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Identifying and Implementing a Machine Learning Model Suitable for Processing Visually Evoked Potential

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Abstract

A Brain-Computer Interface (BCI) is a system that translates brain activity patterns into computer commands, bypassing physical movement. Electroencephalography (EEG) is commonly used to acquire signals in BCI research. Visual evoked potentials (VEPs) are brain responses in the visual cortex to visual stimuli. Recent studies show that exposing individuals to flickering at a consistent frequency generates EEG signals synchronized with the stimulation. Efficient extraction of VEP signals begins with preprocessing raw EEG data. Various machine learning techniques—such as support vector machines (SVMs), recurrent neural networks (RNNs), and convolutional neural networks (CNNs)—are evaluated for their ability to classify VEP components like the P100 wave. Feature engineering methods tailored to VEP characteristics are explored to enhance model performance. This study emphasizes integrating machine learning with preprocessed EEG features from Steady State Visually Evoked Potential (SSVEP) signals flickering at specific frequencies. The dataset includes EEG data from experiments using repetitive visual stimuli with two distinct flicker frequencies. The goal is to identify and implement a suitable machine learning approach that improves the extraction of valuable information from VEP data, facilitating further research into these systems.

Keywords: *Brain Computer Interface (BCI) Electroencephalography (EEG), Steady State Visually Evoked Potential (SSVEP), visual stimuli.*

INTRODUCTION

The average electrical activity measured from different scalp regions, representing the total neural activity of the brain, is referred to as the electroencephalogram (EEG). When a subject is asked to focus on one of the repeating visual stimuli that cause the brain to naturally respond at specified frequencies, such as flickering lights or patterns, SSVEP-based EEG recordings are obtained. The EEG amplifier captures the electrical activity produced by the brain during this period [2]. Signal processing can be used to extract different properties, such as mean, variance, and standard deviation, and show the data in a variety of domains, such as the frequency domain and time domain. Processing data using machine learning models in neurology and ophthalmology, Visually Evoked Potentials (VEPs) is a revolutionary method that provides automatic, accurate, and rapid insights into neurological disorders and visual function. Researchers and medical professionals can discover new avenues for the diagnosis and treatment of visual diseases by utilizing sophisticated algorithms and computational methodologies [3, 4]. This will ultimately improve patient outcomes and deepen

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our understanding of how the brain functions. When a person's peripheral nervous system or musculoskeletal system is damaged, but their central nervous system is unharmed, making them unable to communicate, brain-computer interfaces (BCIs) can be extremely helpful. In this scenario, a brain-computer interface (BCI) can get around the impaired pathways to enable the individual to effectively communicate or engage with their environment. BCIs provide individuals suffering from neurological conditions like paralysis, ALS, or stroke new options for neurorehabilitation [8–10].

Different classification techniques are employed to control the model's accuracy and information transfer rate (ITR), including support vector machines, logistic regression, and linear discriminant analysis (LDA). A functional model of an SSVEP-based BCI is shown below in Figure 1.

