Analysis of brain signal on visual noise affecting driver's attention using deep learning

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***Abstract*—One of the main reasons for road accidents is driver's brain activities during driving, some of which is heavily influenced by roadside visuals like posters, billboards and other objects around. Our objective is to prove that those posters, billboards, and roadside activities are some of the reasons for driver's distraction that create high arousal on negative valence in certain part of driver's brain and causes frequent road accidents. Our experiment shows that images of visually distasteful creates quite opposite reaction to that images of visually pleasing to human brain. Taking pictures from different locations of Dhaka city representing the actual roadside scenario that produces high stimulation in brain and can lead to human errors. In this research, brain data was collected using EEG device by displaying categorically positive, negative, and neutral pictures to the viewers. Collected brain data was analyzed using Deep Learning techniques. From the result, this research established strong correlations between different categories of images and the neural activities in the brain. The results are conclusive about perturbation on visually distracting elements along the roadside which may contribute to minor to major road accidents.**

***Keywords*—** Visual Noise, EEG, Deep Learning, Emotion State, Brain Signal

I. INTRODUCTION

Road accident in high income countries indicate a downward trend in recent decades, though motorization has increased the lives of many soul and community.In large part of the worlds population, road-traffic injury is raising in terms of societal and economic costs significantly [1]. Due to road traffic accidents injury, deaths are a crucial general public health problem in many developing countries where more than 85 percent of people lost their soul from road traffic injuries [2]. Road accident has become a significant problem now a days.Due to a road accident, a family may lose their only earning person. The owner of the vehicle falls on the financial issue. Government has to pay for the road and other structures reconstruction. So, in total, many people are directly and indirectly affected by a road accident.In 2018, at least 7221 people died and 15466 were injured.In 2019, at least 7855 people died and 13330 injured [3]. 634 more people were dying through road accidents one year. There are many reasons for road accidents. In Dhaka the situation in not under control. There are many billboards, posters, roadside activities that may impact the driver's brain. We know that most of the billboards, posters, advertise use fancy, attractive colors that the viewer may attract and read the billboard, etc [4]. At the driving time drivers have to concentrate on the front part of the vehicle. When a billboard or poster come in front of him, most of the time he feel attraction to that poster or billboard. So due to concentration lagging, color effect, environmental activity accident may occur. We took this hypothesis and want to prove that billboards, posters, and roadside activity have an impact on the driver's brain.

II. RELATED WORK

Brain signal analysis has taken the interaction between brain and computer to the next generation. From every image, there are many stimuli generates to our brain neurons. Brain neurons are connected one node to another and make a neural network. These visual signals are integrated through different neurons and come up with a decision [5].

In micro volt, the signals of Electroencephalography (EEG) are taken. Signals of the brain are divided into three types. They are 1) positive, 2) neutral, and 3) negative [6]. For the positive signal, the micro voltage frequency is low. The signals are higher than positive and negative in the neutral signal, giving the highest amplitude in micro voltage [7]. Visual noise is responsible for different types of emotions. These emotions are discernible through high and low arousing pictures when displaying different types of images [8]. Emotions are dependent on brain signals. They are shown an arousing graph 9 [9]. Several methods define emotional steps. For recognition, emotion analysis by approximate (ApEn) and wavelet entropy (WE) were used [10]. Another differential entropy (DE) and energy spectrum (ES) method were used to get better results [6]. Destruction of drivers due to the emotional state has an impact on their driving performance. Non cognitive destruction is happening due to billboards, posters beside the roadside [6]. Due to destruction drivers, the brain cannot perform well as they expected—their concentration on driving decrease due to roadside activity (such as posters, billboard). Low driving performance was detected due to destruction [10]. Colors on the billboard are also responsible for the destruction. When a colorful billboard and poster are coming nearer to the driver, their eye blinks are continuously increased [11]. Dual-task was detected from brain stimuli, so prediction is correct [11]. The neural network can perform well in classifying emotions. Statistical features can be successfully used to classify different types of emotions using the EEG [12].

