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EEG Channel Estimation using CNN-Based Depression Classifier

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ABSTRACT

Depression is a mental disorder that results to deteriorating effects in the lives of many people around the world. Traditional methods of diagnosing depression are based on interviews and questionaries. However, there were studies that have shown the possibilities of detecting depression biomarkers and perform classification. Electroencephalogram (EEG) analysis is one way of doing this. A series of signal processing techniques were used to streamline EEG data into a form which are recognizable by a machine learning algorithm. In this study, a convolutional neural network (CNN) – based depression classifier was used to classify depression using three EEG systems with 5, 16, and 128 channel locations. The aim is to estimate if there are differences in terms of classification performance. Results show that a system with locations for 5 and 16 EEG channels can achieve 98% accuracy like a 128-channel system. Hence, EEG systems with fewer number of electrodes can be utilized for depression classification applications.

Keywords:
Electroencephalogram; Depression; Convolutional neural network

1. Introduction

Depression is a serious mental health issue that affects millions of people around the globe. It can be caused by several factors such as stress, trauma, genetic predisposition, hormonal problems, or chemical imbalances in the brain. The everyday life of a person with depression could be affected by its negative effects and increases the possibility of taking away one's life especially if not treated [1,2]. Depression is characterized by persistent occurrences of low mood states manifested by sadness, anxiety, worry, tiredness, low self-esteem, frustration, and anger which lasts for 2 weeks or more. The NHS of Scotland [3] describes the common symptoms of depression as feelings of hopelessness, poor concentration, comfort eating, excessive sleep or for some, unable to sleep, lacking energy, and having self-harm and suicidal thoughts. Studies have shown that certain

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biomarkers can detect depression through the body's metabolic processes, inflammation, and neurotransmitters, or with non-invasive electroencephalography (EEG) [4-6].

EEG is a method that records electrical signals given off by the movement of neurons in our brain. Medical grade EEG systems are usually used in clinical EEG data analysis for diagnosis. However, low-cost research-grade EEG systems are also available which provide opportunities to explore further innovations in terms of data acquisition with fewer electrodes, and analytical selection of channels for a specific area of interest. Hence, these could be developed into dedicated EEG-based systems for a specific purpose [7].

EEG sensors have gone through several developments and have been used in research through the brain-computer interface (BCI) technology. Digital signal processing (DSP) techniques and machine learning, such as neural networks, play important roles in the creation of intelligent BCI systems that can perform classification, detection, analysis, and even diagnosis in medical science and research [8]. DSP provides a way to design filters that are useful in feature extraction. Learning algorithms are useful in the classification and detection of certain targets given their defining features. Advancements in machine learning techniques include Deep Learning (DL) with CNN. DL is a learning algorithm with a hierarchy of structures that performs multiple processing which is responsible for pattern and data structure recognition [9]. It has reduced the need for manual feature extraction and has been utilized to achieve more efficient computing performance. CNNs are subset systems of DL that were used in motor imagery classification systems [10]. With the addition of artificial intelligence, BCI systems were developed which are useful in the detection, and classification of different emotions [11], epilepsy conditions [12], and in fusion with facial recognition systems for identity verification and authentication [13,14].

In the area of mental health, several studies were able to develop computer-aided diagnoses for depression using BCI. DL has been used to classify patients with major depressive disorders (MDD) using Event Related Potentials (ERP) and Resting State EEG Data [15-18]. In the paper of Fan *et al.,* [19] they used data augmentation which is an important part of EEG data analysis in addition to resting data that has no trigger signals compared to ERPs. They applied an overlapping sliding window to generate more training samples for the resting data simulating samples from ERPs. High accuracies were obtained using different numbers of EEG electrodes for personal identification. The ability of EEG devices to identify depression using only a few channels is a major advantage for mental health applications. This capability not only improves their design, appearance, and usability but also enhances their potential to detect depression. In this study, we examined multiple EEG channels and employed overlapping sliding windows to implement a CNN model for classifying depression. This approach will provide valuable insights for the design of EEG-based devices for mental health purposes.

2. Methodology

The signal processing procedures used for this study are depicted in Figure 1. EEG recordings were obtained from healthy and depressed patients. Three sets of EEG channels were selected specifically 5, 16, and 128, as variations. The EEG datasets were pre-processed and came up with training and test sets for the machine learning using the Deep Convnet Model to possibly predict the presence of MDD.

