frequency analytical techniques that details changes in the frequency content with time, which is useful for the detection of the frequency-dependent SSVEP responses with dynamic nature. In that respect, CWT therefore provided frequency-time features characterizing better the complex dynamics that make up the SSVEP response. The combination of CCA and CWT resulted in further enhancement of the classification accuracy, embedding a richer and more informative set of features and thereby enabling the CNN model to discriminate between different visual stimuli more precisely according to their frequency and temporal pattern.

Average Accuracy: 77.24%

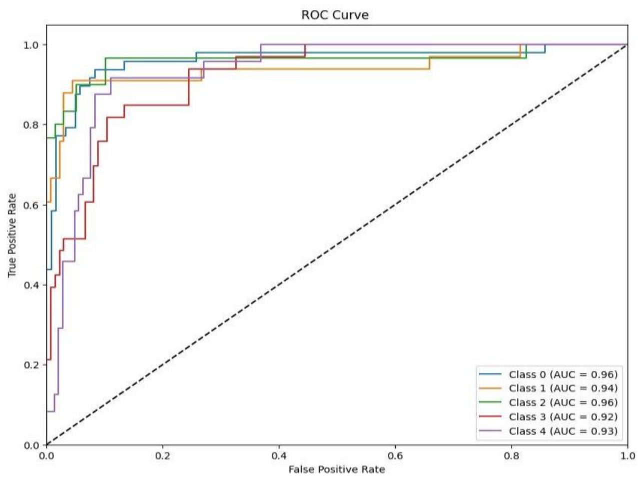
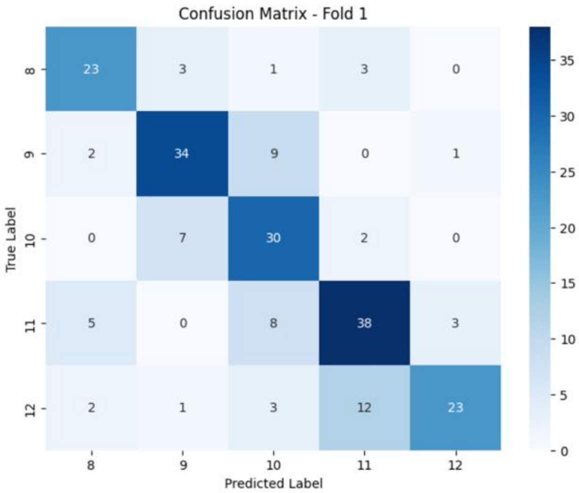


Figure 5.1 ROC-AUC of the model (FastICA + CCA + CWT + CNN)

5.1.1. K-Fold Cross Validation for FastICA + CCA + CWT + CNN:

In this work, the dataset was divided into 5 folds; each of those is used, in turn, to train and then test the model. For every fold, it shows the classification report, including precision, recall, f1-score, and accuracy for every class of frequency. The obtained results, reaching from the model on each fold for different target frequencies (8 Hz, 9 Hz, 10 Hz, 11 Hz, 12 Hz), represent the averaged result over all folds showing performance on the whole.

- Fold 1:

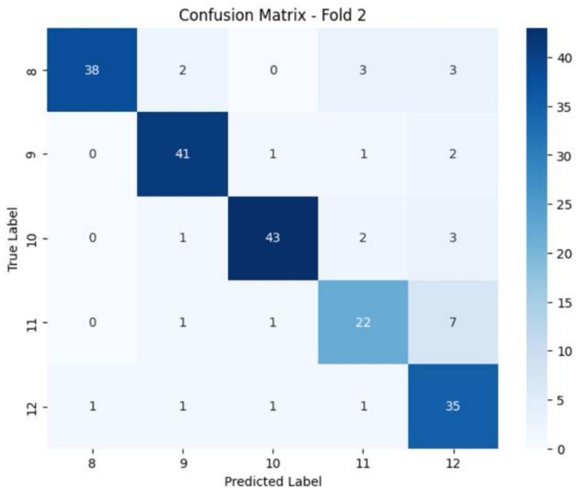


Classification Report for Fold 1

	precision	recall	f1-score	support
8	0.72	0.77	0.74	30
9	0.76	0.74	0.75	46
10	0.59	0.77	0.67	39
11	0.69	0.70	0.70	54
12	0.85	0.56	0.68	41
accuracy			0.70	210
macro avg	0.72	0.71	0.71	210
weighted avg	0.72	0.70	0.70	210

Figure 5.2 Confusion Matrix and Classification Report for fold 1 of 5, FastICA + CCA + CWT + CNN

- Fold 2:

