Effectively reduce the number of EEG channels by deleting nonessential channels

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***Abstract*—Electroencephalogram (EEG) is a commonly used brainwave in medicine, which records continuous and irregular electrical potential fluctuations on the scalp surface through Brain-Computer Interface (BCI) devices. EEGNet is an improved Convolutional Neural Network (CNN) architecture specifically designed for classifying brainwave signals. When collecting EEG brainwaves, the number of electrode channels on the device has an impact on its size and cost. We proposed a method to effectively reduce the number of EEG electrode channels and parameters by "deleting nonessential channels" during the detection of specific events. The impact of removing each channel on classification accuracy was observed and nonessential channels was selected for deletion based on their accuracy rankings. The research results indicate that the accuracy of deleting nonessential channels is higher compared to using all electrode channels, and the number of parameters entering EEGNet is also reduced.**

***Keywords*—EEG, BCI, EEGNet, deleting nonessential channels, reduce parameter.**

I. INTRODUCTION

Electrophysiological measurements of brain activity, such as electroencephalogram (EEG), provide a new non-muscular pathway for human-computer interaction known as Brain-Computer Interface (BCI), which enables the connection between brain electrical signals and machines [1]. BCI has been applied in the medical field, with various applications in emergency rooms and operating rooms [2]. BCI consists of five main processing stages: data acquisition, where brainwave data is recorded using instruments; data processing, involving preprocessing and filtering of the collected data; feature extraction, where specific signals are extracted from the data; classification, where the data is interpreted and classified; and feedback, where the final results are provided to the user [3]. EEG, or electroencephalogram, refers to the continuous and irregular electrical potential fluctuations recorded on the scalp surface using electrodes attached to the BCI device. Research by Richard Caton [4] discovered changes in brainwaves when exposed to visual stimuli. Vernon J. Lawhern et al. developed EEGNet, a compact convolutional neural network (CNN) based on EEG, which utilizes different CNN architectures to create a highly flexible neural network structure [5].

Currently, research on EEGNet focuses on improving CNN architecture for classifying brain waves, demonstrating its superiority over conventional methods and its applications in technology. However, achieving high accuracy in prediction does not necessarily require all electrode channels [6]. Reducing the number of electrodes can improve the comfort of wearing BCI devices [7], and it also helps reduce the computational time required for processing and evaluation [8].

In this paper, publicly available data from MNE [9] were used to delete "nonessential channels. " The validation and testing accuracies of EEGNet were compared before and after deleting channels to verify the ability to reduce the number of EEG electrode channels and thereby decrease the amount of data.

The structure of this paper is as follows: Section 2 describes the relevant background experiments. The research methodology is presented in Section 3. Section 4 provides the results and analysis and Section 5 presents the conclusion.

II. BACKGROUND AND REATED WORK

A. EEG Net

The literature on EEGNet is abundant, focusing mainly on optimizing the EEGNet model for classifying different types of electroencephalograms (EEGs). EEGs can be classified or used for feature extraction using EEGNet, which allows for the incorporation of different CNN components to create novel EEGNet models for various EEG applications.

In their study, X. Song et al. combined the advantages of CNN feature extraction with Long Short-Term Memory (LSTM) to propose a new EEGNet structure called LSDD-EEGNet for detecting depression based on EEG signals. They found that LSDD-EEGNet achieved outstanding performance in the evaluation compared to typical machine learning methods and deep learning models [10].

D. Li et al. replaced the original activation function ELU with SELU in CNN and found that it further improved the regularization effect and increased the convergence speed. They observed that compared to the FBCNet and Deep ConvNet deep learning architectures, the modified CNN with SELU exhibited better decoding performance [11].

M. Riyad et al. developed MI-EEGNet, a convolutional neural network based on the Inception and Xception architectures. By incorporating these advanced models, the neural network was able to learn more diverse and informative features, leading to improved classification performance. Their results demonstrated that MI-EEGNet outperformed existing methods such as the Filter Bank Common Spatial Pattern (FBCSP), Riemannian geometry (RG), and Shallow ConvNet, indicating its superiority in decoding EEG signals [12].