The process begins with EEG recording to measure brain activity, involving the placement of electrodes on the scalp to collect data. Initially, 128 channels capture EEG signals, which are then reduced to 16 channels and further to 5 channels to focus on specific brain regions. The selected channels undergo preprocessing, including noise removal, filtering, and artifact correction, before being sampled to create training and testing datasets. The training dataset is utilized to train a Deep Convolutional Neural Network (Deep ConvNet Model) to recognize patterns associated with Major Depressive Disorder (MDD) from the EEG data. Subsequently, the trained model is applied to the test dataset to predict if an individual has MDD based on their EEG recordings. The output of the model indicates whether the individual is likely to have MDD.

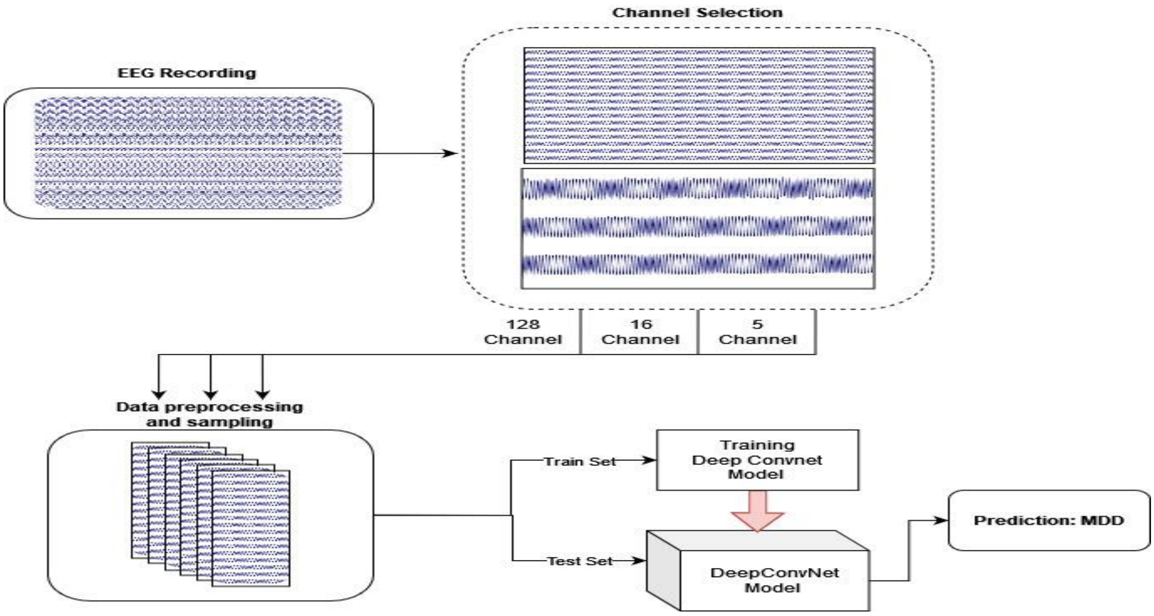

Fig. 1. Signal processing block diagram of the system

2.1 Data Sets

The EEG signals were obtained from the multi-modal open dataset for mental-disorder analysis (MODMA dataset) [20]. All data were collected using a 128-channel HydroCel Geodesic Sensor Net device at a 250 Hz sampling rate. The dataset includes EEG data taken from 53 subjects, 24 subjects with MDD and 29 healthy controls (HC), consisting of 5 minutes of eyes-closed resting state.

2.2 EEG Channel Selection

Low-cost EEG sensors have recently made great progress, thus allowing more possibility of more EEG-based classification systems. To evaluate the usage of such systems, experiments were conducted using 5-channel, 16-channel, and 128-channel EEG devices. The 5-channel EEG is based on the EMOTIV Insight v2.0 which is composed of AF4 and AF3 for the frontal region, T7 and T8 for the temporal region, and Pz for the centre parietal region of the brain. The 16-channel EEG is based on the EEG Electrode Cap of OpenBCI. The 16 channels of this headset are the following electrodes: FP2, FP1, F3, F7, C3, T7, P3, P7, O1, O2, P4, P8, C4, T8, F8, and F4. It can be noticed that there are some channels present in the 5-channel Emotiv Insight v2.0 that are not present in the 16-channel of the OpenBCI due to hardware design and limitations. The 128-channel EEG is mainly based on the given dataset discussed in the previous section. About this, the electrodes of the EMOTIV Insight and OpenBCI are also included in the MODMA Dataset.