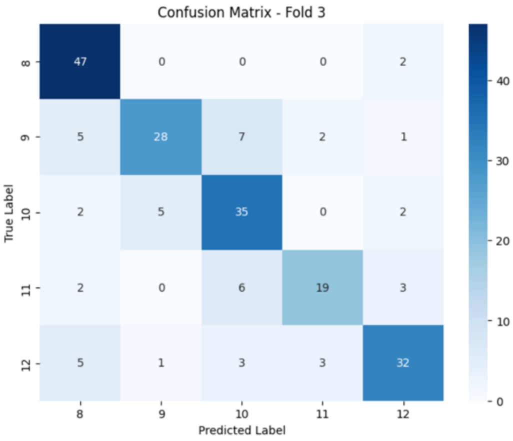


Classification Report for Fold 2

	precision	recall	f1-score	support
8	0.97	0.83	0.89	46
9	0.89	0.91	0.90	45
10	0.93	0.88	0.91	49
11	0.76	0.71	0.73	31
12	0.70	0.90	0.79	39
accuracy			0.85	210
macro avg	0.85	0.84	0.84	210
weighted avg	0.86	0.85	0.85	210

Figure 5.3 Confusion Matrix and Classification Report for fold 2 of 5, FastICA + CCA + CWT + CNN

- Fold 3:

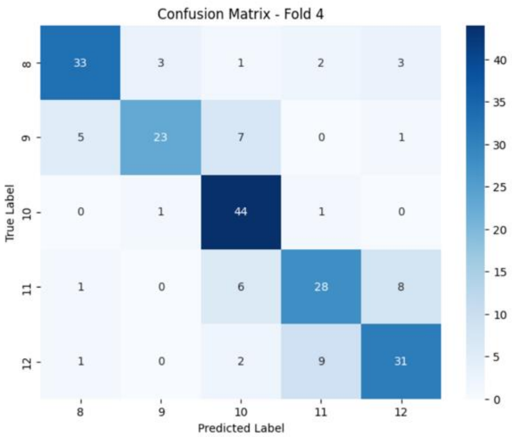


Classification Report for Fold 3

	precision	recall	f1-score	support
8	0.77	0.96	0.85	49
9	0.82	0.65	0.73	43
10	0.69	0.80	0.74	44
11	0.79	0.63	0.70	30
12	0.80	0.73	0.76	44
accuracy			0.77	210
macro avg	0.77	0.75	0.76	210
weighted avg	0.77	0.77	0.76	210

Figure 5.4 Confusion Matrix and Classification Report for fold 3 of 5, FastICA + CCA + CWT + CNN

- Fold 4:

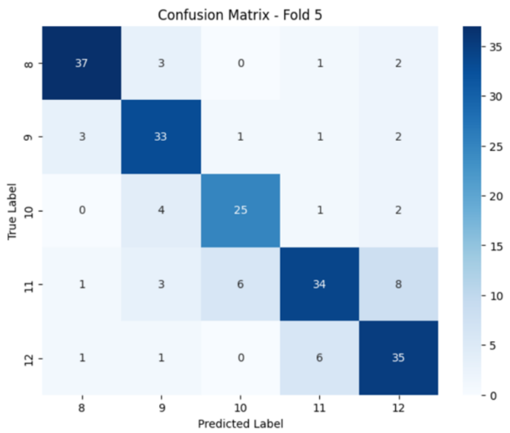


Classification Report for Fold 4

	precision	recall	f1-score	support
8	0.82	0.79	0.80	42
9	0.85	0.64	0.73	36
10	0.73	0.96	0.83	46
11	0.70	0.65	0.67	43
12	0.72	0.72	0.72	43
accuracy			0.76	210
macro avg	0.77	0.75	0.75	210
weighted avg	0.76	0.76	0.75	210

Figure 5.5 Confusion Matrix and Classification Report for fold 4 of 5, FastICA + CCA + CWT + CNN

- Fold 5:



Classification Report for Fold 5

	precision	recall	f1-score	support
8	0.88	0.86	0.87	43
9	0.75	0.82	0.79	40
10	0.78	0.78	0.78	32
11	0.79	0.65	0.72	52
12	0.71	0.81	0.76	43
accuracy			0.78	210
macro avg	0.78	0.79	0.78	210
weighted avg	0.78	0.78	0.78	210

Figure 5.6 Confusion Matrix and Classification Report for fold 5 of 5, FastICA + CCA + CWT + CNN