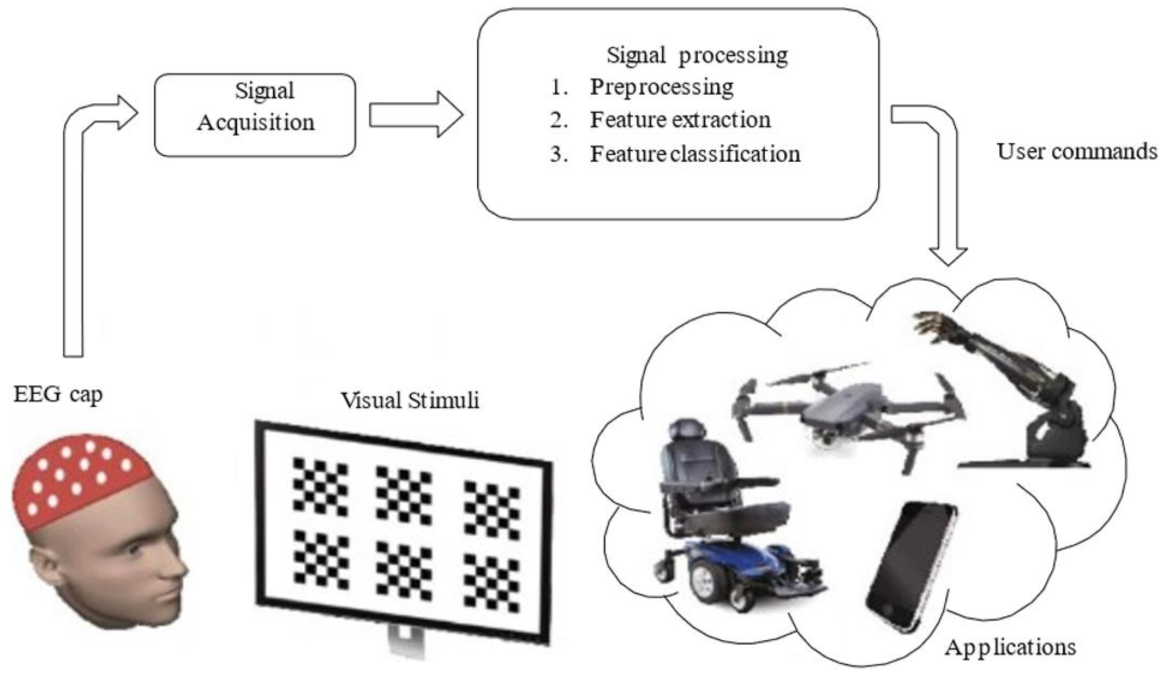

Figure 1. Functional model of an SSVEP-based BCI.

OBJECTIVES

The goal of this study is to further our knowledge of how machine learning methods might improve EEG signal classification, which is important for applications in cognitive neuroscience, neurology, and brain-computer interfaces. This work aims to improve diagnostic accuracy and clinical results in neuroscience research by optimizing EEG signal analysis techniques through the evaluation of different models across a variety of datasets and frequency bands. Block diagram of system is shown in Figure 2.

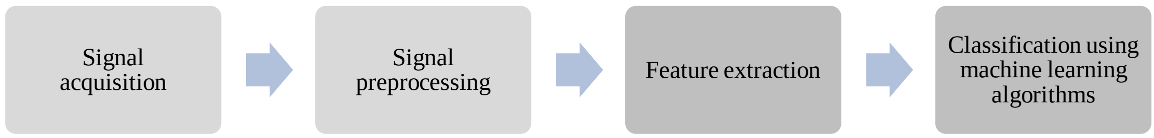

Figure 2. Block Diagram of the proposed systems.

SYSTEM DESIGN

Signal Acquisition

Specialized EEG equipment is used to gather SSVEP-based EEG signals. Before receiving the signal, several requirements must be fulfilled. These include a quiet environment, the absence of any other visual interference in front of the subject, and little to no bodily movement allowed. Intrusive and non-invasive approaches are the two categories of signal acquisition techniques. However, utilizing a non-invasive approach is far more accessible and practical as no surgical means are involved, and the electrodes are placed on the scalp to measure the electrical activities of the brain. Invasive methods involve placing the electrodes directly onto or inside the brain tissue for which the surgical approach is used. Brain with lobes Identification is shown below in Figure 3.

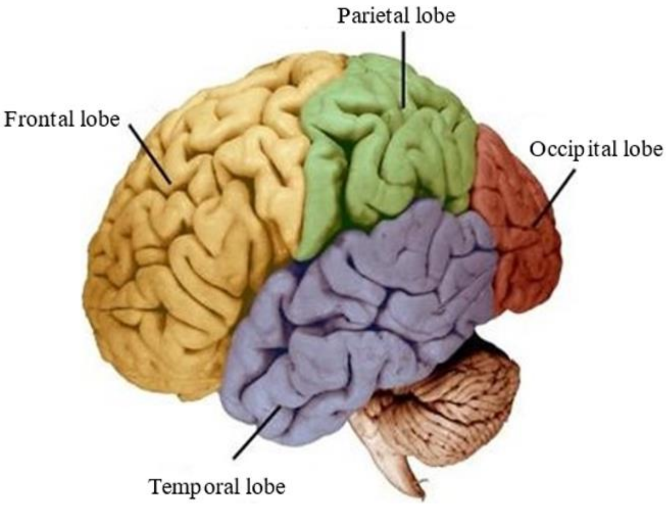

Figure 3. Brain with lobes Identification [1].

