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Hybrid Stacking Ensemble With Augmented Features For Robust SSVEP Signal Classification In BCI

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Abstract— The Brain Computer Interface (BCI) acts to boost human abilities. Steady-State Visual Evoked Potential signals are one of the popular paradigm used in BCI experiments, where precise classification of these signals is the key for system performance. In this paper, we introduced a meta learner, a hybrid machine learning technique used in the classification of SSVEP signals by utilizing stacking ensemble and augmented features. The proposed methodology uses advanced signal processing methods, such as wavelet denoising, for preprocessing electroencephalogram data and extracting patterns. The classification system incorporates a stacking ensemble model, in which several base classifiers such as k-nearest neighbors, decision trees, and support vector machine (SVM) are trained by the extracted features, and their results are calibrated by a meta-learner in order to enhance the accuracy of the class. The new proposed system is tested on SSVEP signal dataset and proves superior performance when compared with single-model traditional methods. Key performance metrics, such as accuracy, F1 score, precision, specificity, recall, and area under the curve for receiver operating characteristic analysis, are presented in order improve the efficiency of the proposed system. It can be seen from the results that the use of stacking ensemble, along with augmented features, presents a strong solution for SSVEP signal classification, with substantial improvements, with achieved accuracy of 97.13%. This novel solution has the potential to improve the performance of SSVEP BCI application.

Keywords: K-Nearest Neighbors(k-NN), Support Vector Machine (SVM), Steady State Visual Evoked Potential, Brain-Computer Interface, Electroencephalogram (EEG)

1. Introduction

BCI(Brain-Computer Interface) s are extensively used to increase human capability in accessing computer systems. Steady State Visual Evoked Potential (SSVEP) signals are used extensively in BCI implementations, for which accurate discrimination of these signals is required for system performance. A set of sensors and signal processing components constitute brain activity monitoring, converting a subject's brain activity into a set of control or communications signals. Brain waves are required first to be captured in this system using brain recorders before they are analyzed. BCIs have been designed in terms of connecting surrounding devices with brain impulses as a command transmitter (1). BCI can be characterized as the direct production of an intermediary through which the surrounding world interacts with electrical signals from brain activity, such as muscles, nerves, and other structures (2). Electroencephalography is a highly effective method of registering brain activity. It is widely used in BCI research due to its numerous advantages, such as great resolution, non-invasiveness, cost-effectiveness, and mobility (3).

There are a unique set of EEG signals, visually evoked potentials, that are elicited when a subject is shown a visual stimulus. The occipital and parietal lobes of the brain generate these electrical impulses at the same frequency as the sensory signal. A quasi-sine wave results due to the excessive exposure of the visual cortex to operational potentials it generates in response to a frequency range from 3.5 Hz up to 75 Hz. This causes the visual cortex to generate pseudo-sinusoidal signals when presented with the stimulus

(4,5). SSVEPs are a brain response produced when a subject looks at a visually presented stimulus flickering at a precise frequency. Owing to their good signal-to-noise ratio together with ease of elicitation, SSVEPs are becoming a leading candidate for non-invasive BCI systems, intended to empower control and communication in severely motor-impaired individuals. A generalized process diagram of SSVEP BCI is shown in Fig1. Classification of SSVEPs has a vital role in ensuring the efficient operation of these BCI systems, since this affects their usability in real-time contexts (6). Conventional SSVEP signal classification methods have mostly used single classifiers, e.g., linear discriminant analysis, k-NN, SVM. These methods, though used with some success, tend not to grasp the complex, non-linear nature of EEG data. In addition, EEG signals are known to be severely impacted by noise as well as artifacts, further deteriorating the performance of traditional classifiers. Such difficulties call for more efficient, accurate, yet robustly designed classification methods capable of coping with the intricacies in EEG data (7).

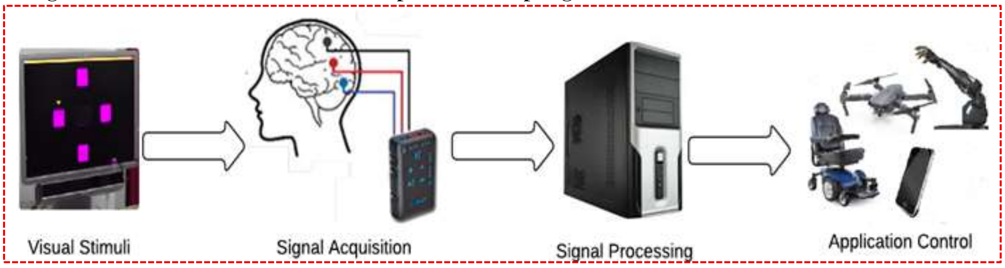

Fig. 1. Generalized process flow of SSVEP BCIs.