X. Deng et al. utilized the Temporary Constrained Sparse Group Lasso (TCSGL) algorithm to enhance the performance of EEGNet. They conducted tests using different datasets and found that the accuracy of their approach surpassed that of FBCSP, C2CM, MB3DCNN, SS-MEMDBF, and EEGNet [13].

W. Huang et al. proposed S-EEGNET, a separable convolutional neural network based on the Hilbert-Huang Transform and bivariate interpolation. They introduced the concept of adding displacement variables to the separable CNN through bivariate interpolation of EEG signals. This approach improved the accuracy of the public dataset by 3.6%, 1.15%, and 1.33%, respectively [14].

B. The number of channels in an EEG system and its accuracy

Electroencephalography (EEG) is a non-invasive medical device [15] that records the electrical potential differences of brain neurons using different numbers of electrodes. It provides valuable information for diagnosis and treatment purposes to doctors and researchers. The coverage of the brain regions may vary depending on the design or application and can include areas such as the frontal lobe, parietal lobe, occipital lobe, and temporal lobe. With advancements in technology, there is no specific limit to the number of electrodes, ranging from over 256 to fewer than 16, which can be adjusted according to different studies or requirements to obtain corresponding experimental results.

S. Tsuchiya et al. attempted to construct an emotion recognition system using EEGNet based on electroencephalography. They used a correlational brainwave recorder with 14 electrodes and achieved an accuracy of 57.6% through correlation-based calculations, surpassing the emotion recognition of Support Vector Machines (SVM) [16].

Z. Cao et al. described the collection of EEG data in a sustained attention task using an immersive driving simulator. Test subjects engaged in simulated driving, where randomly induced lane deviation events occurred. They used a Scan SynAmps2 Express system with 32 electrodes and achieved an accuracy of 80±8.6% using SVM [17].

Y. Miyata et al. investigated the measurement of brainwaves while listening to switch sounds and using machine learning to verify whether the structures and factors obtained in the results of previous studies can identify switches through cross-validation. They used an Emotiv (EPOC Flex) system with 32 electrodes and obtained a certain level of accuracy through cross-validation, outperforming four-class and two-class discrimination methods [18].

V. J. Lawhern et al. introduced a model for EEG using deep convolutional and separable convolutional methods. They compared the accuracy of different database for visual evoked potentials (P300), error-related negativity (ERN), movement-related cortical potentials (MRCP), and sensorimotor rhythms (SMR). They also demonstrated different approaches to visualize the trained EEGNet content. They used a BioSemi Active system with 60 electrodes and achieved accuracy above 80% and even up to 100% [3].

C. Reducing the number of electrode channels

The data from EEG recordings can be influenced by the number of electrode channels in the EEG system. Having too many channels can increase the processing time, while having too few channels can lead to decreased accuracy. Therefore, finding the optimal number of electrode channels to collect accurate data is crucial. Researchers have utilized different methods for channel reduction while maintaining accuracy, demonstrating that accuracy does not necessarily decrease and can even improve after reducing the number of channels. This helps to reduce data processing time during experiments and minimizes the number of electrode channels participants need to wear when collecting data.

K. Ansari-Asl et al. [8] aimed to provide a unique approach to person identification due to various typical fraud attacks. They captured electrical activity using electrodes placed at different locations on the scalp and proposed the Flower Pollination Algorithm, FPAβ-hc, for evaluation using a standard EEG motor imagery dataset. The results showed that using this method, they could achieve higher accuracy with less than half the number of electrodes compared to seven other different methods.

Z. Zou et al. [19] analyzed the experimental results in a brain-computer interface target detection task based on rapid serial visual presentation. The accuracy of 53 electrode positions in the frontal, parietal, and central regions of the brain was found to be higher than that of the entire brain with 64 electrodes. This provides some insights for reducing channels in wearable devices.

W. Mu et al. [20] mentioned that electrode channel selection can reduce the probability of acquiring noise and obtain more accurate data. They sorted the electrode channels based on statistical measures such as correlation, Pearson correlation coefficient, and CSP grades and selected channels based on classification accuracy. The study showed an average improvement of 7.05% in classification accuracy for dataset 1 and 7% for dataset 2.

