Classification of human Facial Portrait using EEG Signal Processing and Deep Learning Algorithms

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Abstract. An electroencephalogram (EEG) is used to evaluate the electrical activity of the brain. While a person sees something, the brain creates a mental precept, this precept captures the use of EEG to get an instantaneous example of what is happening inside the brain all through the precise technique. This study aims to design an automated convolutional neural network (CNN) based deep learning algorithm that can be employed for the visual classification of a human facial portrait using electroencephalography processing. Moreover, EEG information evoked through visible photograph stimuli has been employed through the convolution neural network (CNN) to realize a discriminatory mind recreation manifold of image classifications within the mind-reading process. We have used a 9-channel EEG Mind wave Mobile 2 Headset to record the brain activity of subjects while looking at images of four persons from the dataset. The presented results validate the proposed algorithm as it shows a precision of 80% that has greatly outshined the existing techniques. In further, this study shows that the learned capabilities by CNN-based deep learning models can be employed for automated visual classification that can be used for disabled persons and criminal investigation with further few improvements.

Keywords: Electroencephalogram (EEG), Convolutional Neural Network (CNN), Mindwave Mobile.

1 Introduction and Related Studies

Electroencephalography (EEG) is an electrophysiological technique used to monitor the electrical activity of the human brain. The human brain creates a mental perception of the object captured by the human eye that is essentially a mental impression of that thing. It is possible to capture the precept using brain signals to get a direct illustration of what is happening in the brain during a certain process. The important task here is the decoding of the sensory inputs received from brain impressions that are a fundamental modern technological challenge and constituent of neuroscience expertise [2]. However, the similar category object classification and the distinct human faces identification from brain-activity patterns evoked from visually similar inputs is enormously challenging. The representation of one-layer capabilities of the CNN appears generalized during one-of-a-kind information sets, as these are much likely Gabor filters and coloration blobs, whilst the very last-layer capabilities restrict to the specific dataset. The proposed scheme is based on EEG signals. The recording of the EEG signals is performed by fixing an electrode on the subject scalp using the standardized electrode placement scheme [3] which is shown in Fig. 1. Hence, Neurosky Mindwave Mobile 2 headset is used to extract and record the EEG signals which are further processed by using deep learning algorithms.

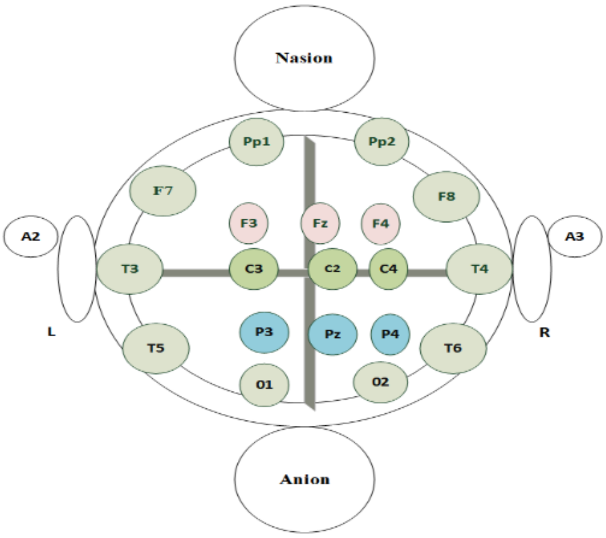

Fig. 1. Standardized electrode placement scheme.