2.3 Pre-Processing Technique

The Z-score standardization was used to normalize the EEG data stream before performing augmentation since the EEG magnitudes are relatively small. Z-score standardization is done by calculating the mean and standard deviation of the input signals and scaling them using Eq. (1).

$$Output\ x,t = (Input\ x,t - m)/\ s \quad (1)$$

where *x* and *t* are the vector positions of the EEG data with respect to the channel *x* and time instant *t*, *m* is the mean, and *s* is the standard deviation.

2.4 Data Augmentation

Each sample is augmented by a sliding window. The sample can be seen as a two-dimensional matrix with a size of Channels x Data points. A segment of 1 second and a sliding window of 0.5 seconds were adopted. The sampling frequency of the data is 250 Hz, so Channels and Points are set at 250 x 125. The data was then split into Train, Validation, and Test sets with a percentage split of 70%, 15%, and 15%, respectively.

2.5 Neural Network Architecture

The neural network chosen as a base for the channel selection comparison is the Deep ConvNet for Raw EEG Signals [6]. It is designed as a general-purpose architecture without any specific features or EEG data types. It consists of four (4) blocks of convolution and max-pooling layers with batch normalization and a final classification layer. The architecture of the learning model used is shown in Figure 2.

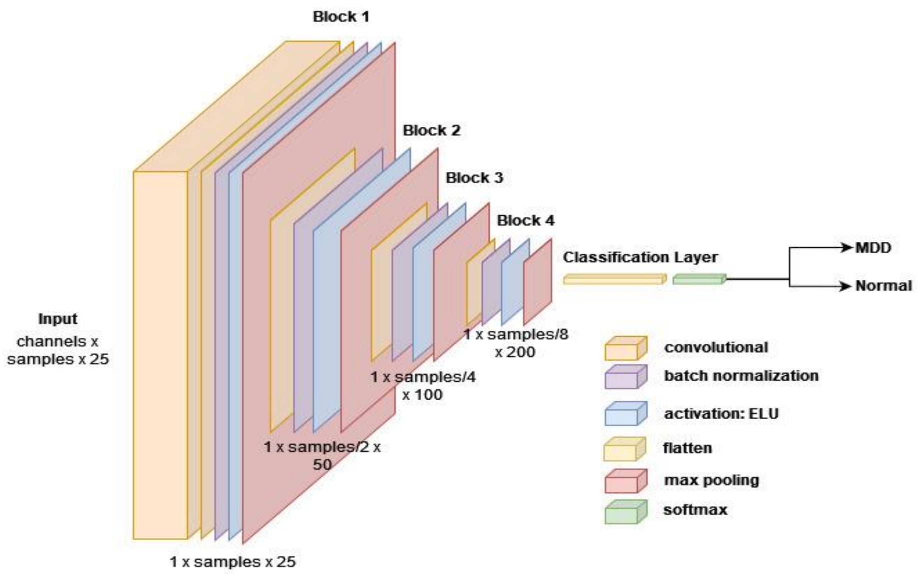

Fig. 2. Deep ConvNet architecture

Table 1 shows the contents of Deep ConvNet blocks. The shape variables are defined as C - the number of channels, S – the number of samples taken which is 250 samples taken, and N – the number of classes, respectively. Block 1 receives the input data and they pass through several layers of two-dimensional convolution layers (Conv2D), normalization, activation layers with Rectified Linear Unit (ReLu) function, pooling, and dropout layer with a value of 0.5. Blocks 2, 3, and 4 are similar blocks that perform feature extractions with higher-order filters. The classification layer uses the SoftMax function to perform the classification tasks between normal EEG patterns versus those with MDD.