Average accuracy: 77.24%

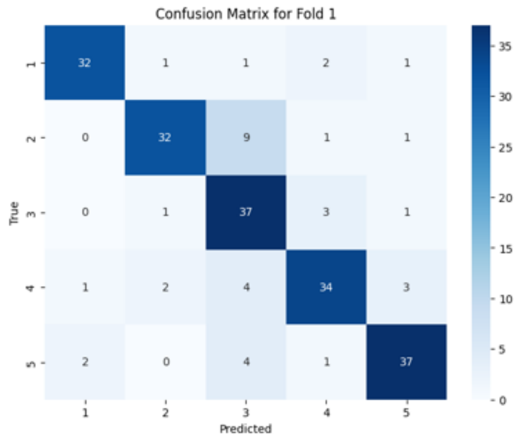
Standard deviation: 4.76%

5.2. FastICA + ShallowConvNet

ShallowConvNet is a lighter version of a convolutional neural network with fewer layers. It was applied for EEG signal classification in your work, **which achieved an accuracy of 79.04%**. While it can be extremely effective in the case of more simple tasks, its performance is not comparable to the more complex model DeepConvNet, as it can learn only simple patterns from the EEG data.

5.2.1. K-fold Cross Validation for FastICA + ShallowConvNet

- Fold 1:

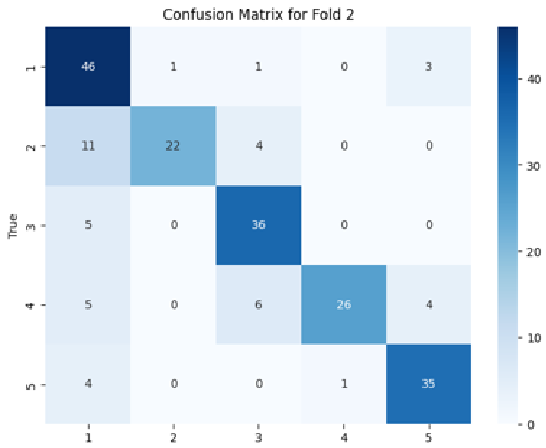


Classification Report for Fold 1:

	precision	recall	f1-score	support
0	0.91	0.86	0.89	37
1	0.89	0.74	0.81	43
2	0.67	0.88	0.76	42
3	0.83	0.77	0.80	44
4	0.86	0.84	0.85	44
accuracy			0.82	210
macro avg	0.83	0.82	0.82	210
weighted avg	0.83	0.82	0.82	210

Figure 5.7 Confusion Matrix and Classification Report for Fold 1 of 5, FastICA + ShallowConvNet

- Fold 2:

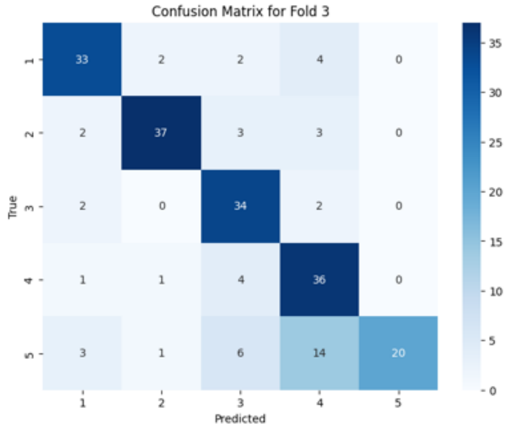


Classification Report for Fold 2:

	precision	recall	f1-score	support
0	0.65	0.90	0.75	51
1	0.96	0.59	0.73	37
2	0.77	0.88	0.82	41
3	0.96	0.63	0.76	41
4	0.83	0.88	0.85	40
accuracy			0.79	210
macro avg	0.83	0.78	0.78	210
weighted avg	0.82	0.79	0.78	210

Figure 5.8 Confusion Matrix and Classification Report for Fold 2 of 5, FastICA + ShallowConvNet

- Fold 3:

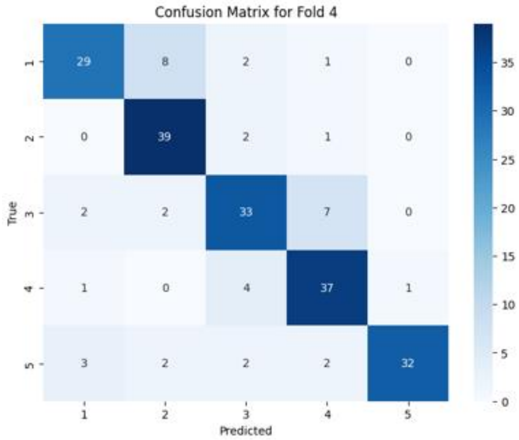


Classification Report for Fold 3:

	precision	recall	f1-score	support
0	0.80	0.80	0.80	41
1	0.90	0.82	0.86	45
2	0.69	0.89	0.78	38
3	0.61	0.86	0.71	42
4	1.00	0.45	0.62	44
accuracy			0.76	210
macro avg	0.80	0.77	0.76	210
weighted avg	0.81	0.76	0.76	210