L. Tong et al. [21] used the DEAP public database and applied the ReliefF algorithm to select EEG channels. They identified the optimal combinations of 6 and 13 electrode channels that achieved the best trade-off between emotion recognition accuracy and slight loss. This reduced the original 32 electrode channels to 13, effectively decreasing the required number of channels, reducing feature dimensions and computational complexity, and improving the efficiency of the experiment. It also laid a foundation for the development of portable and wearable devices.

III. RESEARCH METHODS

A. Constructing EEGNet

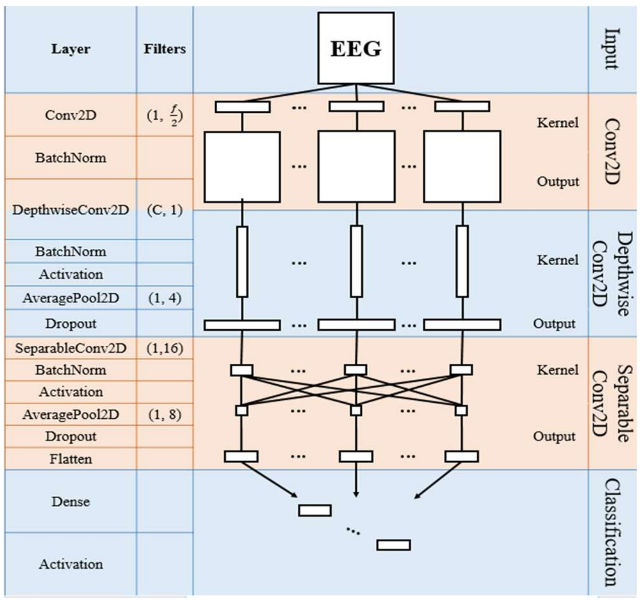

Fig. 1. Overall Visualization of the EEGNet Architecture

EEGNet utilizes convolutional connections between each input and output. The network starts with temporal convolutions, which are used to handle trends and time-dependent features in the time series. Then, deep convolutions are employed to capture channel-specific features and spatial correlations. Finally, separable convolutions, which combine depth-wise convolutions and point-wise convolutions, are utilized to reduce the number of parameters and computations while maintaining the model's performance. The architecture of EEGNet used is depicted in Fig. 1. The detail layers description are illustrated in column one and the corresponding filters are listed in column two. Visualization of the EEGNet architecture is drawn in column three.

B. Deleting nonessential channels

Deleting nonessential channels involves a two-step process. Firstly, each channel is sequentially removed, and classification is performed using EEGNet. The validation accuracy and test accuracy are recorded, and their average is calculated to assess the importance of each channel. Secondly, the channels are sorted in descending order based on their average accuracy. Channels with higher accuracy indicate that their removal has minimal impact on overall accuracy and can be considered as candidate channels for deletion. The channels are then removed in the sorted order, and classification is performed again using EEGNet, with the average accuracy recorded. Fig. 2. illustrates the first step of the experimental procedure - initial channel removal. Fig. 3. shows the subsequent process - deleting nonessential channels.

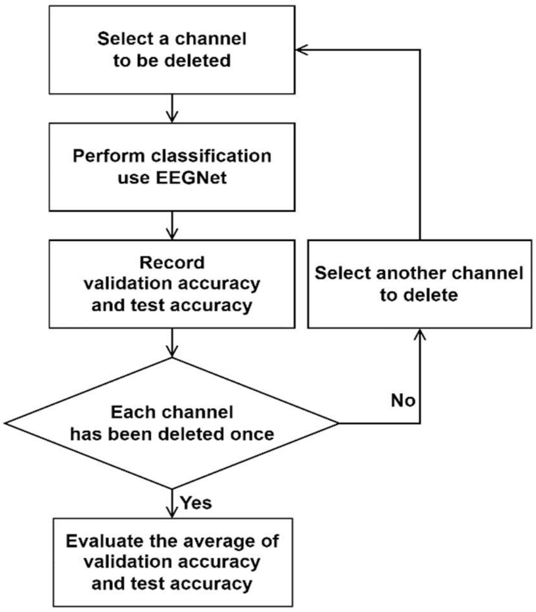

Fig. 2. Initial Channel Deletion Process

In this mechanism, the original EEG data with N channels is processed by sequentially deleting one channel at a time and then classifying it using EEGNet. N sets of validation accuracy and test accuracy are obtained. The validation accuracy and test accuracy of each set are averaged, resulting in N average values for evaluation.

