Refining Human-Data Interaction: Advanced Techniques for EEGEyeNet Dataset Precision

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Abstract. The EEGEyeNet dataset merges EEG data with eye-tracking technology to advance cognitive research at the intersection of brain dynamics and eye movement. By developing machine learning models to predict eye movements from EEG data, we gain insights into perceptual, attentional, and cognitive processes. However, dataset outliers can compromise model integrity and accuracy. This paper explores the impact of outliers on the state-of-the-art model and highlights the benefits of outlier removal. After identifying and removing outliers, we refined the dataset for better model training and accuracy. Integrating advanced modeling methods from EEGViT and EEGViT-TCNet, we achieved a new standard in eye-tracking precision, reducing the RMSE from 51.8 to 48.9. This research underscores the importance of data refinement in advancing Brain-Computer Interfaces (BCI) and their applications.

Keywords: EEG, Gaze Prediction, Machine Learning, Vision Transformer, EEGEyeNet, Data Preprocessing

1 Introduction

Electroencephalography (EEG) is extensively employed in research fields such as neural engineering, neuroscience, biomedical engineering, and brain-like computing, with particular emphasis on brain-computer interfaces (BCIs). Analyzing EEG signals is crucial for the progress of BCIs, as it provides valuable insights into the intricate neural mechanisms of the human brain. Over the last decade, a variety of machine learning and deep learning algorithms have been utilized to process EEG data, leading to significant advancements in several applications. These applications include emotion recognition, motor imagery, mental workload assessment, seizure detection, Alzheimer's disease classification, sleep stage scoring, and many more (Craik et al. (2019); Kastrati et al. (2021a); Roy et al. (2019); Altaheri et al. (2023); Qu (2022); Gao et al. (2021); Hossain et al. (2023); Yi and Qu (2022); Key et al. (2024); Li et al. (2024); Koome Murungi et al. (2023); Zhou et al. (2022); Qu et al. (2020b,c,a, 2018, 2019); Saeidi et al. (2021); Qu and Hickey (2022); Rasheed et al. (2020); Dadebayev et al. (2022); Wang and Qu (2022); Li et al. (2020); Aggarwal and Chugh (2022)).

EEG and deep learning research have been in close proximity for decades, with advancements in both fields contributing to strides in our understanding of the brain. Deep learning algorithms are particularly popular in the context of EEG analysis due to their ability to extrapolate and generalize input information, making them ideal for decoding the complexities and noise within EEG signals into interpretable outputs.

The EEGEyeNet dataset has become a cornerstone in the realm of cognitive neuroscience and machine learning, facilitating the advancement of eye-tracking technologies through the integration of EEG data (Skoglund et al. (2022); Murungi et al. (2023); Dou et al. (2022); Wolf et al. (2022); Rolff et al. (2022); Kastrati et al. (2023); Farago et al. (2022)). The fusion of these disciplines aims to enhance the precision of eye position prediction, a critical aspect in understanding visual attention and neurological behavior. However, the integrity of the EEGEyeNet dataset is compromised by the presence of data points exhibiting eye positions that surpass the physical boundaries of the experimental screen, leading to potential inaccuracies in subsequent analyses and model training.

This paper investigates the impact of such outliers on the performance of predictive models and explores the benefits of outlier pruning to maintain the dataset's integrity. Through meticulous data cleaning, we identified and removed these anomalous data points, aiming to refine the dataset for more accurate model training. By removing only a few outliers, the model's representation of EEG signals is drastically improved. Extending beyond simple outlier removal, our study incorporates advanced modeling techniques from the domains of the EEG Vision Transformer (EEGViT) and EEGViT-TCNet to establish a new benchmark in eye-tracking accuracy. Precise gaze estimation models have numerous applications across various fields such as behavioral science, user experience (Rolff et al. (2022)), or assistive technology (Skoglund et al. (2022)). This demonstrates the significance of reliable models, which require accurate data.

1.1 Research Question

In addressing these objectives, our study aims to answer two key questions:

- How do outliers in the EEGEyeNet Dataset affect predictions of current state-of-the-art (SOTA) models and what do they reveal about the data?
- Can we develop a model with a specific data pruning technique to surpass the current SOTA model by reducing the Root Mean Squared Error (RMSE)?

By addressing these questions, we contribute to the ongoing discourse on EEG data preprocessing and model development, ultimately advancing eye-tracking technology and its applications. Our findings are particularly relevant to the HCI community, as they provide a pathway to more accurate and responsive gaze-based interaction systems, enhancing the overall user experience and expanding the potential of assistive technologies. The full set of source code can be found at https://github.com/JadeW7/EEGViT-TCNet-pruned.