Figure 5.9 Confusion Matrix and Classification Report for Fold 3 of 5, FastICA + ShallowConvNet

- Fold 4:

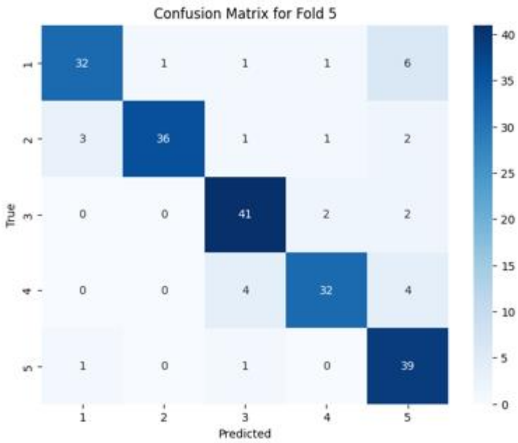


Classification Report for Fold 4:

	precision	recall	f1-score	support
0	0.83	0.72	0.77	40
1	0.76	0.93	0.84	42
2	0.77	0.75	0.76	44
3	0.77	0.86	0.81	43
4	0.97	0.78	0.86	41
accuracy			0.81	210
macro avg	0.82	0.81	0.81	210
weighted avg	0.82	0.81	0.81	210

Figure 5.10 Confusion Matrix and Classification Report for Fold 4 of 5, FastICA + ShallowConvNet

- Fold 5:



Classification Report for Fold 5:

	precision	recall	f1-score	support
0	0.89	0.78	0.83	41
1	0.97	0.84	0.90	43
2	0.85	0.91	0.88	45
3	0.89	0.80	0.84	40
4	0.74	0.95	0.83	41
accuracy			0.86	210
macro avg	0.87	0.86	0.86	210
weighted avg	0.87	0.86	0.86	210

Figure 5.11 Confusion Matrix and Classification Report for Fold 5 of 5, FastICA + ShallowConvNet

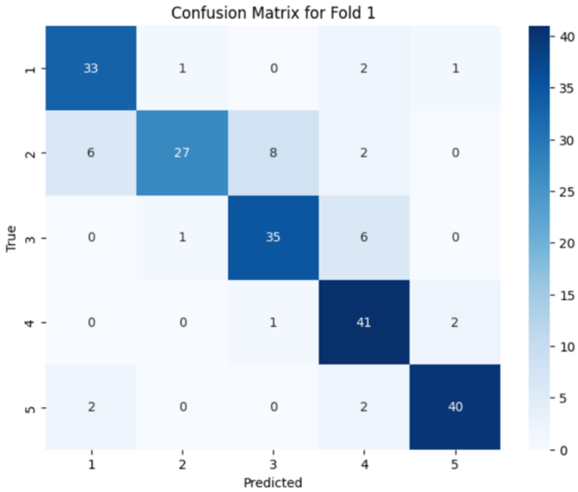
Average Accuracy across folds: 0.8067 ± 0.0321

Average Loss across folds: 0.7000 ± 0.0610

5.3. FastICA + EEGNet

EEGNet is a very light CNN model, optimized for EEG signal classification. Its performance and computational efficiency can be very well balanced towards real-time applications. In your work, **the net reached an accuracy of 84.76%**, showing that it works fine in classifying SSVEP signals while lessening the computational cost when contrasted with DeepConvNet.

- Fold 1:

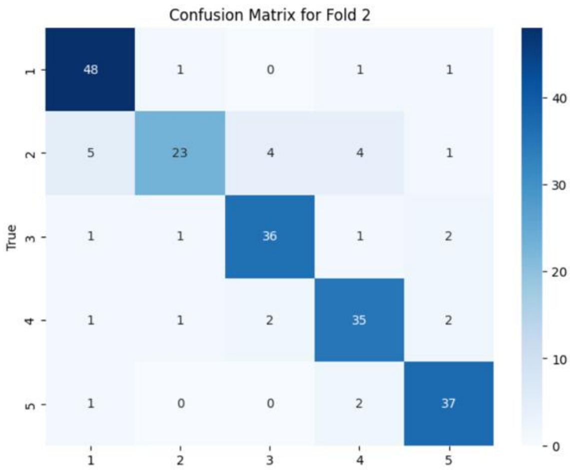


Classification Report for Fold 1:

	precision	recall	f1-score	support
0	0.80	0.89	0.85	37
1	0.93	0.63	0.75	43
2	0.80	0.83	0.81	42
3	0.77	0.93	0.85	44
4	0.93	0.91	0.92	44
accuracy			0.84	210
macro avg	0.85	0.84	0.84	210
weighted avg	0.85	0.84	0.84	210