The evaluation is performed by comparing the average accuracy obtained from the process of deleting one channel at a time and then classifying it using EEGNet. If the average accuracy after channel deletion is higher than the average accuracy without channel deletion, the channel is assumed to be unimportant. This implies that removing that channel would not affect the classification performance of EEGNet and thus can be eliminated. Conversely, if the average accuracy is lower, the channel is assumed to be important, indicating that its deletion would affect the classification performance of EEGNet and therefore should not be removed. This evaluation process is used for the next step of the workflow.

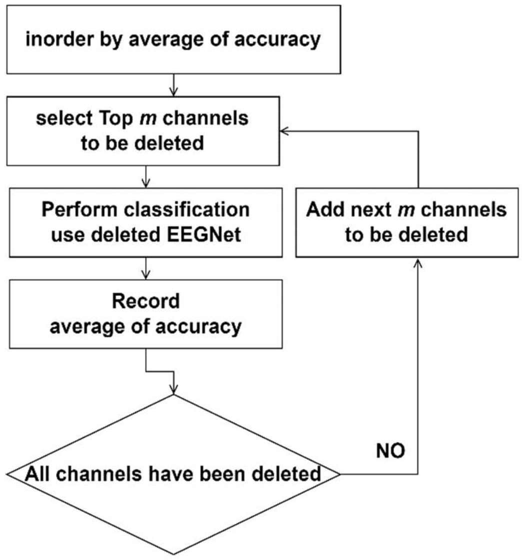

Fig. 3. Process Flowchart for deleting nonessential channels

The number of channels are set as "*m*" to be deleted at each iteration. First, the top "*m*" channels are selected based on their average accuracy ranking and remove them. Then, the modified EEGNet are used to classify the data and the average accuracy are recorded with the reduced (*N* - *m*) channels. This process are repeated by removing the top "*m*" channels again, resulting in a reduced (*N* - *2m*) channel, until all channels have been deleted.

IV. Results and Analysis

This experiment used the publicly available MNE dataset [11], which was acquired using the Neuromag Vectorview system at the MGH/HMS/MIT Athinoula A. Martinos Center for Biomedical Imaging. The data consists of EEG and MEG recordings with 60 electrode channels, sampled at a frequency of 150.15 Hz. The frequency range extends from 0.1 Hz to 40 Hz. The dataset includes event markers for different stimuli, namely, left auditory stimulus (LA), right auditory stimulus (RA), left visual field stimulus (LV), right visual field stimulus (RV), smiling face (visual stimulus appearance), and trigger button press (in response to visual stimulus). The inter-stimulus interval is 750 milliseconds.

The EEGNet architecture proposed by Vernon J. Lawhern et al. [22] was used with the following parameters: 60 electrode channels, sampling frequency of 151, convolutional kernel length of 32 with a quantity of 1, 8 temporal filters, 16 point-wise filters, dropout rate set to 0.5, and 4 classes for the final classification. The dataset was split into training, validation, and testing sets in a ratio of 50%, 25%, and 25%, respectively.

During the initial channel deletion process, each deletion of a different channel resulted in corresponding validation and testing accuracies. The average accuracy, obtained by summing the two accuracies, was sorted, and the results are presented in Table I.