In recent years, ensemble learning approaches have received substantial attention in the realm of machine learning due to their ability to blend a set of distinct models in order to achieve higher predictive accuracy than single models. Among these approaches, stacking ensembles have emerged as a potent tool for boosting the accuracy in classifications by taking advantage of the strengths of several base learners and a meta-learned model in aggregating their outputs in the best possible way. Stacking ensemblers have already been used in several domains, but their use in SSVEP signal classification is not adequately explored.

In this paper, a novel SSVEP signal classification through a hybrid machine learning strategy based on stacking ensembles and augmented feature extraction methods (8) is presented. The traditional methods of SSVEP BCIs are beset by several drawbacks such as the requirements of large calibration data, dependency upon fixed window methods, low subject generalizability, substantial computational requirements, and inferior performance with short data lengths. The limitations demonstrate the necessity of efficient, effective, and flexible methods for enhancing practicality as well as performance in SSVEP BCI systems. In addition, in order to broaden the training data diversity for better model generalization, diverse data augmentation methods, i.e., the addition of white Gaussian noise, time shifting, as well as scaling of amplitude (9,10), are adopted.

Besides, we use principal component analysis (PCA) dimensionality reduction, keeping the most important features in order to decrease the computational load and avoid overfitting. The ensemble model with stacking is made up of diverse base-level classifiers, such as SVM, Decision Trees, and k-NN, whose outputs are integrated by a meta-learner in a manner to maximize the classification (11). The new technique is tested on a set of SSVEP signals, showing major improvements in classification accuracy, F1 score, precision, recall, and some crucial performance metrics in comparison to traditional approaches. The contributions of this study are three-fold:

- Designing a new ensemble stacking framework specifically for SSVEP signal classification.
- Incorporating extensive feature extraction, as well as augmentation methods, for model resilience.
- Rigorous assessment of the suggested methodology in terms of several performance metrics.

This innovative hybrid methodology offers a robust and effective solution for SSVEP signal classification, with the potential to significantly improve the performance of BCI systems and expand their applicability in real-world scenarios.

2. Related Work

Research in the field of SSVEP signal classification for BCI applications has witnessed significant progress over the past few decades. This section reviews the existing literature on SSVEP signal processing, feature extraction, and machine learning techniques, highlighting the advancements and gaps that our proposed hybrid machine learning approach addresses [8]. The classification of SSVEP signals has mainly employed conventional signal processing and machine learning techniques. Reviews performed by Bin et al justified that Canonical Correlation Analysis (CCA) was truly efficient in identification of the SSVEP (12), which reflected its ability to perform well in noisy conditions. But still, CCA and it's modifications such as Multi-set CCA (MsetCCA) and Filter Bank CCA (FBCCA) are sensitive to certain parameters, some of which needs manual tuning and the generalization across subjects or sessions is hampered by noise and variability across subjects and sessions.

In the frequency domain there are common techniques like FFT and PSD estimation which were used in SSVEP classification tasks. The authors applied for Welch's method to PSD estimation to extract characteristics from EEG signals followed by LDA classification (13). These methods are very simple, computationally easy to implement, and although they work with reasonable accuracy for signal-to-noise ratios (SNR) that are relatively high, they fail to capture the non-linear associations which are common in SSVEP signals. However, in the recent past there has been focus on implementing advanced methodologies in deep learning and machine learning for the classification of SSVEP signals in-order to overcome the drawbacks of this method. k-NN, random forests and SVMs have been used to classify features extracted from the EEG signals, with better performance reported and attributed to the models' ability to facilitate learning of complex decision boundaries (14,15).

Deep learning has taken this development further with SSVEP classification realization. CNN and RNN, especially LSTM based architectures have been used for end-to end learning from raw EEG signal. For example, Zhang et al put forward a CNN-based architecture which can directly learn discriminative spatial-temporal features from raw SSVEP data (16). In a paper to the authors' knowledge, they used both CNNs and LSTMs to take advantage of spatial and temporal properties of SSVEP signals for identifying the appropriate frequencies and amplitudes for eliciting steady, robust, and highly accurate brain responses. However, deep learning models demand an immense quantity of labeled data and are also resource hungry and therefore, not ideal for real-time BCI application that demand near-instantaneous response (17).