Figure 5.12 Confusion Matrix and Classification Report for fold 1 of 5, FastICA + EEGNet

- Fold 2:

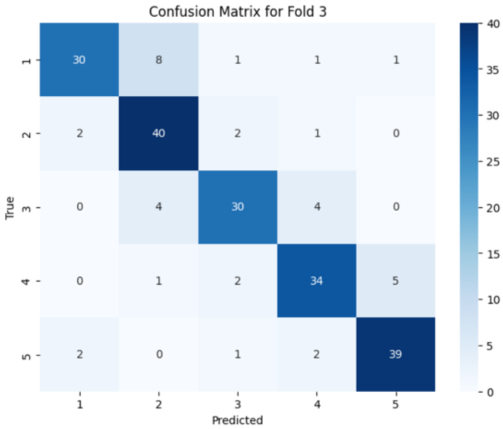


Classification Report for Fold 2:

	precision	recall	f1-score	support
0	0.86	0.94	0.90	51
1	0.88	0.62	0.73	37
2	0.86	0.88	0.87	41
3	0.81	0.85	0.83	41
4	0.86	0.93	0.89	40
accuracy			0.85	210
macro avg	0.85	0.84	0.84	210
weighted avg	0.85	0.85	0.85	210

Figure 5.13 Confusion Matrix and Classification Report for fold 2 of 5, FastICA + EEGNet

- Fold 3:

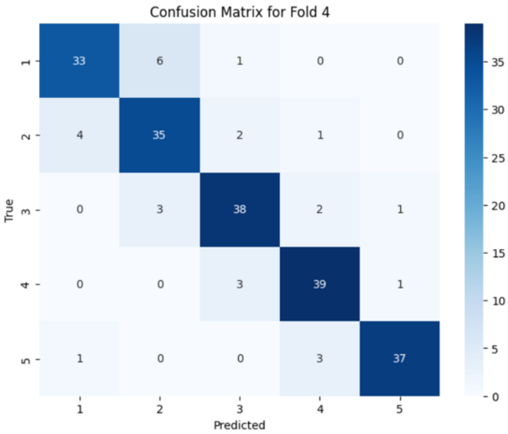


Classification Report for Fold 3:

	precision	recall	f1-score	support
0	0.88	0.73	0.80	41
1	0.75	0.89	0.82	45
2	0.83	0.79	0.81	38
3	0.81	0.81	0.81	42
4	0.87	0.89	0.88	44
accuracy			0.82	210
macro avg	0.83	0.82	0.82	210
weighted avg	0.83	0.82	0.82	210

Figure 5.14 Confusion Matrix and Classification Report for fold 3 of 5, FastICA + EEGNet

- Fold 4:

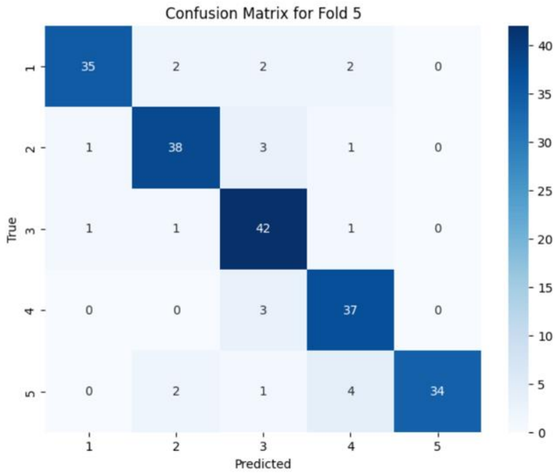


Classification Report for Fold 4:

	precision	recall	f1-score	support
0	0.87	0.82	0.85	40
1	0.80	0.83	0.81	42
2	0.86	0.86	0.86	44
3	0.87	0.91	0.89	43
4	0.95	0.90	0.93	41
accuracy			0.87	210
macro avg	0.87	0.87	0.87	210
weighted avg	0.87	0.87	0.87	210

Figure 5.15 Confusion Matrix and Classification Report for fold 4 of 5, FastICA + EEGNet

- Fold 5:



Classification Report for Fold 5:

	precision	recall	f1-score	support
0	0.95	0.85	0.90	41
1	0.88	0.88	0.88	43
2	0.82	0.93	0.88	45
3	0.82	0.93	0.87	40
4	1.00	0.83	0.91	41
accuracy			0.89	210
macro avg	0.90	0.88	0.89	210
weighted avg	0.89	0.89	0.89	210

Figure 5.16 Confusion Matrix and Classification Report for fold 5 of 5, FastICA + EEGNet

Average Accuracy across folds: 0.8533 ± 0.0216

Average Loss across folds: 0.6263 ± 0.0163

5.4. FastICA + FBCCA

FBCCA is employed to enhance the SSVEP signal, adding a feedback mechanism through classification results to improve the relation between EEG signals and target frequencies. It is employed in many SSVEP-based BCI applications where noise reduction is one of the key factors taken into consideration to ensure high accuracy in the classification. For your data, **it achieved an accuracy of 89.80%**, showing its capability in signal recognition. In the confusion matrix (Figure 5.17), the classes 0,1,2,3,4 correspond to the frequencies 8Hz, 9Hz, 10Hz, 11Hz and 12Hz.