Furthermore, the human judgment of visualization is used that provides an effective combining of multiple dynamic neural networks (DNN) layers to improve the visual quality of generated images. Whereas the result suggests that hierarchical visual information in the brain can be combined competently to recognize perceptual and subjective images [4]. This paper presents a novel approach to feature extraction and automated visual classification from the perceptual content of brain activity. We have used electroencephalography that is a recording process of the electrical activity of the brain that contains invaluable information related to the various physiological states of the brain. In recent research, the researchers have worked on the recording and processing of EEG signals in many fields. The concept of reading and analyzing data from the mind of a person while performing specific tasks has been investigated so far, especially for building brain-computer interfaces (BCI). Most brain-computer interfaces (BCI) studies have carried out binary EEG information types in the absence of specific styles. For example, the researchers implemented CNN for epileptic seizure prediction from intracranial EEG and highlighted the usefulness of bivariate measures of brainwave synchronization [5]. Similarly, for P300 detection researchers used 4 single classifiers with exceptional functions set and 3 multi-classifiers [6]. Recently, other works are pursued using deep mastering to model more complex cognitive models (i.e., audio stimuli, or cognitive load) from mind signals [7-9]. These strategies have proved the capability to use mind indicators and deep mastering for type however, they deal with a small number of class classes, and none of them are related to the visible scene know-how [10-11]. However, these scientific indications are not thoroughly utilized to assemble visible stimuli–evoked EEG classifiers [11]. The underlying concept is to analyze a brain sign discriminative manifold of seen classes by classifying EEG indicators through thought analysis [12]-[15]. We define BCIs as the undertaking of interpreting an item class associated EEG indicators for inclusion into computer vision methods. Whereas, in our research real-time EEG-based human visual records have been used to pick out the picture of the respective man or woman proven to the difficulty through using convolutional neural networks and specific deep reading strategies.

2 Methodology

This paper aims to design an algorithm that can record the EEG signals of the human brain and then process the gathered information for visual classification by using algorithms of deep learning. Neuroscience exquisitely works in approaching the visual scenes evoked by the human brain.

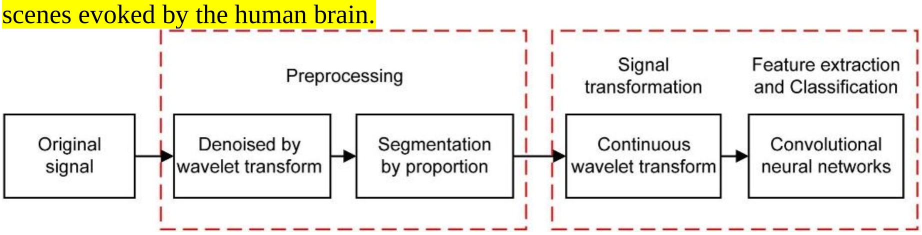

Fig. 2(a): Schematic of Proposed Model

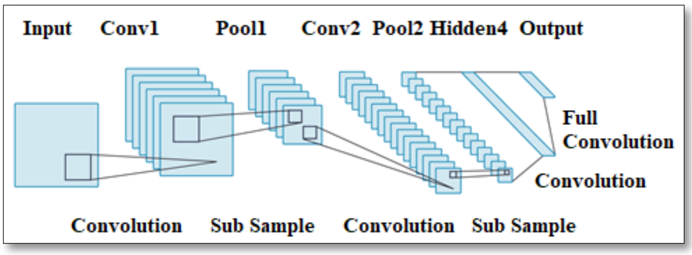

Fig. 3(b): Schematic of Proposed Model and Working of ANN

The deep mastering strategies have the potential to study capabilities at a couple of levels, which makes the machine capable to examine complex mapping feature f: X →

Y directly from the given data, without the assistance of the human crafted features. The foremost characteristic feature of deep learning methods is that their models contain deep architecture. A deep architecture network leads to multiple hidden layers in the network. We have used convolutional neural networks in deep learning for better training and testing of EEG data. However, convolutional neural networks (CNN) are one of the most powerful deep learning neural network models used for object detection and classification. In CNN, all neurons are connected to a set of neurons in the next layer in a feed-forward fashion. The following Fig. 2(a) and (b) illustrate the block diagram of the proposed model and the internal functionality of ANN. An EEG signal is the external manifestation of thinking activity. Since EEG signals have been recorded, people utilize an assortment of strategies to utilize EEG signs to uncover mind movement. In these investigations, EEG signals incited by picture upgrades have been generally utilized in numerous investigations because of stable highlights. The basic architecture of CNN has been shown in Fig. 3 that incorporates three primary sub-blocks, comprising convolution, pooling, and fully connected layers. Seven subjects are shown human facial portraits while EEG data has been recorded. We have considered four human facial portraits shown to each subject and respective EEG data has been recorded.