There have been various enhancements on ensemble learning mechanisms that integrate diverse base classifiers with an aim of boosting generalization as well as robustness for the SSVEP signal classifications. Among methods of creating an ensemble, bagging and boosting can be mentioned (18). Higher order learning algorithms like the AdaBoost and Gradient Boosting have been employed in the prediction of the SSVEP signals with the view of making the predictor correct the errors of the weak predictors making up the entire set of predictors (19). Nevertheless, these methods can be very noisy and prone to overfitting (20). Stacking ensembles, which is complex ensemble learning, have recently been investigated for SSVEP signal classification. Stacking works through incorporating a meta learner which makes an attempt to combine the predictions of other base models to improve performance of the merged model. Relative to the bagging and boosting, the method of stacking can well exploit the advantage of individual classifier, in this way, it is more resistant to over-fitting and noise. However, the use of stacking ensembles in the classification of SSVEP has been sparingly done. In the existing studies, the chances of stacking are not completely utilized, especially when combined with higher feature extraction and augmented data.

The stacking ensembles is a method where the base classifiers are combined to construct a more accurate model. Ensemble learning uses kernel numbers of EEGNet models, enhance the classification performance of SSVEP signals in ear-EEG data. This approach was found to yield better results than the conventional methods such as the canonical correlation analysis. Stacking ensemble models adapted by genetic algorithms for selecting suitable base classifiers and other hyper-parameters have outperformed other models in a variety of datasets. This raises possibility of its use in classification of SSVEP signals although no specific SSVEP study is reported. The neighborhood under sampling stacked ensemble method solves the under sampling problem by incorporating the under sampling methods into the stacked ensemble approach. It has been observed that the proposed approach performs better than non-resampling based stacked ensembles; this could make the method useful especially in SSVEP signal classification where data imbalance could be a problem. Therefore, Stacking ensembles of classifiers can be applied for developing SSVEP signal classification, by increasing the classification accuracy and dealing with the problem of the imbalanced dataset should be used.

Feature extraction is very important since SSVEP signals involve EEG signals which are usually noisy and may vary significantly with the subject under consideration. Conventional techniques for feature extraction have employed spectral features such as FFT and PSD among others, and time domain features including variance and skewness among others. Newer works have considered other features which are obtained after applying wavelet transforms and empirical mode decomposition (EMD) to capture non-stationary aspects of EEGs (21). Some are as follows Data augmentation has proved to be an effective aid in training the models especially when the data set is rather small. For instance, in the case of SSVEP classification, ways of artificially increasing the variety of training samples include addition of Gaussian noise, time shifting, and scale factor of the signal's amplitude (22). Such techniques are useful to enhance model's resistance to noise and variability and avoid overfitting. However, in the current literature, such augmentation methods are often used in isolation, as separate techniques for improving training data.

Therefore, the present research indicates that there are several lacunae in the current literature on the topic despite the remarkable improvements. In fact, classical approaches are also good at some cases, but many of them suffer from noise and variability issues. Deep learning and machine learning models are quite effective but they need large amount of data, and the computational cost can also be high, which eventually hampers real-time applications. The use of ensemble methods, especially stacking has been demonstrated to some extent but there is limited information on how SSVEP can benefit from using machine learning when interfacing with modern features extraction and data augmentation methods (23).

The gaps in the above-mentioned techniques are overcome by a novel technique called Hybrid Machine Learning Approach for SSVEP Signal Classification Using Stacking Ensembles and Augmented Features which incorporates the benefit of stacking ensemble learning along with appreciable feature extraction and data augmentation procedures. Incorporating temporal and spectral aspects of the data set using augmented data, helps the proposed methodology to have higher robustness and accuracy of SSVEP classification. They make the stacking ensemble framework even more useful for generalization of the results as each of the base learners can learn different features of the data. To the authors' knowledge, this is a new approach, which is faster and more efficient for real-time BCI signal processing compared with the standard approach.

3. Methodology

The proposed methodology for developing a novel hybrid machine learning approach for SSVEP signal classification combines advanced signal processing, feature extraction, data augmentation, dimensionality reduction, and ensemble learning techniques. The methodology is structured into several key stages to ensure the accurate classification of SSVEP signals, leveraging the strengths of stacking ensemble learning and augmented features to enhance model robustness and accuracy as described in Fig 2.

