# Classification of Visual Perception EEG signals for a 2D platformer game


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***Abstract*—This research focuses on classifying visual perception brain signals using an OpenBCI headset to capture the EEG signals from the participants. The headset comprises 16 re-configurable dry channels, which poses two challenges: the amount of data and high noise levels. The primary objective is to classify the intent of player movements in a 2D platformer game with a convolutional neural network. Since every player has a distinct EEG footprint for similar intents, we explore the process of training a global model suitable for many players. During the experimental setup, participants were instructed to navigate the player character within the game by solely relying on visual perception, simulating a realistic gaming environment.**

**By leveraging existing EEG models such as EEGNet and ShallowConvNet, along with a newly designed 1D CNN model (Conv1D), the research compares the accuracy of these models on individual participant datasets and pooled datasets. The results reveal that the Conv1D model outperforms the other models, achieving high accuracy (100%) for all individual participants. Moreover, when the models are trained on pooled data, the Conv1D model retains its high accuracy, while the accuracy of the other models significantly decreases. However, when the model was tested on datasets from participants not included in the training phase, suboptimal results were observed, with a maximum accuracy of 41%.**



***Index Terms*—EEG, OpenBCI, CNN, EEGNet, visual perception**


## I. INTRODUCTION

The Brain-Computer Interface (BCI) represents a system designed for the acquisition of brain electroencephalography (EEG) signals, enabling the transmission of such signals to external domains. BCI systems are classified into two categories based on sensor placement: invasive and non-invasive [1], [2]. Invasive BCI systems involve the positioning of electrodes within the skull, whereas non-invasive systems place the electrodes on the scalp to acquire brain signals. Non-invasive BCI systems, while not requiring surgery, may exhibit higher levels of data noise compared to invasive systems. EEG signals captured through a BCI device can be used in several different tasks such as; motor imagery (MI) [3], motor execution (ME) [4], visual imagery (VI) [5], [6] and visual perception (VP) [7]–[10]. BCIs have been the subject of prior investigation within the domain of gaming, employing MI [11], ME [4] and VI [12]. However, the utilization of Visual Perception (VP) for game navigation remains insufficiently studied. VP refers to the process by which the human brain interprets the visual information received from the eyes. Typically, the classification of VP involves presenting participants with images depicting distinct objects, wherein each object is visually represented by a unique picture [7], [8].

This study adopts a solitary image to classify four discrete motion categories. Specifically, he research objective is to categorize VP EEG signals employing a non-invasive OpenBCI headset, which provides a cost-effective, easily accessible, and user-friendly platform for EEG signal acquisition. The objective is to leverage the capabilities of convolutional neural networks (CNNs) to create a robust classification model capable of accurately identifying the intent of player movements (left, right, jump, idle) within a 2D platformer game, as presented in the work by Blašković et al. [13]. While CNNs are commonly utilized for image classification tasks [14]–[16], they have also shown promising results in the domain of EEG-based tasks [17]–[20]. Moreover, this study incorporates an assessment of the model's performance concerning its generalizability and suitability for participants beyond those included the training phase.

## II. RELATED WORK

Several studies have explored classifying visual perception EEG signals using different methodologies and experimental setups. Lee et al. [7] conducted a study using wet electrodes with 32 channels to classify visual perception images. Their experiment involved nine classes from three different categories. The authors achieved a mean accuracy of 24% for the visual perception task. While the accuracy may appear relatively low, this study provides valuable insights into the challenges of classifying visual perception using EEG signals. Bang et al. [8] conducted experiments to classify visual perception using six different shapes. The study involved four participants and obtained an impressive accuracy of 90%. Zhang et al. [9] explored the classification of EEG signals for four objects using data from eight participants, achieving a classification accuracy of 75%. In a different approach, Llorella et al. [10] utilized a black hole algorithm to search for optimal neural network structures for visual perception and visual imagery classification. The study involved classifying 12 objects using EEG signals from 38 participants, obtained from the publicly available database [21]. By optimizing the neural network architecture, the authors aimed to improve the accuracy of visual perception classification, ultimately attaining an accuracy in the vicinity of 30%.