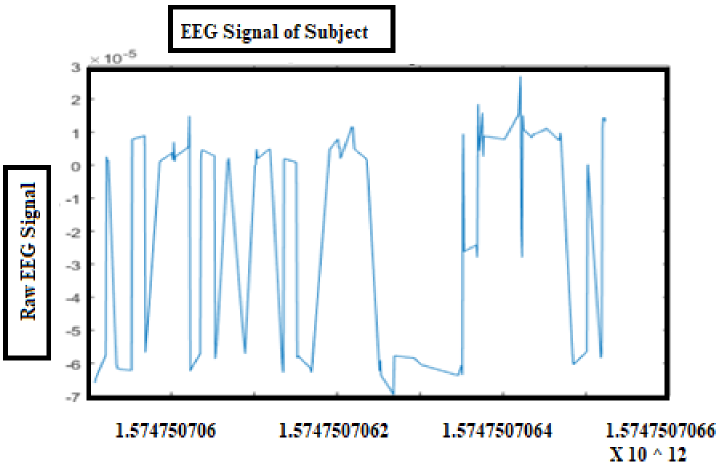

Fig. 3: Raw EEG signal of subject EEG data acquisition

An EEG data of all seven subjects is recorded in the same experimental environment. The dataset used for visual stimuli has been a subset of four human facial portraits. During the experiment, each image has been shown to the subject for 30 seconds followed by 20 seconds pause, and the EEG signals are recorded. A summary of the experimental and random paradigms is shown in Table 1. The experiments are conducted using Neurosky Mindwave Mobile 2 headset having 9 channels and active low impedance electrodes. Sampling frequency and data resolution of the headset are 512 Hz and 12 bits respectively. Raw EEG signals are processed using Hamming and Hanning's windows having low bandpass and Butterworth filters to remove the unwanted noise and distortion in the signal.

Table 1. Summary of experimental and random paradigm

1	Total number of images	4
2	Time for each image	30 sec
3	Total sessions	4
4	Running (Session) time	900 sec
5	Running (overall) time	3600 sec
6	Pause between images	20 sec
7	Total number of recorded signals per subject	80

Raw EEG signal consists of the power spectrum of alpha 8– 12Hz, beta 12 – 40 Hz, and gamma 40 – 100 Hz.

Table 2: The training data of EEG signal of one subject in .csv format

timestampl	poorSignal	eegRawVal	eegRawVal
1.575E+12	26	-101	-2.22E-05
1.575E+12	26	-108	-2.37E-05
1.575E+12	26	-111	-2.44E-05
1.575E+12	26	125	2.75E-05
1.575E+12	26	-86	-1.89E-05
1.575E+12	26	-84	-1.85E-05
1.575E+12	26	99	2.18E-05
1.575E+12	26	-124	-2.72E-05
1.575E+12	26	112	2.46E-05
1.575E+12	26	115	2.53E-05
1.575E+12	26	90	1.98E-05
1.575E+12	26	-109	-2.40E-05
1.575E+12	26	121	2.66E-05
1.575E+12	26	88	1.93E-05
1.575E+12	26	-119	-2.61E-05
1.575E+12	26	-118	-2.59E-05
1.575E+12	26	-124	-2.72E-05
1.575E+12	26	-127	-2.79E-05
1.575E+12	26	-124	-2.72E-05
1.575E+12	26	117	2.57E-05