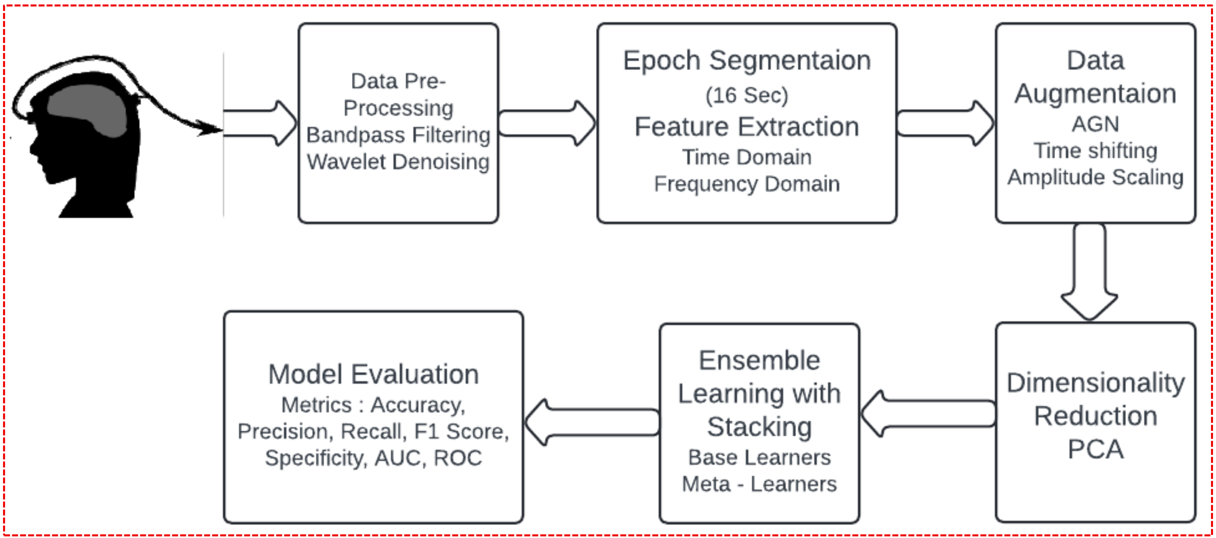

Fig. 2: Block diagram for implementing ensemble learning with stacking

Dataset: The single channel EEG dataset employed for the evolution was obtained from Neuroinformatics, which includes the raw data of single channel dry electrode EEGs for a BCI utilizing SSVEP si4gnals. An Olimex EEG-SMT, a two-channel differential input 10-bit analogue-digital converter (ADC) with a sampling frequency of 256 Hz, was used to collect data using a BCI headset. The indicated dataset has been developed using one of the two channels. The subjects were positioned in a chair 70 centimeters from a 15.6-inch screen with a 60 Hz refresh rate and 1024 x 768pixel resolution. The monitor showed four alternating black-white squares with frequencies of F1=8.57 Hz, F2=10 Hz, F3= 12 Hz and F4=15 Hz, further these frequencies are considered as classes, as the visual stimuli. According to the 10–20 scheme, the electrodes were placed in the Occipital area (Oz) and the Frontal parietal region (Fpz) on the midline sagittal plane. Eleven volunteers put on the data capture head covering and were instructed to concentrate on the visual stimuli for duration of 16 seconds each (24).
The stages in our implementation are described as follows:

3.1 Data Preprocessing

The data fed into the first stage, preprocessing which involves applying filters on the raw EEG data to improve on the quality of the SSVEP signals and eliminate noise. The following steps are carried out in this stage:
Band-Pass Filtering: Further, each raw SSVEP signal is filtered over a band-pass filter(BPF) pertaining to the four frequency bands. This step supports in filtering out the required frequencies which corresponds to the SSVEP response while rejecting interference frequencies and noise.
Wavelet Denoising: To enhance the quality of the signal, wavelet denoising is also used to increase the quality of the acquired signal. This method employs the discrete wavelet transforms for breakdown of the signal and then removing of noise through the thresholding of the wavelet coefficients. We have selected 'db4' wavelet that is most preferred for removing noises from EEG signals. It is useful in the elimination of the noise while at the same time will retain useful parameters in an EEG signal. It involves analyzing the EEG signal, through the wavelet transform and then setting a limit for the coefficient to eliminate the noises then reconstructing the signal to get a better quality of the signal for SSVEP identification. For effective noise reduction, one must choose correct wavelet type and decomposition level, which also distinguishes the input signal.