In a more related research study, Glavas et al. [12] undertook the development of a BCI-controlled game named *Zombie Jumper*. The game was designed to operate through two distinct commands: one for the forward movement and the other for jumping. Specifically, the jumping command required subjects to engage in intentional hard blinks, while the forward movement command necessitated subjects to direct their focus forward and envision themselves moving in that direction. A 4-electrode Muse 2 headband[1] was used to collect raw EEG data from a cohort of 37 participants. Employing a multi-layer perceptron (MLP) model, the aggregated EEG recordings from all participants were subjected to training, yielding an average classification accuracy of 98.74% per participant. Malete et al. [4] developed machine learning models for a 3D game involving forward and backward actions. The study utilized a 14-channel Emotiv Epoc+ device to record EEG data while participants walked in both directions for approximately three minutes. The authors achieved an accuracy of 88% for individual models using Decision Trees.

Previous studies in the field have primarily employed clear images of objects for classification purposes. In contrast, our study adopts a distinct approach by utilizing a noisy image derived from a 2D platformer game. During the experimental setup, participants were instructed to navigate the player character within the game by solely relying on the visual perception of the provided image, simulating a realistic gaming environment. This departure from the conventional use of clear images introduces additional complexity to the classification task. Additionally, in contrast to previous studies where distinct images were employed for individual classification tasks, this study utilizes the same image to classify four different classes, thereby introducing an additional level of complexity to the classification task.

## III. Materials and Methods

**Dataset.** The OpenBCI Neurotechnologist's starter kit[2] headset device and the OpenBCI GUI[3] streaming app were used in this study capture EEG data. The headset is comprised of 16 re-configurable dry sensors/channels, which were utilized to capture the EEG signals from the participants. All 16 channels operate at a frequencies of up to 120Hz; however, for this study, frequencies beyond 60Hz were disregarded as they did not yield any measurable values in the recorded data. Consequently, each data instance comprises 60 values for each of the 16 channels, leading to an array of shape (16, 60). The OpenBCI GUI app captures multiple data instances per second, and the number of captured instances is dependent on the computer's performance, denoted as frames per second (FPS). In this study, instances were captured at a rate of 90 FPS, which resulted in 5400 instances (for one minute recordings) for each action recorded by an individual. Additionally, the Fast Fourier (FFT) [22] option was chosen within the OpenBCI GUI app to transform a signal from the time domain to the frequency domain.

A total of 8 (7 male, 1 female) subjects participated in our experiments (age: mean $\pm$ sd $= 24.8 \pm 1.4$). Each participant in the study was presented with a consistent image (shown in Figure 1) representing the visual context for all four different actions: moving *left*, moving *right*, performing a *jump*, and taking *no action*. Participants were explicitly instructed to interpret and respond to the visual stimulus according to the specified action for each trial. For the actions involving movement (left, right, and jump), participants were free to execute the desired action in any manner they deemed appropriate. For the *no action* condition, participants were instructed to explore various elements within the game, such as ammunition, health, and currency. Each action was recorded separately, and the recording sessions for each action lasted for a duration of one minute. Consequently, each participant contributed four minutes of EEG signal data to the study. Before each recording session, participants had five seconds to focus on the image.

The dataset for each participant was divided into training, validation, and test sets using a split ratio of 60%-20%-20%, respectively. The training set was used to train the machine learning model, while the validation set was utilized to monitor the model's performance and prevent overfitting. The test set was used as an independent dataset to evaluate the model's final performance.

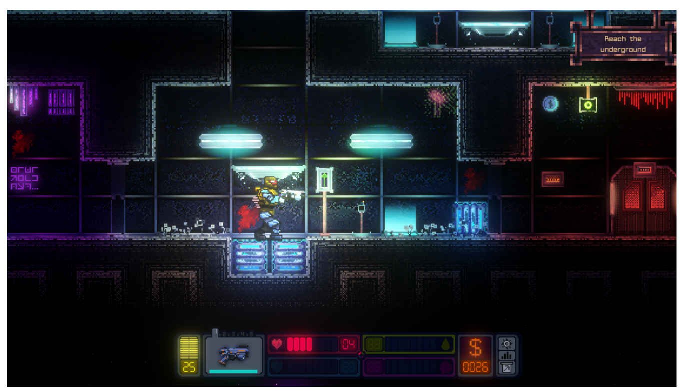

Fig. 1. Game screenshot used during the recording of EEG signals.