Table 1
ConvNet block descriptions

Block	Layer	Output shape	Filter	Activation
Block 1	Input	(None, C, S, 1)	—	—
	Conv2D	(None, C, S, 25)	25	—
	Conv2D	(None, 1, S, 25)	25	—
	BatchNormalization	(None, 1, S, 25)	—	
	Activation	(None, 1, S, 25)	—	ReLu
	MaxPooling 2D	(None, 1, S/2, 25)	—	—
	Dropout	(None, 1, S/2, 25)	—	—
Block 2	Conv2D	(None, 1, S/2, 50)	50	—
	BatchNormalization	(None, 1, S/2, 50)	—	—
	Activation	(None, 1, S/2, 50)	—	ReLu
	MaxPooling 2D	(None, 1, S/4, 50)	—	—
	Dropout	(None, 1, S/4, 50)	—	—
Block 3	Conv2D	(None, 1, S/4, 100)	100	—
	BatchNormalization	(None, 1, S/4, 100)	—	—
	Activation	(None, 1, S/4, 100)	—	ReLu
	MaxPooling 2D	(None, 1, S/8, 100)	—	—
	Dropout	(None, 1, S/8, 100)	—	—
Block 4	Conv2D	(None, 1, S/8, 200)	200	—
	BatchNormalization	(None, 1, S/8, 200)	—	—
	Activation	(None, 1, S/8, 200)	—	ReLu
	MaxPooling 2D	(None, 1, S/16, 200)	—	—
	Dropout	(None, 1, S/16, 200)	—	—
Classification	Flatten	1*S/16*200	—	—
	Dense	N	—	SoftMax

2.6 Evaluation

To evaluate the classification model, a confusion matrix was used. The confusion matrix shows the predicted classification of the model against the actual classification from the given dataset. Inputs to determine the performance metrics given by accuracy, precision, and recall are based on the state of the positives and negatives which is either true or false. True positive is the number of samples that are correctly predicted as positive. False positive is the number of samples that are incorrectly predicted as positive. False negative is the number of samples that are incorrectly predicted as negative. True negative is the number of samples that are correctly predicted as negative. With these inputs, performance metrics are computed using Eq. (2), Eq. (3) and Eq. (4), respectively. Eq. (5) defines the F1 score of the model which combines precision and recall scores to compute the number of times a correct prediction was made across the entire data set.

$$Accuracy = \frac{TP+TN}{TP+FP+FN+TN} \tag{2}$$

$$Precision = \frac{TP}{TP+FP} \tag{3}$$

$$Recall = \frac{TP}{TP+FN} \tag{4}$$

$$F1\ score = \frac{2(Prec)(Rec)}{Prec+Rec} \tag{5}$$

where *TP* – true positive, *TN* – true negative, *FP* – false positive, *FN* – false negative, *Prec* – precision, *Rec* – recall.

Aside from these performance metrics, the training time of each model as well as the amount of memory used by the dataset before and after the pre-processing, and data augmentation were considered. These are for the assessment of the memory processing budget of the classifier. This is additional information for the design of the hardware requirements of this system.

3. Results

3.1 Performance Metrics

Table 2 summarizes the performance metrics result of the classifier according to the number of electrode channels using the test data sets. The accuracy of the classifier for each electrode set is more than 98%. The precision of the 5- and 16-channel EEG are higher as compared to the 128-channel EEG. The recall at 5- and 128-channel EEG is more than 98%. However, the 96% precision and recall for the 128- and 16-channel EEG, respectively, are relatively high enough to be considered. The F1-score for all the electrode sets is more than 98%. In terms of training time, and memory, the EEG that has 128 electrodes has the longest training time among the three sets of electrodes, and at the same time, it has occupied the largest amount of memory which is already expected due to the large amount of data stored. An increasing trend in terms of memory space usage is seen as the number of electrodes increases. However, the training time didn't have an increasing trend to verify the effect of the increase or decrease of electrodes in a set.

Table 2
Classifier performance

Performance Metrics	Number of Electrodes		
	5	16	128
Accuracy	98.28%	98.13%	98.16%
Precision	98.14%	100%	96.67%
Recall	98.75%	96.70%	100%
F1-Score	98.44%	98.32%	98.31%
Training Time (mins)	26.97	24.11	34.93
Memory (before pre-processing)	72.7MB	250MB	2.14GB
Memory (after pre-processing)	306MB	979MB	7.70GB

3.2 Validation Set Accuracy and Losses

The validation set accuracy and losses for each trained model relative to the number of electrodes were also plotted as shown in Figure 3, Figure 4 and Figure 5 showing the 5-channel, 16-channel, and 128-channel EEG, respectively. It can be noticed that all three models were able to acquire a validity accuracy value of close to 1.0 which supports the high accuracy performance of the model as presented in section 3.1. The figures also show that all three models were able to lessen the loss in only 100 epochs with an early onset of 20 epochs for the 5- and 16-channel EEG. This metric shows that the models were able to capture the validation dataset which results in better predictions as the number of epochs increases.