The brain's SSVEP-based response is observed to peak in the vicinity of the parietal and occipital lobes. As a result, the electrodes used to record EEG signals are positioned close to the parietal and occipital lobes [5].

In our research, we place five electrodes on PO_3, POz, PO_4, O_1, and O_2 respectively, three on the Parietal lobe and two on the occipital lobe of the brain is shown in Figure 4. A saline conductive gel is used to improve the electrical conductivity between the electrodes and the scalp by reducing impedance and giving a stable signal.

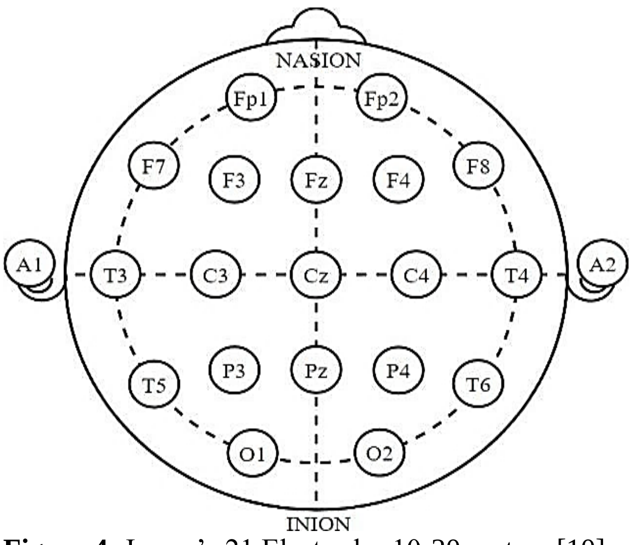

Figure 4. Jasper's 21 Electrodes 10-20 system [10].

The most common frequencies used in SSVEP-based experiments are between 5-30 Hz. Frequencies in the alpha (8-12) and beta (12-30) are usually preferred due to signal-to- noise ratio and minimal interference is depicted in Table 1.

Table 1. Frequency bands.

Frequency Band	Range of frequency in Hz
Delta	0-4
Theta	4-8
Alpha	8-12
Beta	12-30
Gamma	>30

In this study, we implanted five electrodes, three on the parietal lobe and two on the occipital lobe of the brain, on PO_3, POz, PO_4, O_1, and O_2, respectively. By lowering impedance and providing a steady signal, a saline conductive gel is utilized to increase the electrical conductivity between the electrodes and the scalp. The checkered board used for visual stimulation at 8.57, 10, 12 and 15Hz is shown below in Figure 5.

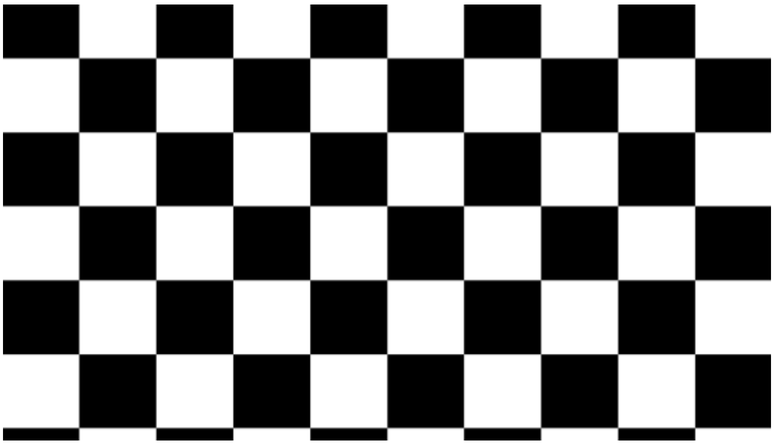

Figure 5. Checkered board used for visual stimulation at 8.57, 10, 12 and 15Hz

Signal Preprocessing

Subsequently, the obtained data graph is transformed into a "CSV" or "excel" file, allowing the data to be organized into rows and columns for additional signal processing. The data can be imported further using MATLAB program. Bad channels that do not offer reliable information or whose data has been affected by outside causes must be eliminated before importing the data. Any muscle or eye blinking artifacts that could tamper with the real SSVEP data are eliminated.