3.2 Epoch Segmentation and Feature Extraction

Upon pre-processing signals, it is segmented into epochs of fix size for analysis of time frames in which SSVEP response is deemed to occur. The cleaned signals are segmented into epochs of 16 seconds each. The duration of 16 seconds matches the time of presentation of the visual stimulus. This 16 second epoch

length ensures that the SSVEP response is stable, well-aligned with the stimulus, and provides enough data for robust frequency-domain feature extraction, while reducing the impact of noise and artifacts.
Filters are applied in both the frequency domain and the time domain so that features might be obtained from each epoch representing all aspects of the signal. Time domain features include mean activity level, skewness, kurtosis, and variance by which the amplitude distribution and shape of the signal is characterized. The Frequency-Domain Features are generated from FFT for computing for the frequency characteristics of the signal while PSD is computed through Welch method which gives a more accurate estimate of the distribution of power in the signal across frequencies (25).

3.3 Data Augmentation

To enhance the diversity of the training dataset and to provide model generalization, several data augmentation techniques are employed to the extracted epochs. To improve the diversity of the training dataset and to provide model generalization, several data augmentation techniques are applied to the extracted epochs.

Different noise conditions are stimulated to the original signal by adding the random Gaussian noise to enable the model to handle real-world variations. Circle delay by the fixed number of samples for time shifting of the signal takes place. This also aids the model to generalize better since the temporal position of the features is shifted about. And then the signal amplitude is multiplied to some random number that might represent fluctuations of the EEG signal under different conditions or when recorded from different subjects (26).

3.4. Dimensionality Reduction

Dimensionality reduction is employed because of very high dimension of the feature space arising from detailed feature extraction. PCA retains the variance origins that contribute to the most significant amount of variance while at the same time simplifying the feature space. This step is useful in time saving, avoiding overfitting of model of high topological complexity and model interpretability.

3.5. Ensemble Learning with Stacking

The core of the proposed methodology is the stacking ensemble learning model. Ensemble learning model is among the most effective ways of increasing a system's performance. To enhance the reliability of the model along with general performance of the predictions, multiple independent models are combined. Stacking combines multiple base classifiers to leverage their complementary strengths:

Base learners: The base classifiers such as k-NN, decision tree, and SVM are trained on the training dataset. These classifiers are selected because they have different learning approaches and thus, the combination of the classifiers' strengths is expected to be optimal.

Meta learner: Predictions from the base classifiers are then used as input features in a meta learner which is usually a logistic regression or any other classifier. The meta learner optimally combines the predictions of base learners to improve overall classification accuracy.

3.6. Model Evaluation

To assure the credibility of the hybrid stacking ensemble model and its effectiveness for the multi-class classification problem, various performance measures are used. These are accuracy, F1 score, recall or sensitivity, precision, specificity and the area under the curve of the ROC curve. These metrics enable a comprehensive assessment of the various aspects of classification of the proposed model.

Cross-validation establishes different validation by using partially visible and unseen data. k-fold cross validation process is one of the methods of the cross-validation. To ensures that each fold contains samples from all the classes in nearly equal ratio the data set is divided into k equal halves. In our exploration we employ the somewhat standard 10-fold cross-validation process in our analyses. Since every part of the dataset will be utilized in training at some point in the process, the method of doing the validation of the model used here is the k-fold cross validation. It ensures that the model is assessed based on some data that are not real and this provides a better real-life situation appraisal of the model.

The novelty of the proposed system is SSVEP classification method based on stacking ensemble technique. This framework combines multiple base classifiers to leverage their individual strengths and enhance overall predictive performance: This framework combines multiple base classifiers to leverage their individual strengths and enhance overall predictive performance. Among the classifiers used by the

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proposed system are k-NN, SVM, and Decision Trees. All the base learners are trained on the reduced feature set thereby giving different views of the data. Each of the base learners makes its prediction which is then passed to the meta learner that learns how to combine these outputs in order to come up with the final classification. Logistic Regression is used as the meta-learner because it offers great performances especially when used with binary and multiclass classification fields.