Correlation analysis was used to classify the emotional state. This research deep neural network was used to classify the emotional state and prove the destruction of driver's attention for billboard, poster, and roadside activities.

III. Methodology:

The scientific process of EEG signal analysis is followed during this experiment. They are data collection from EEG signal, data prepossessing, data analysis, train test, output [13].

A. Image collection and Classification

The image collection is an important part of this research. For collection of images at different location of Dhaka city was chosen. The different time slot was chosen to take the different quality of images. For soothing images free road, road without billboard posters and morning time were selected. Noisy images were taken from full of billboard and regular working day.

Images were classified manually. The image which creates soothing, refreshing feelings are categorized as good and image which creates angry, anxious, disturbing feelings are categorized as bad or noisy image. Images which have both good and noisy scenario are categorized as neutral images [14]. All the images were resized by dimension. A fixed frame size 2048*1532 was chosen. At the run time if all the image file size is different and big time delay occur thus file size was reduced. The pixel sizes of images were same as previous to maintain the image quality.

B. Experimental Setup

The experiment has done in a room that has low audio noise and absence of visual destruction objects been maintained. Conducting this experiment, a healthy 21 years old male was chosen. He had no physical lacking. A desktop slider application was built. The slider software was made using C language as the emotive device run through C platform. No system delay due to the different platform has occurred.

- EEG device: EMOTIVE EPOC+ 14 Channel Wireless Headset.
- Programming language : Python, R
- Python Version : 3.7
- Anaconda Environment : Anaconda 3
- IDE : Jupyter notebook, Rstudio
- Python libraries : TensorFlow, Keras, NumPy, pandas, matplotlib

C. EEG data collection

An EEG wearable headset was placed on the subject's head. All the nodes were wet using the conducting solution to get the accurate result from brain signal. The time segment of each image display time was fixed. When one segment was completed, a CSV(comma-separated value) file was generated. A short display time was selected to avoid dull type signals.

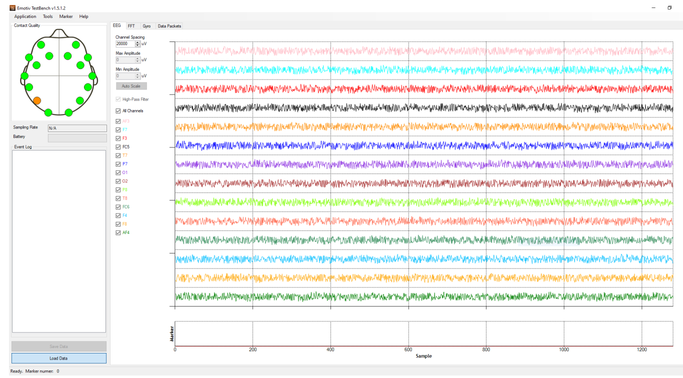

Fig. 1. 14 channels analog data

D. Data Preprocessing

There were many channel signals that do not influence the brain data. They give the signals according to other functionality of other body part activity. Elimination of those columns causes brain signals has no dependency on those irrelevant columns. 24 columns value was found. Based on functionality, those columns are dropped, and 14 channels remained.A high pass filter was used to eliminate the slow frequencies. The three quality images were marked. Positive, neutral and negative images were marked as +1, 0, and -1.

E. Data Analysis

After processing EEG data analysis was done by three steps. At first summary function was called in RStudio. Data was analyzed through mean value. Calculated the differences of mean as following positive – negative, positive-neutral and negative-neutral. Secondly generated the 14 channel value in correlation matrix. From the matrix visually seen the activation of channels for positive, negative and neutral data. Lastly checked the validation of the data set using deep learning model.

F. Summarized data

After the preprocessing of EEG data using RStudio, those datasets were summarized. From the summarization minimum, 1st quartile, median, mean, 3rd quartile, maximum were found. Then the difference between positive, negative and neutral datasets was calculated.