Filtering is a procedure that is used to improve the quality of the raw data and extract relevant information. Different types of filters, such as

1. Bandpass filters are used to extract only the necessary signals. These bandpass filters remove certain frequency ranges that are associated with EEG activity.
2. Low-pass filters: These filters allow signals below a certain frequency threshold to pass while attenuating higher frequency signals.
3. High-pass filters: Contrary to Low-pass filters these filters enable the transmission of signals that surpass a specific frequency threshold while attenuating lower- frequency signals.
4. Notch filters: Notch filters target specific frequencies to attenuate.

This preprocessed data can be plotted in the Time domain as shown below in Figure 6.

The Fast Fourier Transform (FFT), a popular digital signal processing (DSP) technique used to convert signals from one domain to another, such as from the time domain to the frequency domain and vice versa, can be used to convert time domain data into the frequency domain. Two important techniques—the Discrete Fourier Transform (DFT) and its inverse counterpart—are used to accomplish this transformation. The data can be accurately shown in the frequency domain, displaying signal peaks at the proper frequencies that were utilized to elicit the subject's SSVEP response as shown in Figure 7.

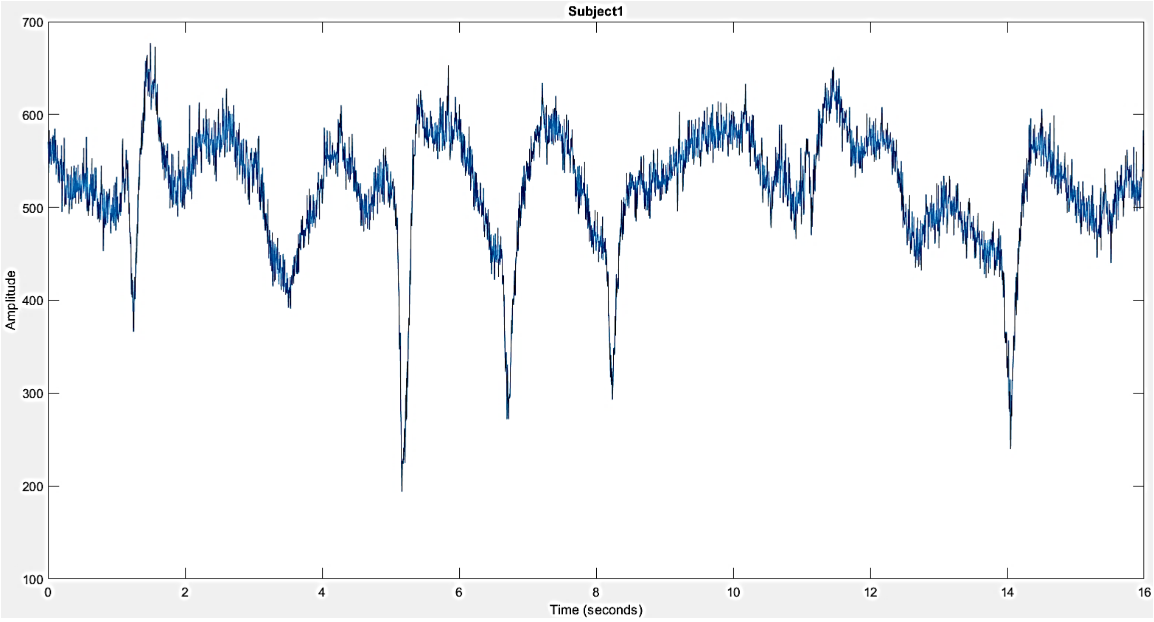

Figure 6. Raw EEG signal data displayed in the time domain.