**Models.** 2D convolutional layers are commonly used when designing EEG models [23], [24]. The input shape of the 2D CNN model is structured with three dimensions, typically organized in the format $(channels, samples, 1)$, where $channels$ represents the number of EEG signal channels, while $samples$ denotes the number of readings or frequencies obtained from each channel. The last dimension is empty and is only present since 2D CNN model expects a three-dimensional input. When CNNs are applied to image data, the last dimension of the input tensor commonly represents

[1]https://choosemuse.com/muse-2
[2]https://openbci.com/
[3]https://github.com/OpenBCI/OpenBCI_GUI

the channels associated with different color components, such as red, green, and blue (RGB).

In work by Lee et al. [7], they introduced a 1D CNN model for the classification of visual perception and visual imagery EEG signals. Unfortunately, the lack of detailed architecture specifications in their publication hindered our ability to replicate their model precisely. Despite this limitation, we adopted a similar approach inspired by their work and devised a simplified 1D CNN model. Our model design encompassed a single 1D convolutional layer comprising 16 filters, with a kernel size of 3 and the Rectified Linear Unit (ReLU) activation function. Subsequently, a max pooling layer was incorporated, utilizing a kernel size of 3. The output from the max pooling layer is then flattened, preparing it for the subsequent fully connected layer. The fully connected layer is incorporated with the softmax activation function, facilitating the classification of the four distinct classes on our specific task (see Table I). To assess the performance of our proposed model, we conducted a comparative analysis with several well-known EEG models, namely EEGNet [23] and ShallowConvNet [24]. While ShallowConvNet authors introduced DeepConvNet, experimentation with the DeepConvNet model was not feasible in this study due to its lack of explicit adaptation for devices with a limited number of channels, such as the 16-channel device employed in this study. The limitation arise from the dimension reduction caused by the convolutional and pooling layers, resulting in negative dimensions.

The Adam optimizer [25] was employed with a learning rate of 0.001 to optimize all models utilized in the experiments. A batch size of 64 was utilized for training. To prevent overfitting, the early stopping technique [26] was applied with a maximum number of epochs set to 100. Specifically, if the model failed to exhibit improvements in validation performance over four consecutive epochs, the training process was terminated, and the weights corresponding to the best validation performance were reinstated. This approach ensured that the models were trained effectively while mitigating the risk of overfitting to the training data.

To ensure the reliability of the results and account for any potential variability, all experiments were conducted three times and only the average values of the obtained results were reported.

| Layer | Parameters |
|---|---|
| Conv1D | $filters = 16, kernel\_size = 3,$ $activation = relu, input\_shape = (60, 16)$ |
| MaxPooling1D | $kernel\_size = 3$ |
| Flatten | |
| Dense | $units = 4, activation = softmax$ |

TABLE I
MODEL ARCHITECTURES USED IN THE STUDY.

## IV. EXPERIMENTS AND RESULTS

The evaluation of the introduced 1D CNN model involved two distinct experiments. The initial experiment focused on comparing the model's performance against a well-known EEG model, while the second experiment delved into exploring the model's knowledge transferability and its ability to generalize across participants.

### A. Model comparison

A comparative analysis between the EEGNet, ShallowConvNet and the introduced 1D CNN (Conv1D) model is conducted in this experiment. Each model was individually trained and evaluated using participant-specific datasets to assess their ability to capture individual differences and specific characteristics in EEG signals. Additionally, a combined dataset that integrated data from all participants was used to train the models, enabling an investigation into their performance in capturing overarching patterns and trends across the entire participant pool.

The results of the experiment are presented in Table II. The EEGNet and ShallowConvNet models demonstrated a high classification accuracy for all individual participants, with the exception of participant P_5, for whom the accuracy was noticeably lower. The high classification accuracy achieved by EEGNet and ShallowConvNet models indicates their effectiveness in capturing the distinctive features and patterns within the visual perception EEG signals for the majority of participants. However, the relatively lower accuracy observed for participant P_5 suggests that there may be individual variations in the EEG signals that pose challenges for these models in accurately classifying their intentions. In contrast to the EEGNet and ShallowConvNet models, the Conv1D model exhibited high classification accuracy for all individual participants.