TABLE. I. AVERAGE ACCURACY RANKING FOR INITIAL CHANNEL DELETION

Rank	Deleted Channel	Validation Accuracy	Test Accuracy	Average Accuracy	Rank	Deleted Channel	Validation Accuracy	Test Accuracy	Average Accuracy
1	EEG058	94%	86%	90%	31	EEG050	90%	79%	85%
2	EEG012	86%	93%	90%	32	EEG024	86%	82%	84%
3	EEG027	85%	94%	90%	33	EEG054	88%	81%	84%
4	EEG018	89%	90%	90%	34	EEG052	83%	83%	83%
5	EEG026	92%	86%	89%	35	EEG005	86%	79%	83%
6	EEG039	89%	89%	89%	36	EEG017	79%	86%	83%
7	EEG003	90%	86%	88%	37	EEG048	89%	76%	83%
8	EEG011	88%	89%	88%	38	EEG004	81%	83%	82%
9	EEG034	92%	85%	88%	39	EEG028	88%	75%	81%
10	EEG044	93%	83%	88%	40	EEG001	76%	86%	81%
11	EEG046	89%	88%	88%	41	EEG047	81%	82%	81%
12	EEG053	90%	86%	88%	42	EEG009	85%	76%	81%
13	EEG002	88%	88%	88%	43	EEG021	75%	85%	80%
14	EEG031	88%	88%	88%	44	EEG013	82%	78%	80%
15	EEG014	89%	86%	88%	45	EEG036	79%	81%	80%
16	EEG025	86%	89%	88%	46	EEG055	82%	78%	80%
17	EEG033	89%	86%	88%	47	EEG032	86%	72%	79%
18	EEG059	90%	83%	87%	48	EEG010	81%	76%	78%
19	EEG016	85%	89%	87%	49	EEG029	81%	69%	75%
20	EEG045	89%	85%	87%	50	EEG060	74%	75%	74%
21	EEG020	86%	86%	86%	51	EEG037	75%	68%	72%
22	EEG008	85%	88%	86%	52	EEG051	78%	64%	71%
23	EEG015	88%	85%	86%	53	EEG019	76%	63%	69%
24	EEG030	89%	83%	86%	54	EEG035	71%	63%	67%
25	EEG040	89%	83%	86%	55	EEG023	76%	57%	67%
26	EEG007	88%	83%	85%	56	EEG038	63%	69%	66%
27	EEG042	85%	86%	85%	57	EEG006	65%	65%	65%
28	EEG043	88%	83%	85%	58	EEG041	63%	60%	61%
29	EEG049	88%	83%	85%	59	EEG056	68%	53%	60%
30	EEG022	83%	86%	85%	None	None	86%	84%	85%

Based on the obtained results, the evaluation is as follows:(1) Delete the first-rank channel, EEG058: Validation accuracy is 94%, Testing accuracy is 86%, and Average accuracy is 90%. The average accuracy is higher than the average accuracy with no channels deleted, indicating that the channel is nonessential; (2) Delete the last-rank channel, EEG056: Validation accuracy is 68%, Testing accuracy is 53%, and Average accuracy is 60%. The average accuracy is lower than the average accuracy with no channels deleted, indicating that the channel is considered important.

TABLE. II. VALIDATION AND TEST ACCURACY AFTER CHANNEL DELETION

Channel Deletion	Test Accuracy
None	84%
Top10	83%
Top20	81%
Top30	82%
Top40	89%
Top50	83%

TABLE. III. THE RESULTS OF DELETING NONESSENTIAL CHANNELS

select delete channel	Deleted Channels	number of channels
None	None	60
Top10	EEG058,EEG012,EEG027,EEG018,EEG026,EEG039,EEG003,EEG011,EEG034,EEG044,	50
Top20	EEG058,EEG012,EEG027,EEG018,EEG026,EEG039,EEG003,EEG011,EEG034,EEG044, EEG046,EEG053,EEG002,EEG031,EEG014,EEG025,EEG033,EEG059,EEG016,EEG045,	40
Top30	EEG058,EEG012,EEG027,EEG018,EEG026,EEG039,EEG003,EEG011,EEG034,EEG044, EEG046,EEG053,EEG002,EEG031,EEG014,EEG025,EEG033,EEG059,EEG016,EEG045, EEG020,EEG008,EEG015,EEG030,EEG040,EEG007,EEG042,EEG043,EEG049,EEG022,	30
Top40	EEG058,EEG012,EEG027,EEG018,EEG026,EEG039,EEG003,EEG011,EEG034,EEG044, EEG046,EEG053,EEG002,EEG031,EEG014,EEG025,EEG033,EEG059,EEG016,EEG045, EEG020,EEG008,EEG015,EEG030,EEG040,EEG007,EEG042,EEG043,EEG049,EEG022, EEG050,EEG024,EEG054,EEG052,EEG005,EEG017,EEG048,EEG004,EEG028,EEG001,	20
Top50	EEG058,EEG012,EEG027,EEG018,EEG026,EEG039,EEG003,EEG011,EEG034,EEG044, EEG046,EEG053,EEG002,EEG031,EEG014,EEG025,EEG033,EEG059,EEG016,EEG045, EEG020,EEG008,EEG015,EEG030,EEG040,EEG007,EEG042,EEG043,EEG049,EEG022, EEG050,EEG024,EEG054,EEG052,EEG005,EEG017,EEG048,EEG004,EEG028,EEG001, EEG047,EEG009,EEG021,EEG013,EEG036,EEG055,EEG032,EEG010,EEG029,EEG060	10