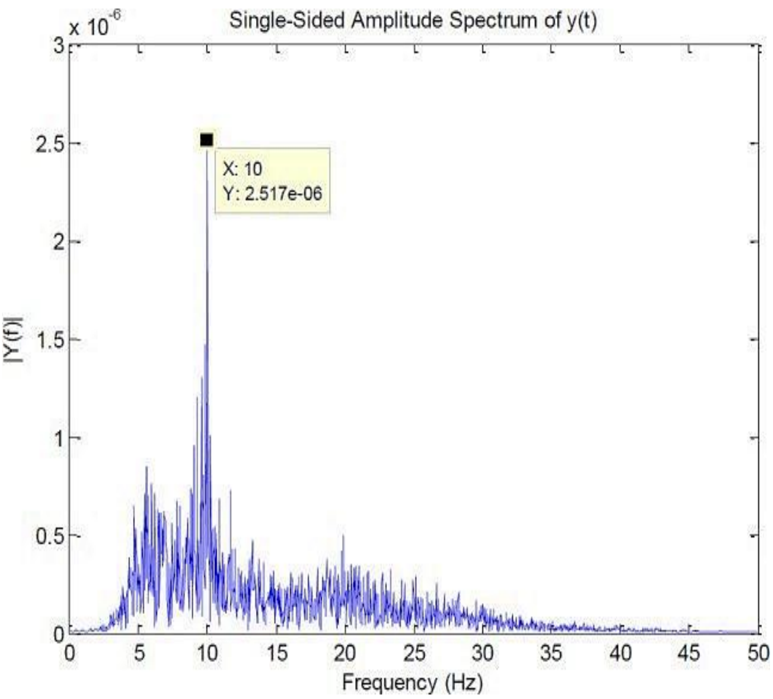

Figure 7. Frequency domain diagram of SSVEP response in stimuli frequency 10Hz [11].

Other types of filtering mechanisms are also used to reduce the noise and interference of the signal.

Feature Extraction

From the preprocessed EEG data, characteristics from various domains are retrieved. These features will aid in our understanding of the signals and in our ability to distinguish between various frequency-stimulated signals. Additionally, characteristics can differ between electrodes; that is, signals produced by placing one electrode on the occipital region of the brain and the other on the parietal side will have distinct characteristics.

We are interested in the following statistical time domain features: mean, variance, and standard deviation. Additional variables such as skewness and kurtosis are employed for the analysis and classification of these signals.

Power spectral density (PSD) is a key technique for feature extraction in frequency domain analysis. The periodogram approach is used in this work to determine the power spectral density. FFT is useful for more than only retrieving EEG subbands, though; it can also be used to extract statistical parameters like spectral energy and spectral centroid.

For the classifier learner to distinguish between these EEG signals that are obtained via different SSVEP based frequency stimulation to the subject, a features matrix is then created in which all the features are arranged so that they can be differentiated based on the frequency with which the subject was stimulated. Following the development of the feature matrix, the data is labeled based on how frequently the corresponding visual stimulus occurs. For instance, label each trial appropriately if the stimulus frequency is 10 Hz, 12 Hz, or 15 Hz [6].

Classification Using Machine Learning Algorithm

The training and testing subsets of the dataset are made up of feature matrices and the labels that go with them. The testing subset is used to evaluate the classifier's performance, and the training subset aids in the training process.

Several machine-learning methods are used to classify signals. Random Forests, k-NN, and Support Vector Machines (SVM) are often employed algorithms for EEG categorization. We can also employ several SVM kinds, like:

a. Cubic SVM
b. Fine Gaussian SVM
c. Linear SVM
d. Quadratic SVM

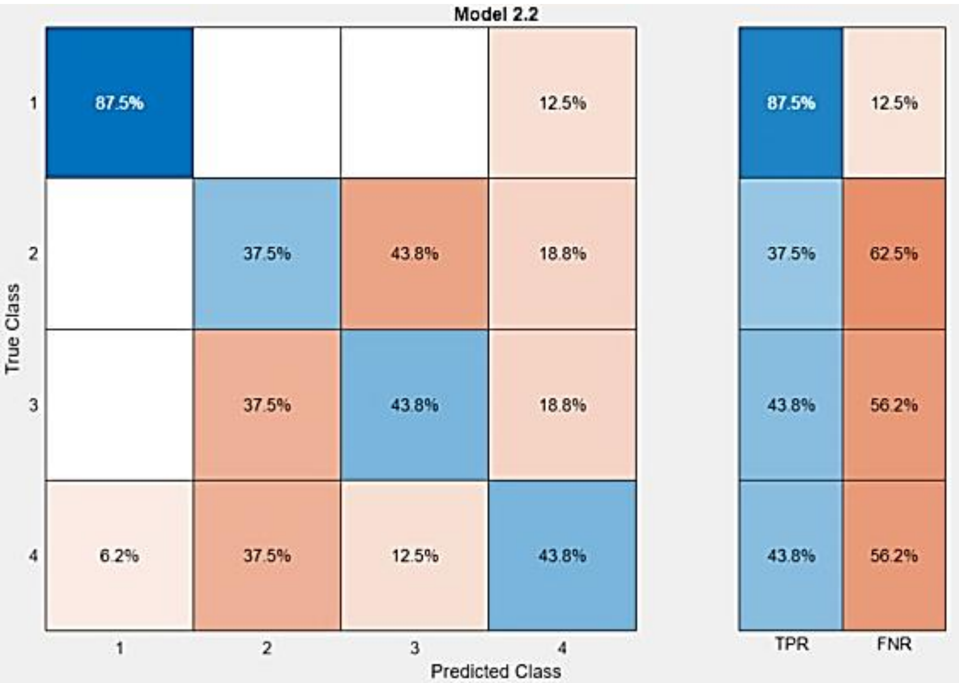

Figure 8. Confusion matrix for a training dataset using SVM.

The chosen training dataset will be used to train the classifier, which is where the previously stated algorithm learns to translate feature vectors to matching labels.

The classifier analyzes the data based on characteristics, considering several evaluation criteria such as accuracy and information transfer rate (ITR). where the classifier uses the extracted features and feature matrix to determine how well the algorithm can distinguish between signals that are recorded using various frequencies. To further analyze the classification results, the classifier learner gives us a scatter plot and confusion matrix is shown in Figure 8.

By modifying the kernel size and SVM regularization settings, we can further optimize the classifier's hyperparameters. We can export the trained classifier for additional use once the classification process is finished and the desired outcomes are obtained.

Future Scope

There are many fascinating directions that the fields of neuroscience and machine learning could take in the future when it comes to studying Visually Evoked Potentials (VEPs). This study focuses on the Brain-Computer Interface (BCI) use of SSVEP-based EEG signals, which presents several automations and medical prospects and lays the groundwork for several intriguing avenues for future research and development [7].

The prospective applications of SSVEP-based EEG signals for BCI are described in the following future scope:

Medical applications

People with severe motor limitations, like those with locked-in syndrome or advanced ALS, can communicate thanks to BCIs based on SSVEP. Users can produce distinct neural responses in their brains that can be interpreted as orders or messages by concentrating their attention on various visual stimuli. In addition, these systems can be utilized to operate a variety of assistive technology, including robotic arms, wheelchairs, and smart home appliances. Because of this, disabled people can become more independent by managing their surroundings and completing things that would be difficult or impossible for them otherwise [8, 9].

1. *Entertainment and gaming industry:* An SSVEP-based BCI system can improve the user experience by giving users a more engaging and dynamic interface.
2. *Personalized BCI systems:* In the future, BCI systems might incorporate adaptive learning techniques to adjust to each user's unique brain signal. These approaches might continuously gather user feedback and modify to provide a more customized experience.

CONCLUSION

We introduce this type of visual stimuli using a checkered board that flickers with alternating light and dark squares, to which the brain naturally produces a response known as the Visually Evoked Potential (VEP) at specific frequencies. In this paper, we deal with visually stimulating the user and then acquiring EEG signal from the user using various frequencies from alpha and beta frequency bands.

Following preprocessing, significant temporal and frequency domain features are retrieved from the collected signal. A feature matrix is created and assigned labels based on various frequencies. Our primary focus has been on the integration of electroencephalography (EEG) with contemporary machine learning techniques. By employing contemporary classification methods, we were able to uncover new information and ascertain the precision with which the system distinguishes between signals of various frequencies. These BCI systems, which are based on SSVEP, can be combined and applied in a variety of fields, including medicine.

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