G. Model selection

For experimenting, the deep neural network was selected. Processing EEG data deep learning model gives a good result. The deep learning model is time-efficient and can process a huge amount of data comparatively short time than machine learning [15].

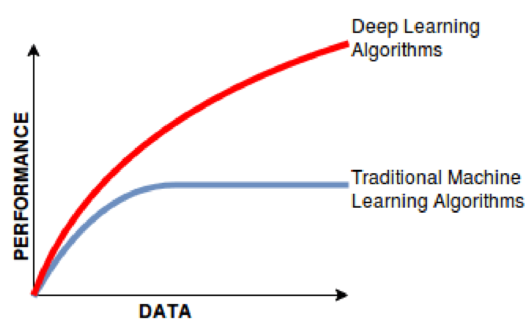

Fig. 2. Deep learning Vs. Machine learning

H. Train and test

Using a deep learning model trained and tested the data set in various ways. Thus trained and tested our model with a ratio of 80% and 20%. At first, trained the model with 80% positive data and tested 20% positive data.

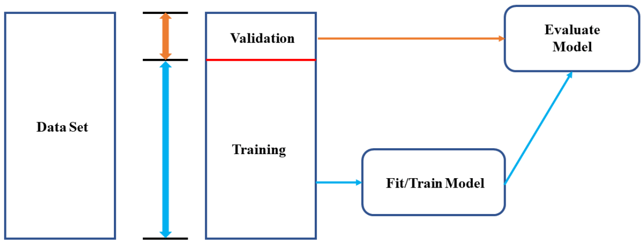

Fig. 3. Data train test model

Then trained with positive 80% and tested negative 20% data set. Later on, trained the model with negative 80% data and tested by negative 20% data. Again we trained with negative 80%and tested with positive 20% data. Then trained the deep neural network model with neutral 80% data and tested by 20% positive data. Later trained with neutral 80% data and tested by negative 20% data. Lastly, we trained our model with neutral 80% data and tested with neutral 20% data. We have experimented again and again to get the expected output.

IV. Result and Discussion

A. Statistic Analysis

In table I, the summary function was called. At first, the summary function was used to calculate the min, 1st quartile, mean, median, max, and 3rd quartile. Then the differences between positive-negative, positive- neutral, negative- neural. Then compare Mean with another channel. The research shows that the negative dataset's amplitude is always higher than the positive dataset's amplitude. Compare with all other datasets found a similar result. The frequency of the negative dataset is higher than the positive dataset. Less frequency data is more sleepy than high-frequency data [16]. That means more frequency data are noisier. Thus it is partially saying that negative data is noisier than positive data. Moreover, it is an effect on human attention detection.

TABLE I
Difference between each channel.

	AF3	F7	F3	FC5	T7	P7	O1	O2	P8	T8	FC6	F4	F8	AF4
						POSITIVE - NEGATIVE DIFFERENCE								
Min. :	0.513	0	0	-2.051	0	-1.026	0	0	0	0.513	-0.513	0	2.051	0.513
1st Qu.:	49.872	-25	34	38.564	130	-78.641	-8	-23	-46	28.846	-76.769	66	-80.128	-18.846
Median :	28.718	-20	-16	23.282	80	-100.03	-21	-49	-115	-49.179	-132.54	-5	-11.949	42.051
Mean :	16.292	-5	0	14.65	60	-54.583	12	-22	-69	2.875	-65.213	-1	-38.144	-9.778
3rd Qu.:	-4.743	58	0	0.744	37	-43.487	28	-40	-85	13.026	16.077	-66	2.103	-16.538
Max. :	-0.512	1	0	0.462	0	0.462	0	-1	0	-0.462	-1.538	0	-1.487	-2.051
						POSITIVE - NUTRAL DIFFERENCE								
Min. :	1.026	0	0	0	0	0	0	0	0	0.513	0	0	1.538	1.026
1st Qu.:	37.795	19	53	46	64	-10	-36	4	7	-25.154	-45	50	-31.282	-76.795
Median :	41.692	-23	37	5	11	-30	-61	-35	-112	-70.179	-104	116	48.718	14.538
Mean :	19.031	-13	29	35	19	-10	-19	-12	-64	-17.125	-56	29	-2.261	-4.709
3rd Qu.:	28.59	-47	47	94	8	-33	27	-49	-127	13.026	-11	6	11.026	37.872
Max. :	-0.974	0	-1	0	0	1	0	-1	-3	1.538	-2	0	-1.025	-1.513
						NEGATIVE - NUTRAL DIFFERENCE								
Min. :	0.513	0	0	2.051	0	1.026	0	0	0	0	0.513	0	-0.513	0.513
1st Qu.:	-12.077	44	19	7.436	-66	68.641	-28	27	53	-54	31.769	-16	48.846	-57.949
Median :	12.974	-3	53	-18.282	-69	70.026	-40	14	3	-21	28.538	121	60.667	-27.513
Mean :	2.739	-8	29	20.35	-41	44.583	-31	10	5	-20	9.213	30	35.883	5.069
3rd Qu.:	33.333	-105	47	93.256	-29	10.487	-1	-9	-42	0	-27.077	72	8.923	54.41
Max. :	-0.462	-1	-1	-0.462	0	0.538	0	0	-3	2	-0.462	0	0.462	0.538