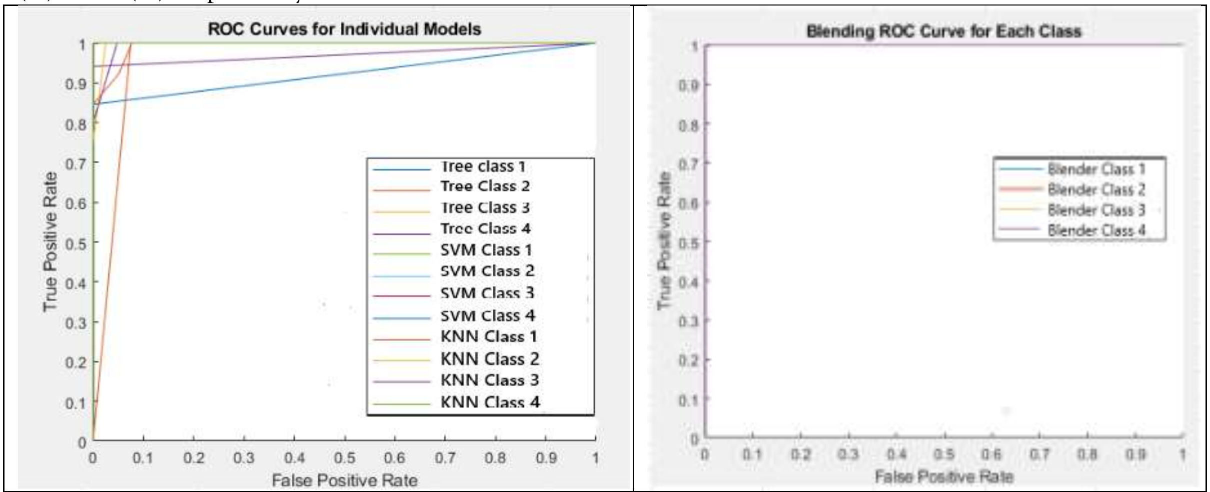
The stacking ensemble framework is a powerful method for enhancing model performance by combining predictions of multiple base classifiers through a meta-classifier. Below are the steps involved in constructing and utilizing a stacking ensemble:

Our proposed hybrid machine learning approach effectively combines advanced signal processing, data augmentation, feature extraction, dimensionality reduction, and stacking ensemble techniques to improve SSVEP signal classification. This innovative methodology offers significant improvements over traditional methods, providing a robust and accurate solution for BCI applications.

4. Results and Discussion

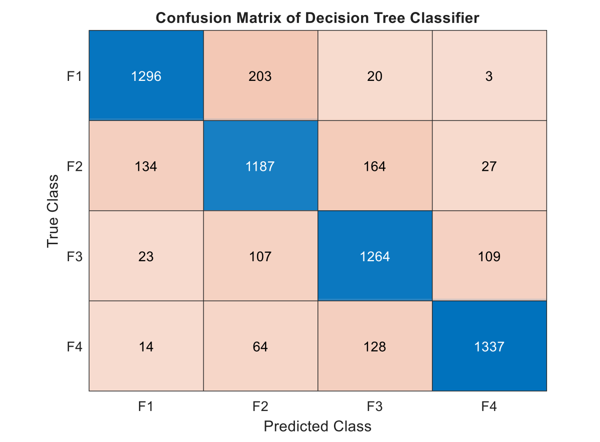
The stacking ensemble model, combined with comprehensive feature extraction and data preprocessing, provides a novel approach to EEG signal classification compared to traditional methods. A stacking ensemble model is used, where the outputs of the base learners are used as input features to train a meta-learner. This meta learner aims to learn the optimal combination of base model predictions to improve classification performance. The ROC curves of the individual models (Decision Tree, SVM and k-NN) and the Blender ROC curves were obtained as shown in the Fig.. 3:

In this work SSVEP signal with four frequency classification problem was undertaken, and it was found that when individual traditional machine learning algorithms like k-NN, SVM, decision tree and a meta learner were deployed, result are observed as confusion matrices are illustrated in Fig. 4 (A), 4(B), 4(C) and 4(D) respectively.

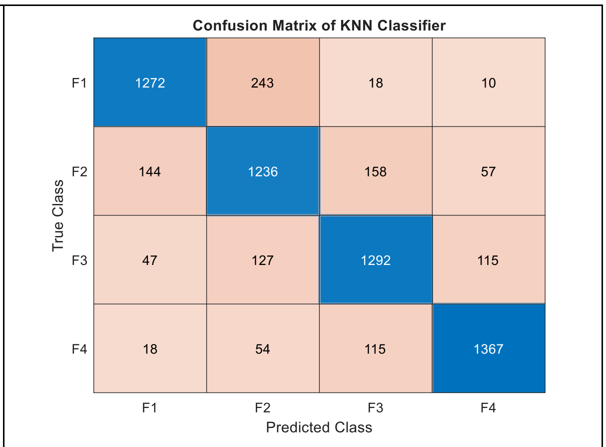


A. ROC Curve for Individual Models	**B.** ROC Curve for Meta Learner

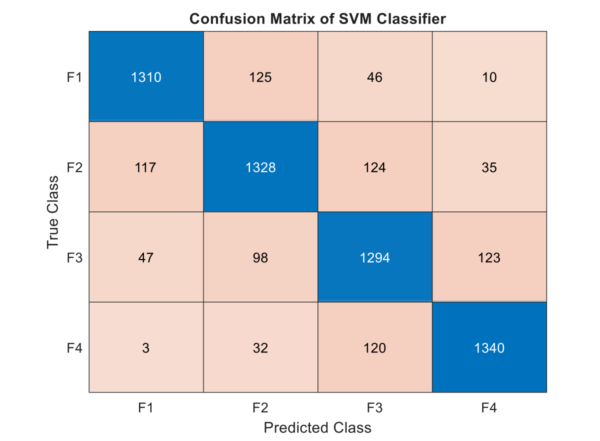
Fig. 3: ROC Curves for individual models and Meta learner (blenders) for all 4 classes