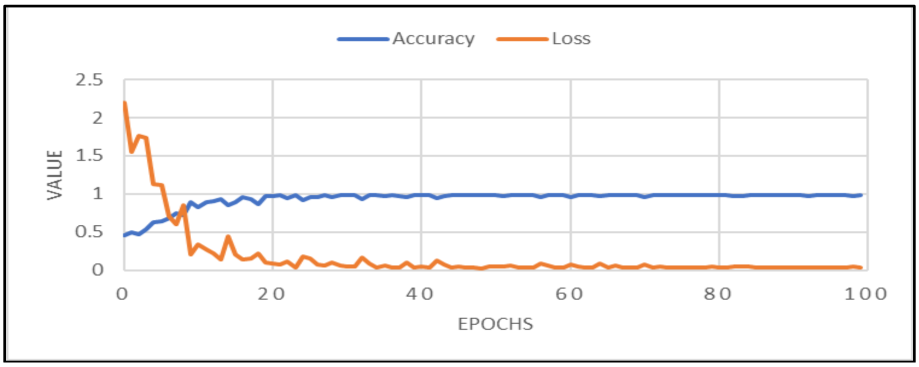

Fig. 3. Validation set accuracy and losses for 5-channel EEG

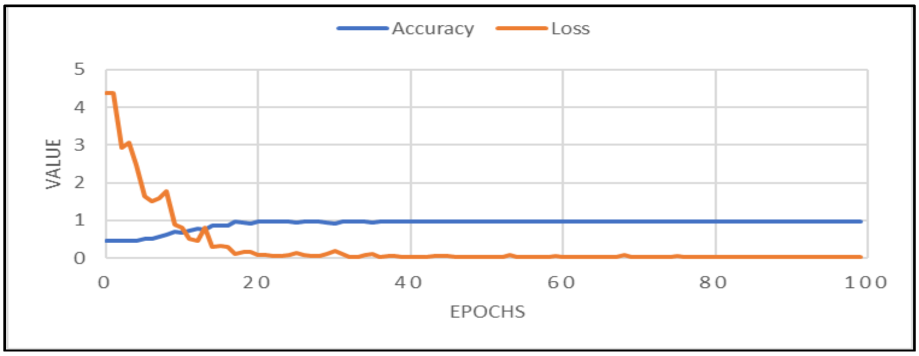

Fig. 4. Validation set accuracy and losses for 16-channel EEG

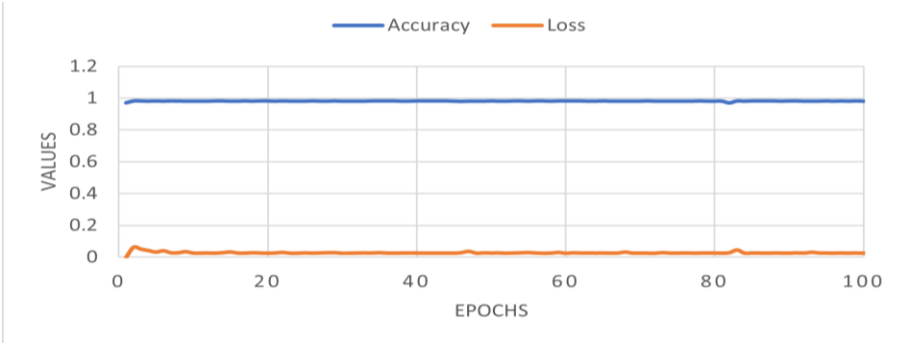

Fig. 5. Validation set accuracy and losses for 128-channel EEG

Despite these similarities, it is also important to note that the three models have different times before they become stable. In Figure 3, the accuracy graph stabilized after around 40 epochs; in Figure 4, the accuracy graph stabilized after 20 epochs, and in Figure 5, the accuracy graph stabilized after 2 epochs only. These differences will not matter as the number of epochs increases which only makes the trained models more accurate in predicting the values.

4. Conclusions

In this paper, channel locations of two (2) different low-cost EEG systems were compared with a larger 128-channel higher-grade EEG system. These channel locations were compared on a multi-modal open dataset for mental disorder analysis. In the evaluation of the dataset, the 5-channel, and 16-channel representing different EEG systems achieved a similar performance to the 128-channel system with 98% accuracy. Calculating the total training time, using the standard percentage difference formula, on all three systems shows a percent difference of 26% and 37% on the 5- and 16-channel systems, respectively. There is a significant difference in the size of the datasets when comparing the three different channel location systems, with the largest difference of 187% between the datasets for the 5- and 128-channel systems. Compared with the 128-channel location system, the other two systems can also be used to achieve similar results with the advantage of storage being less and being faster to train.

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