Table 1. *Abbreviation Table*

Abbreviation	Definition
AI	Artificial Intelligence
ML	Machine Learning
DL	Deep Learning
EEG	Electroencephalography
ET	Eye-Tracking
BCI	Brain-Computer Interfaces
HCI	Human-Computer Interaction
ViT	Vision Transformer
CNN	Convolutional Neural Network
TCNet	Temporal Convolutional Network
SOTA	State Of The Art
RMSE	Root Mean Squared Error

2 Related Work

2.1 Deep Learning in EEG

The history of EEG signal processing has seen a notable evolution, especially with the advent of deep learning techniques. Traditional machine learning methods, although effective to a certain extent, often struggle to capture the intricate and high-dimensional nature of EEG data. However, the landscape changed with the introduction of deep learning models, notably convolutional neural networks (CNNs) and recurrent neural networks (RNNs), which brought about a paradigm shift in this field.

Moreover, the application of the Transformer architecture has transcended various domains within deep learning (Wang and Wang (2022); Fuhl et al. (2023); Xiang and Abdelmonsef (2022); Modesitt et al. (2023); Mishra et al. (2023)). The Vision Transformer (ViT) particularly stands out for its impact on both Computer Vision and EEG analysis (Yang and Modesitt, 2023), showcasing its versatility and effectiveness in handling complex data structures such as EEG signals.

2.2 Vision Transformers

ViTs have generated significant impacts in numerous fields and are utilized for their excellent performance in many tasks, often surpassing the results of state-of-the-art Convolutional Neural Networks (CNNs) when trained on large datasets (Dosovitskiy et al. (2020)). Although initially designed for classifying images, ViTs are surprisingly accurate at analyzing EEG data due to their effectiveness with grid-like data. The key to their success lies in their self-attention mechanism, which plays a crucial role in capturing long-range dependencies. Unlike traditional CNNs, which rely on convolutional layers to process local receptive fields and gradually build up global context through multiple layers, ViTs can capture long-range dependencies in the data directly. This is achieved through self-attention, which allows the model to weigh the importance of each part of the input data relative to every other part, facilitating a more holistic understanding of the data's structure and relationships. This capability is crucial for tasks requiring a comprehensive understanding of spatial and temporal relationships within the data.

2.3 Temporal Convolutional Networks

Additionally, the Temporal Convolutional Network (TCNet) has become a favored option across different domains in deep learning, including EEG signal processing (Ingolfsson et al., 2020). Specialized architectures such as TCNet enhance the detection of subtle features that might be overlooked when using CNN models alone (Bai et al., 2018). TCNet enhances temporal feature detection through causal convolutions and dilations, allowing it to handle long-range dependencies and temporal correlations more effectively.

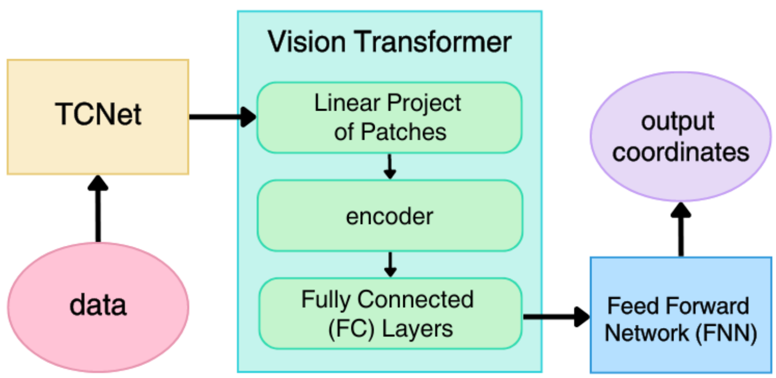

Fig. 1. *The architecture of the EEGViT-TCNet (Modesitt et al., 2024).*

2.4 Fusing Pre-trained ViTs with TCNet

The integration of pre-trained Vision Transformers (ViTs) with Temporal Convolutional Networks (TCNet) represents a cutting-edge methodology in the realm of EEG regression (Modesitt et al. (2024). This fusion combines the spatial feature extraction capabilities of ViTs with the temporal analysis strengths of TCNet, resulting in significantly improved model performance for EEG signal analysis. The EEGViT-TCNet model demonstrates the fastest state-of-the-art performance in EEG regression tasks by efficiently capturing both spatial and temporal features of EEG data. When combining TCNet's capabilities with pre-trained Vision Transformer models, the model's accuracy increased significantly on EEG regression tasks, decreasing the RMSE by 3.6 millimeters (Modesitt et al. (2024)). With this collaborative integration of feature extraction with the adaptability of architectures such as ViT, a promising approach is offered for developing models that excel across a wide range of EEG datasets (Figure 1). The ViT component excels in learning complex spatial representations, while the TCNet component excels in identifying complex temporal dependencies. By pre-training the ViT on large image datasets, they ensure robust feature extraction which, when combined with TCNet's temporal processing, leads to superior accuracy and speed in EEG regression tasks.