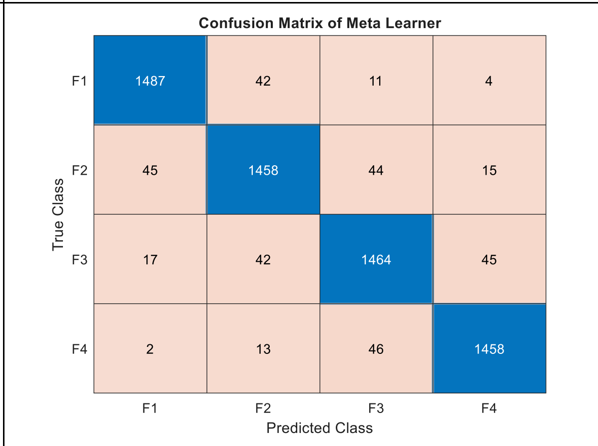
A. Confusion Matrix of Decision tree classifier



B. Confusion Matrix of K-NN classifier



C. Confusion Matrix of SVM classifier



D. Confusion Matrix of Meta Learner

Fig. 4: Confusion matrices

We obtained the above confusion matrices for various classifiers used as indicated in Fig. 5. Comparing performance metrics across different classifiers (decision tree, k-NN, SVM, and meta learner) based on several evaluation metrics such as accuracy, specificity, precision, recall, is illustrated in Table 1.

Table 1: Performance parameters of various Machine learning models

Metric	**Decision Tree**	**K-NN**	**SVM**	**Meta Learner**
Accuracy (Efficiency)	88.05%	86.63%	91.60%	97.13%
Specificity	89.86%	89.57%	91.90%	97.01%
Precision	90.63%	89.83%	91.80%	97.06%
Recall (Sensitivity)	86.46%	83.96%	91.29%	97.25%
F1 Score	0.88	0.87	0.92	0.97
Negative Predictive Value (NPV)	85.40%	83.57%	91.40%	97.20%
False Positive Rate (FPR)	10.14%	10.43%	8.10%	2.99%
False Discovery Rate (FDR)	9.37%	10.17%	8.20%	2.94%

Area Under the Curve (AUC)	0.96	0.95	0.99	1
Metric	Decision Tree	K-NN	SVM	Meta Learner
Accuracy (Efficiency)	88.05%	86.63%	91.60%	97.13%

The following observations were made in our work

- Meta learner has the overall best results with the highest accuracy of 97.13% and the highest F1 score of 0.97. It also has the lowest FPR (2.99%) and FDR (2.94%), which means that the classifiers distinguish between images with the target concept and those without it with higher accuracy.
- The second one is SVM which represents the high values of the accuracy of 91.60%, of specificity of 91.90%, of precision 91.80%, and of recall of 91.29%.
- Decision Tree and SVM outperform k-NN with lower recall of 83.96% and accuracy of 86.63%. Decision tree is similarly relatively accurate but slightly lower in specificity and recall as compared to SVM though has higher precision.

The results reveal that the meta learner model is the most accurate amongst the base classifiers of decision tree, k-NN, and SVM in all metrics used. Blending or stacking technique for the meta learner, this demonstrates the benefit of combining base classifiers like decision tree, k-NN, and SVM to leverage their individual strengths. The above obtained results can be illustrated as a spider plot as shown in the above fig. 5.