From the above table, we can sort the channels based on the importance form low to high. Therefore, we arrange the 5 cases in the following experiments. The test accuracy for different cases of "deleting nonessential channels" are as follows: (1)No channels deleted: Test accuracy is 84%; (2)Top 10 channels deleted: Test accuracy is 83%; (3)Top 20 channels deleted: Test accuracy is 81%; (4)Top 30 channels deleted: Test accuracy is 82%; (5)Top 40 channels deleted: Test accuracy is 89%; (6)Top 50 channels deleted: Test accuracy is 83%. Table II shows the test accuracy after selecting the channels to be deleted. Table III shows the remaining channels and their quantities after deletion.

From the above experimental results, it can be observed that selecting the deletion of the top 40 channels results in the highest test accuracy. Although there is a slight decrease in the test accuracy for all other channel deletion choices, the accuracy is still within an acceptable range refer to Table II.

Table III presents the selected deleted channels and the count of remaining channels, showcasing the results of deleting nonessential channels. It can be observed that by choosing to delete the top 40 channels, there were 20 channels remaining.

When no channels are deleted, the number of parameters is 2148. However, it can be noticed that the number of parameters entering EEGNet significantly decreases when channels are deleted (refer to Fig. 4.) This indicates that this method effectively reduces the number of electrode channels, resulting in reduced data storage and computational requirements.

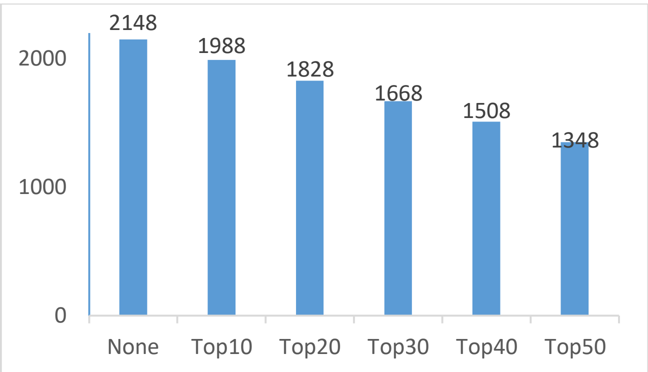

Fig. 4. Shows the number of parameters entering EEGNet for each scenario of channel deletion

V. CONCLUSIONS

In this paper, the effective reduction of electrode channels was achieved by deleting nonessential channels, leading to reduced processing time and data volume in EEG analysis. The results demonstrate that selecting the deletion of the top 40 channels yields the highest accuracy, while significantly reducing the data volume entering EEGNet. It is worth noting that the performance of deleting other numbers of channels is not poor, but choosing to delete the top 40 channels provides the best accuracy, along with a significant reduction in data volume.

The approach of selecting channels for deletion based on the combined validation and test accuracies, followed by sorting, has been validated in this study. It effectively reduces the number of electrode channels and improves the accuracy performance. It offers a valuable insight without the need for complex algorithms. Furthermore, future research can explore more advanced methods, such as deleting channels one by one based on their rankings rather than removing them in groups of ten, to further reduce the number of channels in a precise and efficient manner without compromising accuracy.

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