Fig. 2 shows an EEG sign of and a subject that is extricated by utilizing an application and plotted in MATLAB. The EEG signal of each subject for each image is then labeled to avoid any inconvenience during the testing and training of the CNN. Table 2 shows the training data set of EEG signal of each subject in .csv file format. Existing methodologies essentially concatenate the time sequence from numerous channels into a solitary characteristic vector, disregarding historical elements, which, rather, contain principal data for EEG action understanding [2, 15]. To include such dynamics in our representation we concatenate the time sequence, and we employ the LSTM-recurrent ANN due to their ability to track long-term dependencies of their input data sets. In further, the EEG signals have been evaluated at different points by using different software to do the model building. Fig. 3 shows a diagram of the proposed approach, in the above segment a low dimensional portrayal for fleeting EEG signals filmed whilst subjects glanced at pictures of the subject is found out by the encoding element, and the processed EEG traits are utilized in the preparation of a picture classifier. In the underneath area, a CNN is prepared to appraise EEG includes legitimately from pictures; at that point, the classifier prepared in the previous stage is utilized for mechanized order short of the need for EEG information for new images. The encoder and classifier preparation is completed over inclination drop using the class name related to the picture that appeared while every EEG grouping has been recorded.

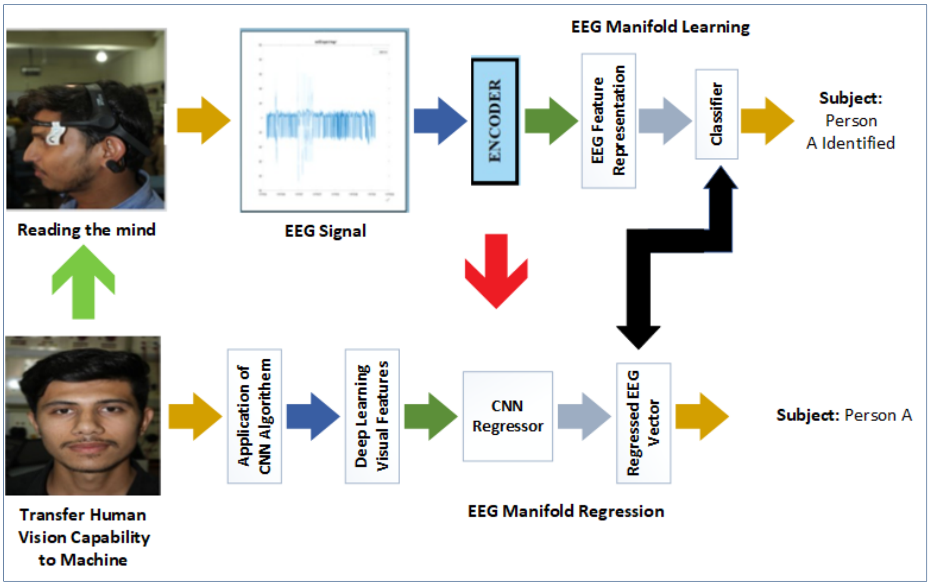

Fig. 4. EEG Manifold learning and Regression with Identifier and Subject

After preparing, the encoder can be utilized to produce EEG features from information EEG sequences, while the order system will be utilized to foresee the individual's picture for an info EEG includes portrayal, which can be registered from EEG signals. The following Figure 4 illustrates an EEG Manifold learning and Regression with Identifier and Subject. The primary layers of CNN endeavor to get familiar with the general features of the pictures, which are regular between numerous undertakings, in this way we introduce loads of these layers utilizing prepared models, and afterward, gain proficiency with loads of last layers without any preparation in a start to finish setting. CNN is programmed and modified by using the SoftMax layer with the regression layer for classification as shown in Fig. 5. The CNN-based regressor has different layers such as Conv. layer, Max pool layer, Average Max pool layer having different stride and different padding [10]. Long short-term memory LSTM and CNN models, just as profound and shallow CNN models, speaking to the best in class in profound learning for BCI errands having significantly better-quality deviation. The flow chart provided in

Fig. 5 shows a detailed flow of this work. A Long Short-Term Memory (LSTM) is a profound learning framework that keeps away from the evaporating angle issue. An LSTM is typically increased by repetitive doors named overlook entryways. In further, an LSTM forestalls back engendered mistakes from evaporating or detonating. Rather, blunders can stream in reverse through boundless quantities of virtual layers unfurled in space.