B. Correlation Matrix

For visual representation, a correlation function was used. From the correlation matrix in fig 5, it is easy to understand that in negative dataset; there is a strong correlation between each channel.Here (T7,AF3), (AF3,P8), (AF3,T8), (AF3,F8), (T7,P8), (T7,T8), (T7,F8), (T7,AF4), (p8,f8) those channel have strongly positive correlation and (AF3,O2), (AF3,FC6), (AF3,F4), (AF3,AF4), (T7,FC6), (O2,F8), (T8,FC6), (T8,F4) those channel have strongly negative correlation. For positive matrix in fig 4, low connectivity was found and their only two channels (t7,f7), (p7,t7) have strongly negative correlation. The neutral data set was moderately connected with each node.

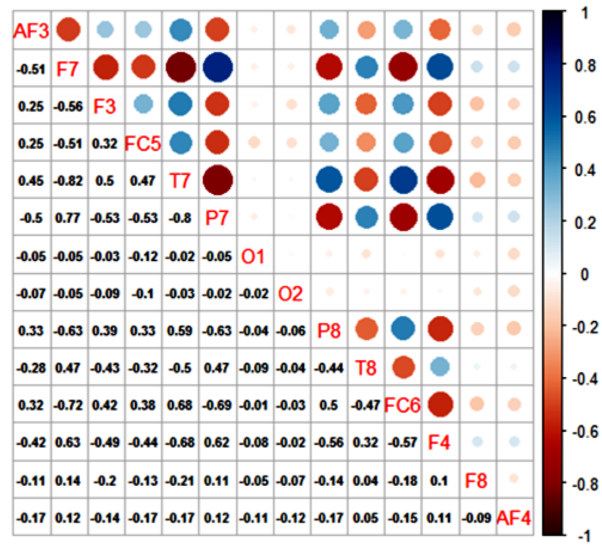

Fig. 4. Positive data set correlation matrix.

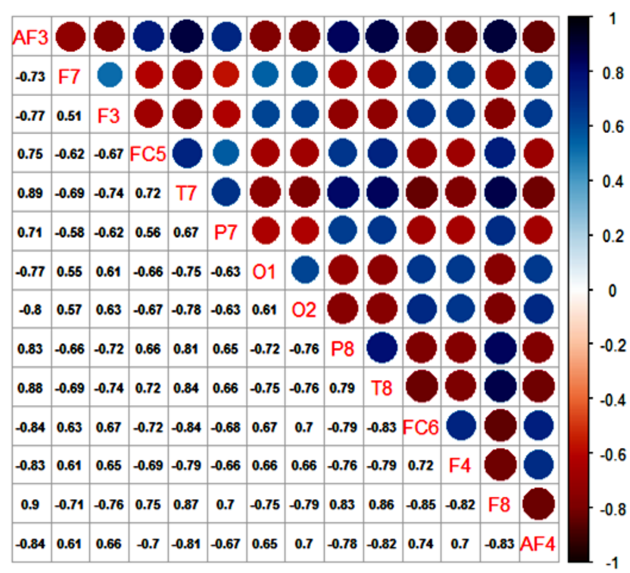

Fig. 5. Negative data set correlation matrix.