Accuracy:89.80%

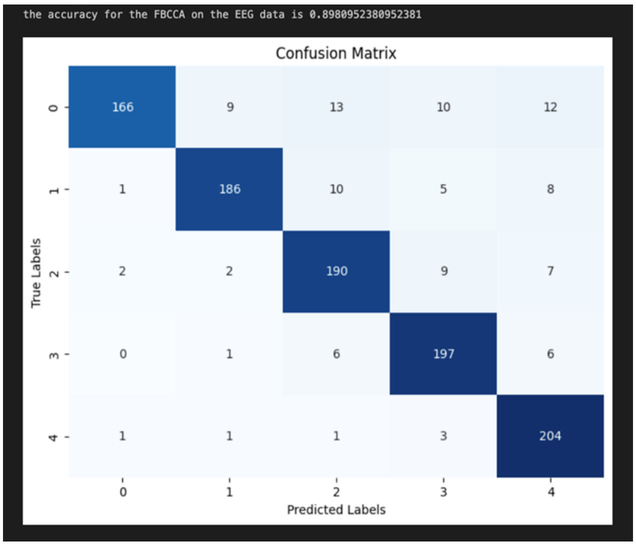


Figure 5.17 Confusion Matrix for FastICA + FBCCA

5.5. FastICA + FBCCA + CNN

FBCCA has been applied to extract the correlation between the EEG data and the target stimulus frequencies for helping in isolating the SSVEP response from noise. It did well but, without a feedback mechanism, **it achieved 90.47% accuracy**. That shows it is effective for SSVEP signal enhancement but may require additional methods for optimal performance. In the confusion matrix (Figure 5.18), the classes 0,1,2,3,4 correspond to the frequencies 8Hz, 9Hz, 10Hz, 11Hz and 12Hz.

Accuracy:90.47%

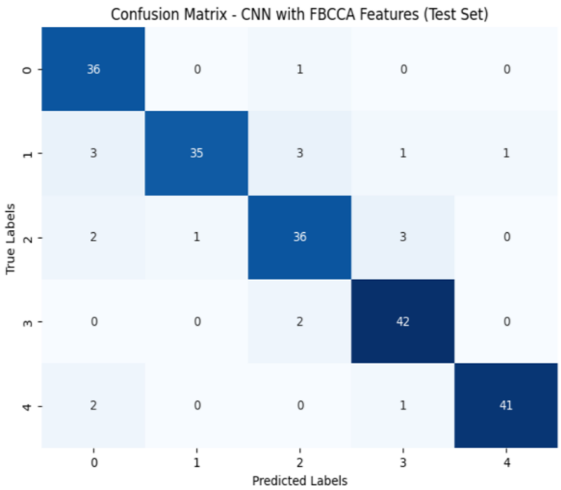
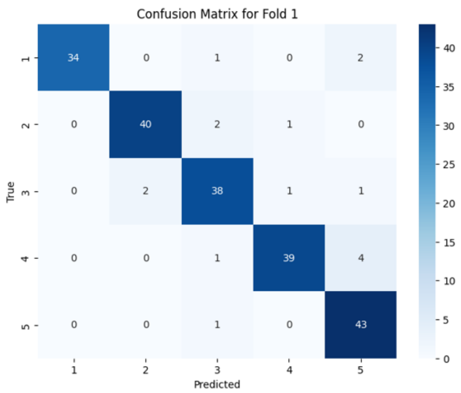


Figure 5.18 Confusion Matrix for FastICA + FBCCA + CNN Classification Result

5.6. FastICA + DeepConvNet

DeepConvNet is a deep learning-based model for the processing of the EEG signals. Consisting of several convolutional layers, its architecture has the potential to automatically learn complex spatial and temporal features of the EEG signals. In your work, **the best accuracy is 91.9%,** which means that DeepConvNet works best at classifying SSVEP signals.