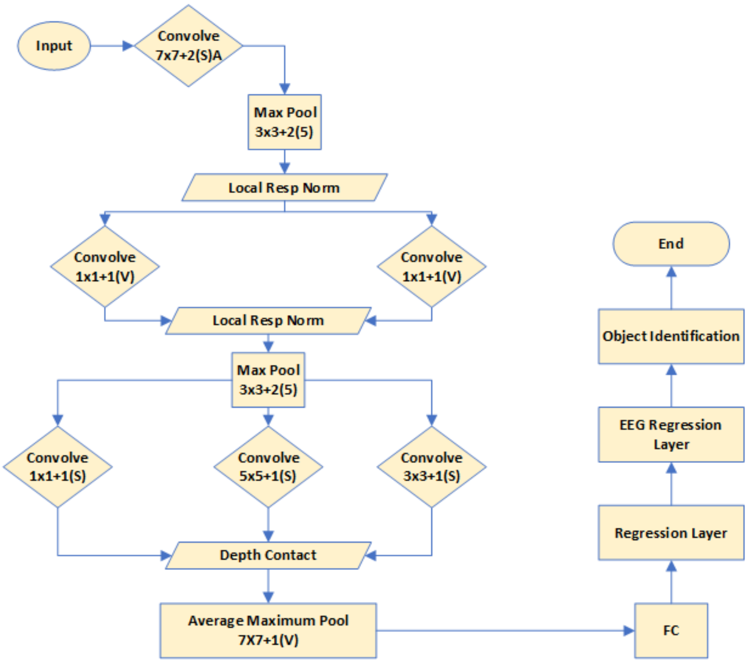

Fig. 5: CNN-based Regressors

LSTM models with up to a few LSTM layers which include 32 to 256 LSTM memory cells seemed. Since it isn't viable to understand the tremendous model shape a previous, precise configuration has been trained and monitored on the validation set [16-22]. The fine consequences have been finished with a single layer and 128 LSTM memory cells, which are normal with consequences acquired [9]. The concept of studying the thinking of people at an identical time as performing unique responsibilities investigated to build brain laptop interactions.

3 Performance Analysis and Results

The dataset is divided into training validation and test sets for the fraction of 80% training and 20% testing. In further, the data is again evaluated using different software to monitor the division of data into training and testing sets.