3 Methods

3.1 The EEGEyeNet Dataset

Obtaining eye-tracking data involves intricate and costly procedures, demanding specialized equipment, skilled operators, and participant approval. The integration of such data with EEG recordings further complicates the data collection process. Consequently, studies exploring the interplay between brain activity and eye movements often encounter limitations due to the scarcity of suitable datasets. The introduction of the EEGEyeNet dataset (Kastrati et al. (2021b)) alleviates this challenge by providing a comprehensive dataset incorporating both EEG and eye-tracking data. The EEGEyeNet dataset is a collection of electroencephalogram and eye-tracking data of 365 participants, 190 males and 166 females, with ages ranging from 18 to 80, consisting of three benchmark tasks: Left-right, Angle/Amplitude, and Absolute position.

Collection Method/Details EEG data was collected through the EEG Geodesic Hydrocel system, containing 128 channels and capturing at 500 Hz. Prior to recording, the impedance of each electrode was ensured at levels below 40 kOhm (kilo-ohms, a unit of electrical resistance). The eye position was also recorded with the ET EyeLink 1000 Plus, an infrared video system, also at the same sampling rate of 500 Hz. Participants then maintained a stable head position via a chin rest, placed 68 cm away from a 24-inch monitor.

Task Description While there are three tasks for which data is collected, the pre-trained EEGViT-TCNet utilizes the large grid data, where participants are asked to fixate on a series of dots as shown in Figure 2. 25 dots placed in all areas of the screen are displayed in a pseudo-randomized order for 1.5 to 1.8 seconds each. 27 dots per block were measured with a total of five random blocks repeated 6 times during the measurement, resulting in 810 stimuli for each participant.

EEGEyeNet Initial Preprocessing Because of the various external factors (temperature, air humidity, or outside noise), the EEG data collected from each

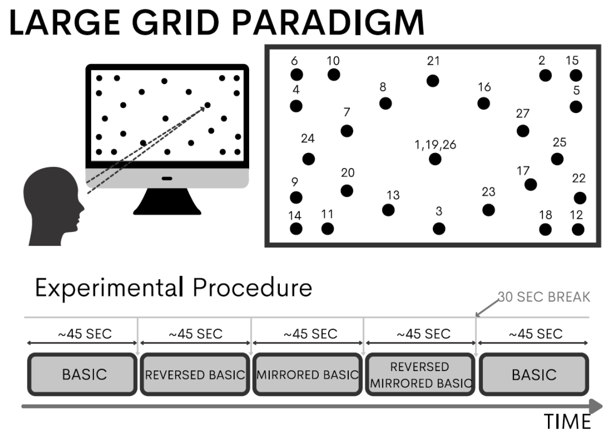

Fig. 2. *Schematic diagram of the experimental setup and the placement of stimuli on the screen (Kastrati et al., 2021b).*

participant could have resulted in more prominent signals of interest through reflexive eye movements, muscular noise, or heart signals. As such, the EEG data from the original EEGEyeNet dataset was preprocessed minimally or maximally with the toolbox from Pedroni et al. (2019). Maximal preprocessing addresses the aforementioned unwanted physiological signals by applying an independent component analysis in combination with Pion-Tonachini et al. (2019), a pre-trained classifier that allows for the removal of data that has a probability estimation of larger than 0.8 for reflecting external activity. Minimal preprocessing involves determining and filtering data with a 40 Hz high-pass filter and a 0.5 Hz low-pass filter. Given that the state-of-the-art model employs minimally preprocessed data, our focus was aligned with this approach.