When the models were trained on pooled data, the EEGNet and ShallowConvNet models exhibited substantially lower accuracy compared to the Conv1D model. The EEGNet model achieved an accuracy of 29%, while the ShallowConvNet model achieved an accuracy of 64%. In contrast, the Conv1D model demonstrated a significantly higher accuracy of 96%. The results suggests that the Conv1D model was able to effectively learn and extract the shared patterns and features across participants, enabling it to achieve a high level of accuracy. However, it is important to note that the generalizability of the model's performance to a significantly larger number of participants remains uncertain.

| Dataset | EEGNet | ShallowConvNet | Conv1D |
|---|---|---|---|
| P_1 | 100% | 99% | 100% |
| P_2 | 100% | 100% | 100% |
| P_3 | 97% | 98% | **100%** |
| P_4 | 99% | 100% | 100% |
| P_5 | 35% | 46% | **100%** |
| P_6 | 99% | 99% | **100%** |
| P_7 | 99% | 100% | 100% |
| P_8 | 99% | 100 | 100% |
| P_All | 29% | 64% | **96%** |

TABLE II
TEST ACCURACY FOR EEGNET, SHALLOWCONVNET AND THE CONV1D MODEL. THE MODELS WERE TRAINED AND EVALUATED ON EACH PARTICIPANT'S DATASET SPEARATELY (P_1 - P_8), AND ALL PARTICIPANT DATASETS COMBINED (P_ALL).

### B. Knowledge transferability between participants

The objective of this experiment is to investigate the transferability of the trained model from one participant's dataset to another participant, and to assess the extent to which the model can be applied across different individuals. In addition, the examination of the model's performance is extended to training with pooled data. This evaluation is conducted in three distinct ways to provide a comprehensive analysis:

- the model's performance is assessed for individual participants when it is trained on the combined dataset comprising EEG signals from all participants (noted as *P_All*),
- the model's performance for individual participants is measured after training it on the combined dataset excluding the participant for whom the evaluation is being conducted (noted as *P_All_Other*),
- assessment of the model's generalizability that involved training it on each individual separately and subsequently evaluating its performance on all other participants individually.

The confusion matrix depicted in Figure 2 provides a visual representation of the results obtained from various participant combinations in our evaluation. The figure is structured in a way that the x-axis corresponds to the participant's data used for training the model, while the y-axis represents the participant's data used for evaluating the model's performance. Test data used to evaluated the model was never used in the training split. Note that the cells displaying (-) values indicate combinations that were not executed due to data availability limitations. For example, if the model is trained on the pooled data of all participants (*P_All*), there will be no separate participant dataset (*P_All_Other*) that is distinct from P_All. As a result, it is not feasible to evaluate the model's performance on such combinations, leading to (-) values in those specific cells of the confusion matrix. Subsequent paragraphs provide a comprehensive analysis of the results, focusing on specific combinations of participants.

When the model was trained and tested using the combined dataset of all participants (*P_All, P_All*), a high average test accuracy of 99% was achieved. The obtained result demonstrates the exceptional performance of the model when trained and tested on a pooled dataset. Despite combining the data from multiple participants, the model exhibited strong generalization capabilities and maintained high accuracy levels.

The model's performance was also favorable when trained on the combined dataset of all participants (*P_All*) and evaluated on the individual test datasets of each participant. The average test accuracy values exhibited variation among participants, ranging from approximately 83% to 99%. Notably, the participant combination (*P_All, P_5*) demonstrated an average test accuracy of 83%, which involved a female participant. The observed lower test accuracy in this particular combination could potentially be attributed to the gender disparity within the dataset. To obtain a more comprehensive analysis,