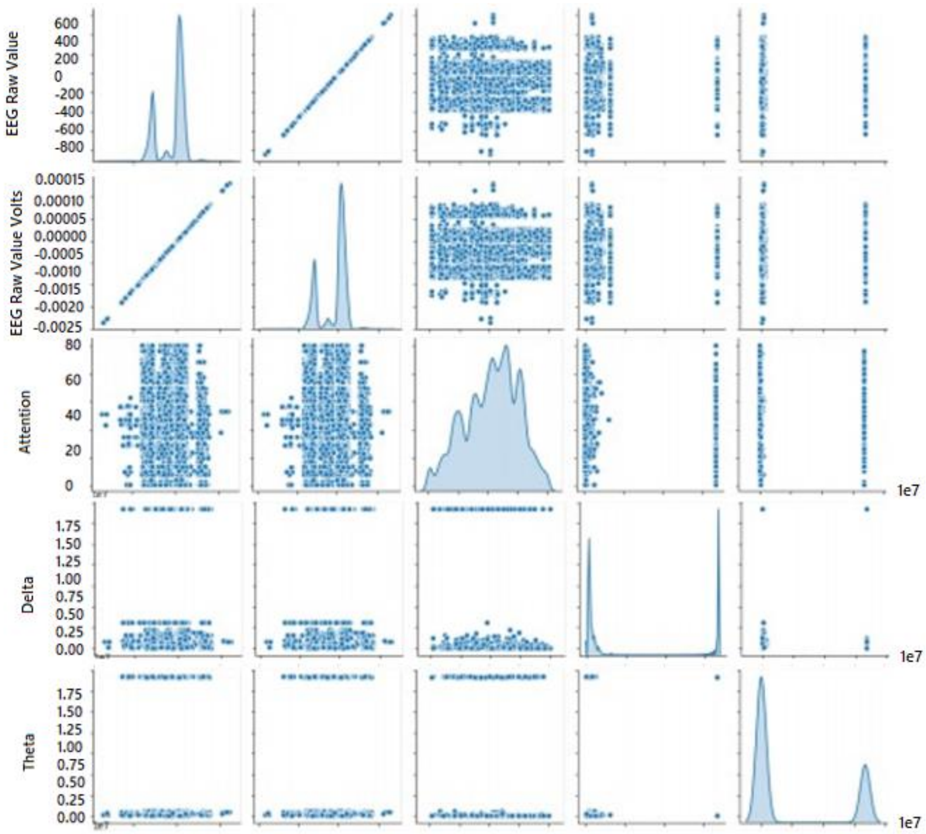

Fig. 6: Graphical Representation of training data

We have ensured that the signals created by each subject for a solitary picture are all connected in a solitary split. The entire model design had taken just dependent on the aftereffects of testing split which makes the test split uncontaminated and solid quality file for definite understanding. The classifier has been used in Fig. 6 for the exactness of the prepared encoder. A similar classifier is utilized on CNN relapsed EEG highlights for robotized visual order.

Table 3: The training data of EEG signal of one subject in CSV format

Schemes	Universal – Accuracy (%)	Transfer – Accuracy (%)	Increase (%)
Proposed CNN	62.1	80	17.9
MLP [3]	55.7	62.3	6.6
LSTM [3]	63.6	67.2	5.8

The proposed stacked LSTM encoder approach had the option to arrive at 70% characterization exactness, which extensively beats the exhibition of 29% more than 12 classes of their dataset accomplished in the visual scenes has been recorded for 30sec with the time interim of 1ms. Table 2 also represents that the time may influence the grouping execution. Table 2 shows for 30sec with the goal that the subject imagines the picture highlights of the individual. The best execution has been taken valiantly when adjoining perfect conditions have been given to the subject. Along these lines, the visual order has been enacted after the underlying visual acknowledgment process in the visual cortex of prosperity. Table 3 provides a comparative analysis of the proposed model and the existing illusion detection scheme proposed in [3]. The comparison has been performed based on Universal accuracy and transfer accuracy. Table 1 depicts a considerable improvement of the CNN application.

4 Conclusion and Future Works

In this paper, the human brain-driven preprogrammed visual classification strategy has been proposed. It involves a predominantly two-phase CNN-based LSTM model to learn visual improvements evoked by EEG information utilizing a most minimized strategy for the portrayal of such information. The methodology shows serious execution explicitly worried to other EEG learning portrayals of different article classes as in relevant on ongoing human cerebrum forms engaged with visual acknowledgment of individual pictures. It reveals the emotional substance of our psyche, and it gives an approach to get to, investigate, and share the substance of our discernment, memory, and creative mind. The promising outcomes have been accomplished in visual acknowledgment utilizing computer vision, AI, and neuroscience by moving human visual abilities to the machines. The affirmative designed autonomous system using mind-reading technology can be implemented for a criminal investigation. Image Reconstruction is admissible in court because unlike a polygraph, which relies on emotional responses, our technique uses EEG to see how the brain reacts to pictures related to a crime scene.

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