3.2 Data Preprocessing

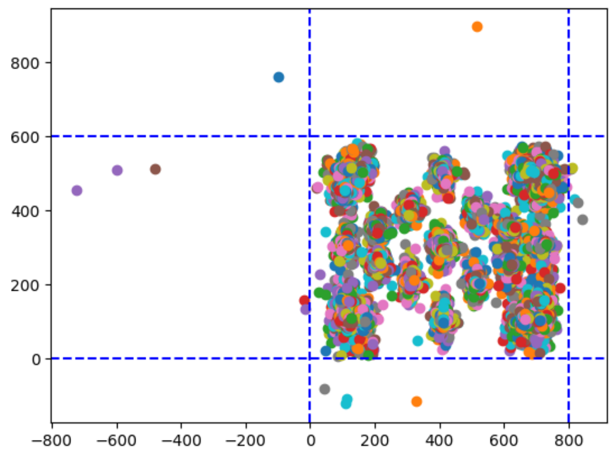

Fig. 3. *Visualization of the EEGEyeNet Absolute Position data. 15 outliers lie outside of the designated (0-800, 0-600) range.*

We conducted a meticulous data-cleaning process of the minimally preprocessed data regarding the absolute position task on the large grid paradigm. We eliminated all data points with eye positions outside the experiment screen's dimensions of 800 x 600 pixels (Kastrati et al., 2021b). As shown in Figure 3, we found that these outliers make up 15 out of 21,464 total samples. As such, data points with coordinates outside of this dimension can reasonably be considered errors. This scrutiny of each data point's x and y coordinates ensured the retention of only valid, physically plausible samples for model training and testing.

3.3 Application of Pruned Data

Building upon the foundations laid by EEGViT and EEGViT-TCNet, our research leverages the synergistic potential of Vision Transformers and Temporal Convolutional Networks. These technologies, known for their prowess in advanced machine learning regression tasks, were integrated into our model architecture to refine EEG-signal analysis, enhancing the precision of eye-position predictions. We fed our cleaned data into the EEGViT-TCNet model to discern the effects of the outliers on the accuracy. Previously, the EEGViT and the EEGViT-TCNet split the data into the same subsets for training, testing, and validation, as shown in Figure 4.

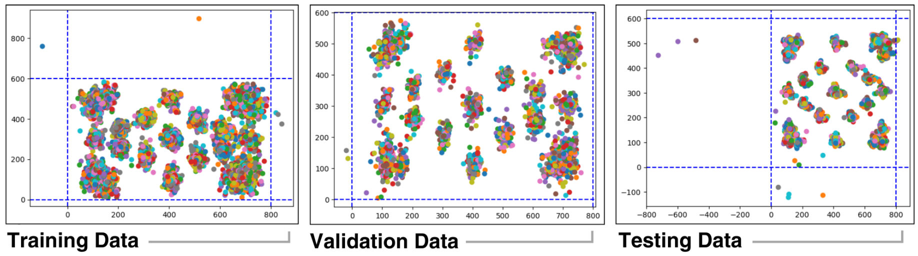

Fig. 4. *Visualization of how the SOTA model splits the EEGEyeNet Absolute Position data into training, validation, and testing subsets. Several outliers lie outside the designated range of (0-800, 0-600).*

Figure 4 elucidates the distribution of the outliers across the training, testing, and validation sets. The EEGViT-TCNet was trained on a subset of the data with 5 outliers, validated on a subset of the data with 3 outliers, and tested on a subset of the data with 7 outliers. Thus, by eliminating these outliers, we have removed any potential adverse effect in all phases of the model development process.

4 Results

Subsequent retraining of the state-of-the-art model on this pruned dataset yielded significant improvements in predictive accuracy. This enhancement was measured by the Root Mean Squared Error (RMSE), representing the Euclidean distance in millimeters between the predicted and actual gaze positions. Our findings in Table 2 revealed a marked enhancement in model performance, with RMSE values decreasing from 51.8 to 48.9. By removing only 15 data points, and only 5 in the training data, or stimuli, in the dataset, 0.0007% of the total data, there was a 6% increase in accuracy on the SOTA model.

Table 2. *Root Mean Squared Error (RMSE) loss in millimeters for different models on the Absolute Position Task. Lower RMSE values indicate better performance as they represent closer estimations to the actual values. The values represent the mean and standard deviation of 5 runs. All Transformers in the table are pre-trained.*

Model	Absolute Position RMSE (mm)
Naive Guessing	123.3 ± 0.0
KNN	119.7 ± 0
RBF SVR	123 ± 0
Linear Regression	118.3 ± 0
Ridge Regression	118.2 ± 0
Lasso Regression	118 ± 0
Elastic Net	118.1 ± 0
Random Forest	116.7 ± 0.1
Gradient Boost	117 ± 0.1
AdaBoost	119.4 ± 0.1
XGBoost	118 ± 0
CNN	70.4 ± 1.1
PyramidalCNN	73.9 ± 1.9
EEGNet	81.3 ± 1.0
InceptionTime	70.7 ± 0.8
Xception	78.7 ± 1.6
ViT-Base	58.1 ± 0.6
EEGViT	55.4 ± 0.2
EEGViT-TCNet	51.8 ± 0.2
EEGViT-TCNet (Pruned)	**48.9 ± 0.2**

Our research establishes the pruned version of EEGViT-TCNet as the current benchmark, the most accurate model for the absolute position grid task of EEGEyeNet. In comparison to the baseline Naive Guessing model, which had an RMSE of 123.3, the pruned EEGViT-TCNet model's RMSE of 48.9 represents a substantial reduction, reinforcing the importance of data integrity and preprocessing in achieving high model performance.