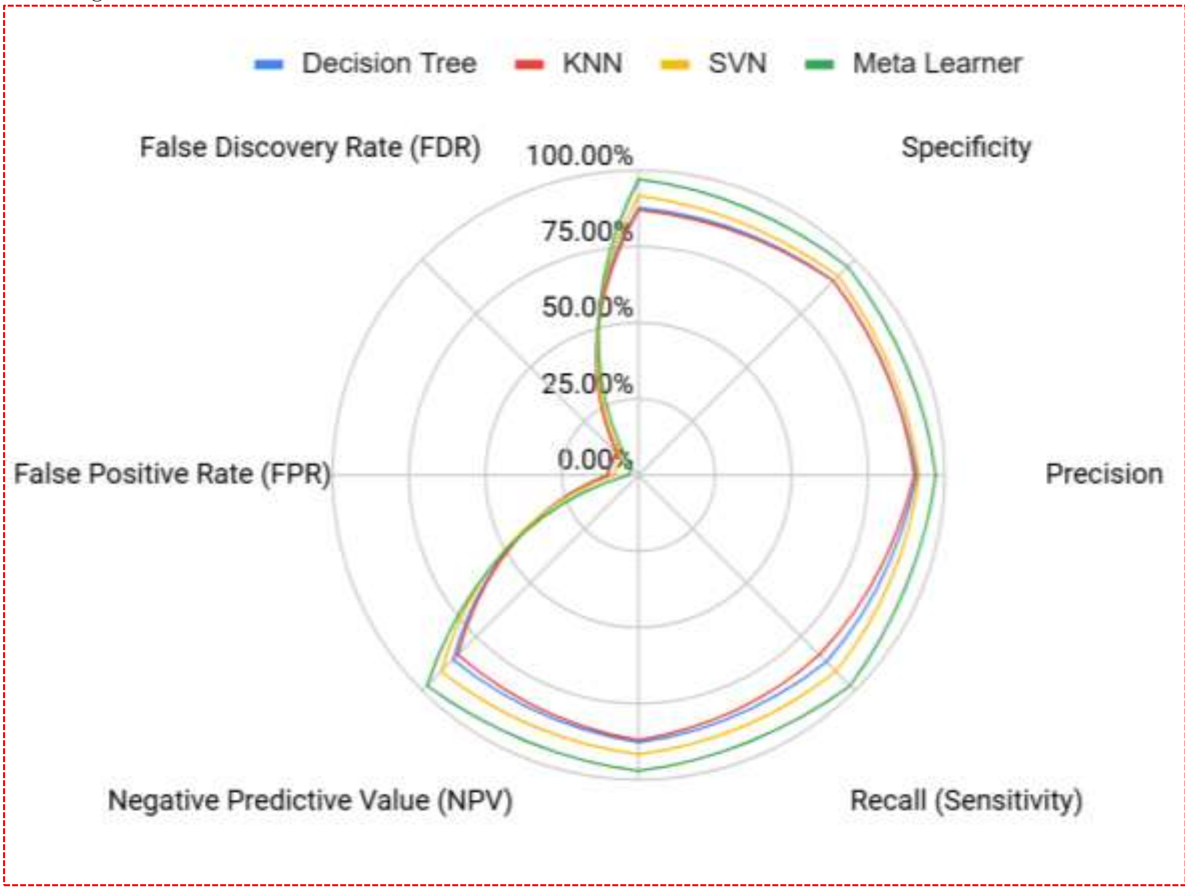


Fig 5: Spider plot of various metric for the classification

5. CONCLUSION

This study presents a robust machine learning framework for EEG signal classification using both time and frequency domain features, combined with data augmentation techniques like noise addition, time shifting, and amplitude scaling to enhance generalization. Dimensionality reduction via PCA preserved 95% of variance, reducing computational cost and improving model interpretability. A stacking ensemble of SVM, Decision Trees, and k-NN with error-correcting output codes achieved over 97% classification accuracy—an improvement of 13% over individual classifiers. Evaluation metrics, including accuracy, recall, specificity, precision, F1 score, AUC, and confusion matrix, confirmed the model's effectiveness. This framework demonstrates the superiority of ensemble learning for EEG signal classification and offers a solid foundation for future BCI research.

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Conflict of Interest
The authors declare no conflict of interest on this topic.

Author Contributions
- Srinivas Rao Gorre: Original draft, Formal analysis, conceptualization, data curation, methodology.
- Ravichander Janapati: Conceptualization, validation, and visualization, review and Supervision
- Ch.Rajendra Prasad: Review, Edit and Supervision

Ethics Approval
Not applicable.

Data availability
Not applicable.

Abbreviation
EEG - Electroencephalogram
BCI - Brain Computer Interface
SVM - Support Vector Machine
k-NN - k-Nearest Neighbor Algorithm
PCA - Principal Component Analysis
ROC - Receiver Operating Characteristic
CCA - Canonical Correlation Analysis
CNN - Convolutional Neural Network
RNN - Recurrent Neural Network
LSTM - Long Short-Term Memory
SSVEP - Steady State Visual Evoked Potential
FFT - Fast Fourier Transform
PSD - Power Spectral Density

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