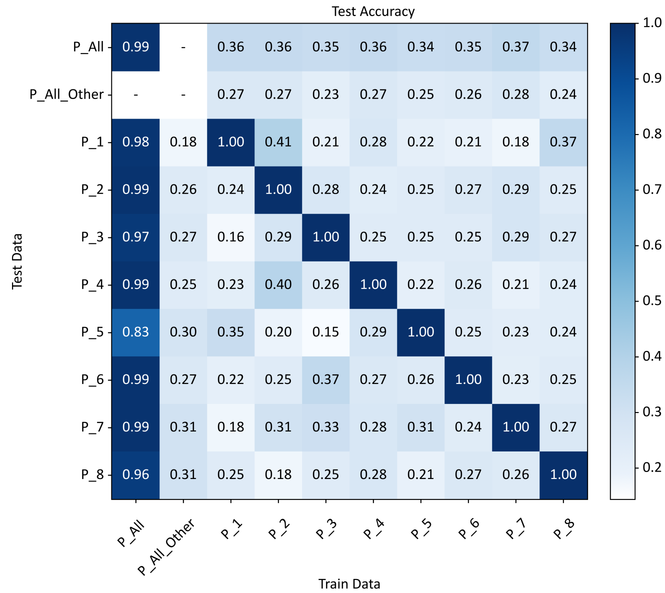


Fig. 2. Confusion matrix of test accuracies for various train-test dataset splits. P_1 - P_8 denotes each participants dataset, P_All denotes a pooled dataset, and P_All_Other denotes a dataset with a certain participant excluded from the training data.

further investigation and consideration of diverse participant demographics would be valuable.

The average test accuracy ranged from 34% to 37% when the model was trained on each individual participant (*P_1 - P_8*) separately and subsequently evaluated on the combined test dataset (*P_All*). The lower test accuracy suggests the presence of inter-individual variations within the EEG data, which hinder the model's ability to perform consistently well for all other participants.

The model's performance was notably poorer when trained on a dataset consisting of all participants except one (*P_All_Other*), with the excluded participant's data serving as the test dataset for evaluation. The average test accuracy for individual participants in this experiment ranged from 18% to 31%. These results indicate that the model would likely exhibit subpar performance when faced with data from new participants who were not included in the training process.

When training the model on data from each individual participant (*P_1 - P_8*), while evaluating it on a test dataset comprised of all other participants (*P_All_Other*), the accuracy slightly improved compared to the previous experiment. However, the average accuracy still ranged from 23% to 28%. These results indicate that individually trained models do not generalize well to other participants. The test accuracy values observed in both cases indicate a consistent level of accuracy in differentiating between the excluded participant's data and the data of the remaining participants and vice versa.

Finally, we examined the performance of the model when it was trained on the dataset of each individual participant (*P_1 - P_8*) and evaluated on the datasets of other participants separately. This analysis aimed to assess the model's ability to generalize from one participant's data to another participant's data. The test accuracy values varied across the different participant combinations, ranging from approximately 15% to 41%.

Notably, when comparing twin brothers, the test accuracy for the second brother (*P_2*) was 41% when the data from the first brother (*P_1*) was used to train the model. In contrast, when the training was reversed and the model was trained on the second brother's data (*P_2*) and evaluated on the first brother's data (*P_1*), the accuracy dropped to 24%. This discrepancy suggests that the model's performance is influenced by individual variations even within genetically similar individuals.

## V. Conclusion

In this study, the effectiveness of a 1D CNN model (Conv1D) for classifying the movement intentions in a 2D platformer game using EEG data was investigated. A comparison was conducted with well-known EEG models, EEGNet and ShallowConvNet, and their performance was evaluated on both individual participants and pooled data. The Conv1D model demonstrated superior accuracy across all individual participants, surpassing the performance of both EEGNet and ShallowConvNet models. Furthermore, even when the models were trained on pooled data, the Conv1D model maintained its high accuracy, while the accuracy of EEGNet and ShallowConvNet models experienced significant accuracy reduction. The Conv1D model demonstrated excellent performance when trained and evaluated on each individual participant's dataset, achieving an accuracy of 100%. However, when the model was evaluated on participants' datasets that were not included during the training phase, suboptimal results were observed. The accuracy decreased significantly in these scenarios (41% maximum), indicating that the model did not generalize well to unseen participants.

Future research should involve a larger and more diverse participant population to assess the model's performance in capturing shared patterns across a broader range of individuals. Moreover, alternative research directions could explore the utilization of preexisting pretrained models and personalization (fine-tuning) techniques to reduce data requirements while achieving high accuracy outcomes for new participants.

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