- Fold 1:

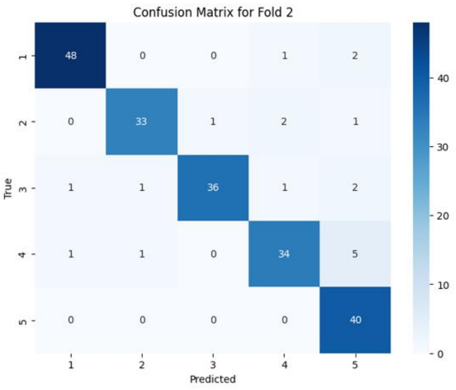


Classification Report for Fold 1:

	precision	recall	f1-score	support
0	1.00	0.92	0.96	37
1	0.95	0.93	0.94	43
2	0.88	0.90	0.89	42
3	0.95	0.89	0.92	44
4	0.86	0.98	0.91	44
accuracy			0.92	210
macro avg	0.93	0.92	0.93	210
weighted avg	0.93	0.92	0.92	210

Figure 5.19 Confusion Matrix and Classification Report for fold 1 of 5, FastICA + DeepConvNet

- Fold 2:

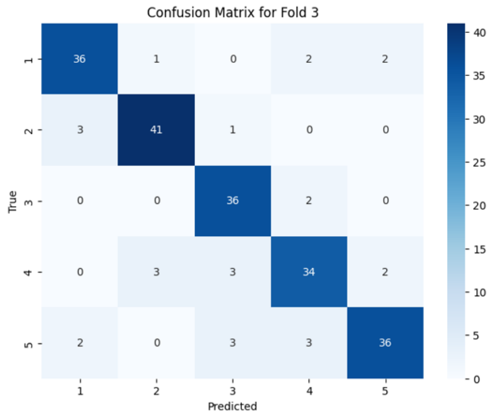


Classification Report for Fold 2:

	precision	recall	f1-score	support
0	0.96	0.94	0.95	51
1	0.94	0.89	0.92	37
2	0.97	0.88	0.92	41
3	0.89	0.83	0.86	41
4	0.80	1.00	0.89	40
accuracy			0.91	210
macro avg	0.91	0.91	0.91	210
weighted avg	0.92	0.91	0.91	210

Figure 5.20 Confusion Matrix and Classification Report for fold 2 of 5, FastICA + DeepConvNet

- Fold 3:

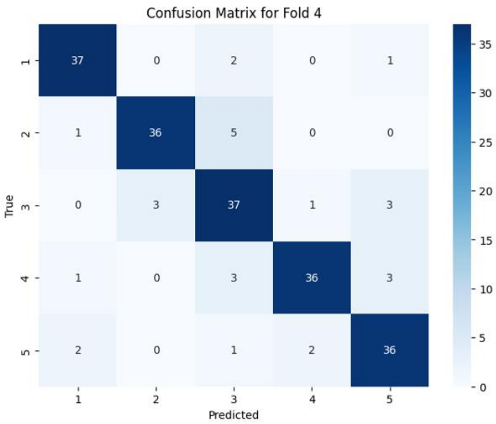


Classification Report for Fold 3:

	precision	recall	f1-score	support
0	0.88	0.88	0.88	41
1	0.91	0.91	0.91	45
2	0.84	0.95	0.89	38
3	0.83	0.81	0.82	42
4	0.90	0.82	0.86	44
accuracy			0.87	210
macro avg	0.87	0.87	0.87	210
weighted avg	0.87	0.87	0.87	210

Figure 5.21 Confusion Matrix and Classification Report for fold 3 of 5, FastICA + DeepConvNet

- Fold 4:

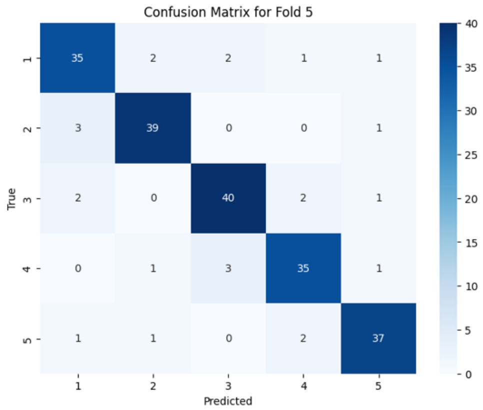


Classification Report for Fold 4:

	precision	recall	f1-score	support
0	0.90	0.93	0.91	40
1	0.92	0.86	0.89	42
2	0.77	0.84	0.80	44
3	0.92	0.84	0.88	43
4	0.84	0.88	0.86	41
accuracy			0.87	210
macro avg	0.87	0.87	0.87	210
weighted avg	0.87	0.87	0.87	210

Figure 5.22 Confusion Matrix and Classification Report for fold 4 of 5, FastICA + DeepConvNet

- Fold 5:



Classification Report for Fold 5:

	precision	recall	f1-score	support
0	0.85	0.85	0.85	41
1	0.91	0.91	0.91	43
2	0.89	0.89	0.89	45
3	0.88	0.88	0.88	40
4	0.90	0.90	0.90	41
accuracy			0.89	210
macro avg	0.89	0.89	0.89	210
weighted avg	0.89	0.89	0.89	210

Figure 5.23 Confusion Matrix and Classification Report for fold 5 of 5, FastICA + DeepConvNet

Average Accuracy across folds: 0.8914 ± 0.0220
Average Loss across folds: 0.3193 ± 0.0305

6. CONCLUSION AND FUTURE DIRECTIONS

6.1. Conclusion

The entire learning within this second phase of the capstone project has been immensely enriching and expanded our understanding of the optimization techniques of BCI models, especially with respect to SSVEP signal classification. Different preprocessing and feature extraction techniques for quality and reliable EEG data were developed to classify them into their respective classes of SSVEP. Furthermore, advanced signal classification models, such as CNN, were used in order to enhance the accuracy of the signal classification.

Further iterations included testing different methodologies for feature extraction, including CCA, frequency-time features using CWT, and further models comprising an 'FBCCA' DeepConvNet, ShallowConvNet, and EEGNet. The project demonstrated the strength for using CNN models in this domain, where DeepConvNet provided a maximum accuracy of 91%, hence showing its potential toward real-time SSVEP-based Brain-Computer Interface applications.

Besides this, we applied K-fold cross-validation to ensure that our models would be robust and generalized. We obtained variable yet promising accuracy ranges within folds of 70%-85%. These results showed the potential of the different approaches but at the same time pointed out further refinements and optimizations continuously needed for BCI systems.

In this phase, we successfully developed and fine-tuned a model that emphasized the integration of preprocessing, feature extraction, and classification steps, underlining the importance of cascaded processing in improving the performance of classification. This phase substantially took our understanding of BCI optimization forward and laid the way for further progress relating to real-time processing and classification of EEG signals.

6.2. Future Directions

The major deliverables at the end of Phase-3 of the project will be a Final Project Report and the publication of a research paper regarding the findings. This is where the final project report will give the holistic view, starting with acquiring the data and preprocessing to the feature extraction and various techniques for classification with results. This includes giving out methodologies, algorithms used, and a rationale on the choice of techniques such as FBCCA, CCA, CWT, and CNN in the SSVEP signals classification. Finally, performance analysis and model comparisons will discuss the outcomes with a view to how important it is in SSVEP-based BCI systems.

At the same time, it will publish a research paper that summarizes major findings and contributions of this project in targeting an appropriate journal or conference on EEG signal processing, BCI, or machine learning. In sum, this project will be based on the novelty of using a more advanced signal enhancement like FBCCA and CCA, feature extraction with Continuous Wavelet Transform, and performance evaluation of deep models for EEG classification. As such, the paper looks forward to contributing much information helpful in BCI research related to enhancing the accuracy and efficiency of SSVEP-based systems.

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APPENDIX

SSVEP	Steady-State Visual Evoked Potentials are brain signals evoked by the visual stimuli of flickering at certain frequencies, which have been used in many applications in BCI.
FBCCA	Feedback Canonical Correlation Analysis-Advanced signal enhancement technique in order to improve the correlation of EEG signals with target frequencies; this is normally done in BCI systems regarding SSVEP detection
CCA	CCA is an abbreviation for Canonical Correlation Analysis; it is a statistical method of finding a relationship between the EEG signal and target stimulus frequencies in order to have better detection of SSVEP signals.
CWT	Continuous Wavelet Transform: This is a time-frequency analytical technique, which elicits both the temporal and frequency characteristics of the EEG signals to enhance the feature extraction for SSVEP classification.
CCN	Convolutional Neural Network; A deep learning model for the purpose of automatic feature extraction and classification that is normally used for EEG signal processing in a BCI system
DeepConvNet	It is a special CNN architecture that is multi-layered and deep in nature to extract features from EEG data in a profound way, reaching a high classification performance on SSVEP.
ShallowConvNet	This is a shallow, smaller version of the CNN model applied for EEG

	classification. For instance, shallow networks do not perform well compared with deeper networks: DeepConvNet.
EEGNet	A lightweight CNN architecture, optimized for the classification of EEG signals, balancing computational efficiency with high performance in SSVEP detection for BCI applications.
k-Fold CV	It is a model evaluation technique that involves partitioning the dataset into K subsets and training the model K times with different subsets to ensure its robustness and avoid overfitting.
BCI	Brain-Computer Interface, an approach to interaction within one and the same cognitive human interface between the nervous processes and the external environment mainly with the help of non-invasive EEG method used directly without interpreting purposes