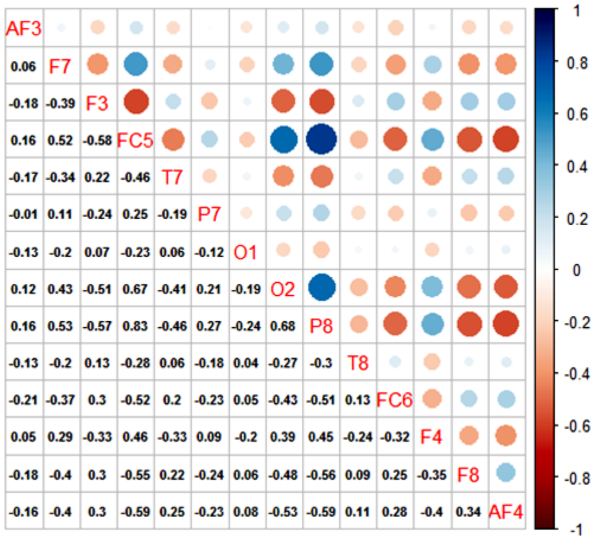

Fig. 6. Neutral data set correlation matrix.

C. *Deep Neural Network*

In the deep learning model, tried some parameters to get good accuracy. From various parameters, optimizer adam, epoch value 10, batch size 50 were fixed.

Trained positive and tested with negative accuracy was 0%. Then trained with negative and tested by positive accuracy was 0%. Again trained with positive, negative, and tested by neutral accuracy was nearer 50%. This accuracy was expected.

TABLE II
DNN TRAINING RESULT.

Scenario		**RMSE**	**Accuracy(%)**
Train(80%)	Test(20%)		
Positive	Positive	0	100
Positive	Negative	0.9906	0
Positive	Neutral	0.9989	0
Positive&Negative	Positive	0.4854	99.7
Positive&Negative	Negative	0.5659	98.6
Positive&Neutral	Positive	0.1012	98.8
Positive&Neutral	Neutral	4969	99
Negative&Neutral	Negative	0945	99.1
Negative&Neutral	Neutral	0.3468	100
Positive	Positive&Neutral	0.4152	49.93
Positive&Neutral	Positive&Negative	0.7065	50.07

In table II, easily understands that deep learning models can classify positive, negative, and neutral images. The RMSE value is low and accuracy value is high.So, that's why the deep learning model is good.

From the above Statistic Analysis and Correlation Matrixes clearly understand that for noisy or negative images activation of brain lobes are high. For positive images activation of lobes are low.so it is Proved that noisy images produces high brain activity than that of good images .

V. Conclusion and Future Work

Based on hypothesis images create an impact on the viewer. For different image, different brain signals are generated. In this paper, from statistical result opposite type of signals are detected. One type has a low voltage amplitude, and another type has a high amplitude of voltage. Moderate voltage amplitude was found for the neutral picture. Duration of displaying images and brain signal generated time matching with each other. For positive image, the brain's signal amplitude is low and negative image, the brain's amplitude is high. From correlation visually represented that for the positive image, most of the brain's lobes activation is low, and for the negative image, most of the lobes activation is high. Neutral images show moderately activation of brain lobes. Using the deep neural network (DNN) can specifically identify three types of images from dataset.

In the future subject of the experiment will change one from many. Various body parameters such as blood pressure, body temperature, heart rate, hormone test, oxygen saturation to understand of subject's body condition will be taken. Then experiment will be conducted through car simulator showing the different type of billboard, posters and different roadside activity (such as greenly road, countryside road).

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