5 Discussion

Our study not only highlights the critical importance of data integrity but also showcases the efficacy of combining advanced machine learning techniques, like those in EEGViT and EEGViT-TCNet, for precise gaze estimation applications. Demonstrated by notable enhancements in RMSE for the state-of-the-art model in EEGEyeNet, existing outliers pose a risk to both the overall accuracy and the integrity of the model, even throughout the training phase.

The distribution of outliers across the training, testing, and validation sets of the EEGViT-TCNet (Figure 4) may partially elucidate the impact of anomalous points. The influence of these outliers on other models might differ from that on the state-of-the-art model, owing not only to differences in model architecture but also to the varying methods researchers used to split the EEGEyeNet dataset. Nonetheless, the reduction in RMSE observed when training the EEGViT-TCNet on the cleaned data highlights the potential for similar improvements in other models. Models previously developed for the absolute position task on the EEGEyeNet data might also experience comparable accuracy increases. Given that each model learns to predict absolute position uniquely, there is a possibility for an even greater reduction in RMSE with other models.

The continuous improvement in accuracy underscores the importance of building upon previous research, resulting in a total reduction of 74.4 RMSE from the baseline of Naive Guessing, which was 123.3 RMSE. However, all of the foundational research was conducted on data containing outliers. With the identification of these outliers and the availability of pruned data, future research can potentially achieve even greater error reduction.

Furthermore, improving the accuracy of the model is not the only objective. By reporting these anomalies in data, researchers in intersecting fields may also find value in these specific data outliers, leading to insights into the underlying causes, whether that be human error, mislabeling, or genuine special circumstances. This can inform broader cognitive and perceptual research, providing a more nuanced understanding of human-computer interactions.

The implications of our findings extend beyond cognitive research to practical applications in Human-Computer Interaction (HCI). Enhanced EEG and eye-tracking models can significantly improve adaptive user interfaces, making them more responsive and intuitive. This refinement can benefit assistive technologies, enabling better communication aids for individuals with disabilities. Additionally, the precision improvements can elevate virtual and augmented reality experiences, making interactions more seamless and immersive.

Moving forward, it would be valuable to continue exploring data preprocessing techniques along with the integration of Transformers and neural network architectures to further enhance accuracy with EEG data. Additionally, exploring various deep learning techniques on different datasets for comparative studies (An et al. (2023a,b); Jiang et al. (2023); Lu et al. (2023); Chen et al. (2024); Gui et al. (2024); Ma (2022); Ma et al. (2024); Tan et al. (2023, 2021); Qiu et al. (2023); Zhao et al. (2024); Zhang et al. (2022, 2023)) could provide valuable insights and further enhance the field. Such advancements will not only elevate the performance of predictive models but also expand the potential of HCI technologies, driving innovation in user-centric applications and setting new standards for BCI development.

6 Conclusion

Through the implementation of a thorough data-cleaning process, we systematically erased outlier observations in the EEGEyeNet dataset. By excluding data points lying outside of the screen's dimensions, we ensured the integrity and reliability of the dataset.

Our results demonstrate a significant improvement in predictive accuracy, underscoring the critical importance of data integrity in ML applications. The reduction in RMSE for the EEGViT-TCNet model highlights the potential for similar enhancements in other models when outliers are meticulously managed.

With ongoing development in EEG classification, the strive towards continued improvements in the accuracy of feature extraction with new architectures reinforces the importance of meticulous data preprocessing in enhancing performance and reliability for real-world applications. Our findings suggest that even minor adjustments in data quality can lead to substantial gains in model accuracy, which is crucial for applications in Brain-Computer Interfaces, adaptive user interfaces, and assistive technologies.

This study not only advances our understanding of the role of data integrity in model performance but also sets a new benchmark for EEG-ET predictive models. The implications extend to improving the efficacy of BCIs and related technologies, potentially benefiting individuals with disabilities and enhancing user experiences in virtual and augmented reality environments.

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