

# Eye Blinking EEG Signal Analysis Using Brain Computer Interface Devices

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**Abstract**— In this paper, electroencephalogram signals were acquired and analyzed during different physical activities like rest, anger, and eye blinking. The eye blinking artifact in electroencephalogram signal is studied and analyzed. For this purpose, an Open-Source Brain-Computer Interface device is used for the acquisition of electroencephalogram signals from a single subject (me). The brain waves were acquired at a regular interval, and around 142 instances of eyeblinks were recorded. Eyeblinks preprocessing was done in MATLAB using Butterworth filters. I have developed the algorithm to find the duration of eye blink using MATLAB. Also, I have applied various techniques like Independent Component Analysis (ICA), Machine Learning Algorithm (Random Forest Classifier, Gradient Boosting, Logistic Algorithms) to determine the EEG signals were eyeblink signals or not. Among all the techniques and algorithms, Random Forest Classifier has the highest accuracy.

**Keywords**— *Electroencephalogram (EEG), EEGLAB, MATLAB, Brain Waves, Open Source BCI, ICA, Machine Learning*

## I. INTRODUCTION

The human brain is one of the most complex systems found in our body, and an exacting task to understand the brain, brainwaves. Different techniques have been evolved from past to understand the brainwaves. Among them the most used technique is Electroencephalogram. Both invasive and non-invasive EEG recording have an increasing role in neuroscience and brain computer devices interfaces. The invasive devices should be inserted in brain by surgery while non-invasive devices can be easily fit into the scalp. Using non-invasive devices is a simple and fast process to analyzing the brain activities. However, signal quality from invasive devices is 20 to above 100 times better than the simultaneously obtained from non-invasive devices [1]. While dealing with eye blink and movements EEG signals, the use of non-invasive devices has significant signal quality as compared to the invasive devices. Comparing blink related artifacts in non-invasive and invasive EEG, simultaneously recorded from prefrontal and motor cortical regions using an approach suitable for detection of small artifact contamination. As expected, it is found that blinks to cause pronounced artifacts in non-invasive EEG both above prefrontal and motor cortical regions [1]. In this experiment we have used non-invasive devices from OPENBCI and Emotiv to analyze brainwaves. We are more focused in analyzing brain activities due to eye movements and controlling other devices like RC car, drone using brain waves.

EEG signal is bio-potential generated from brain activities, represented as voltage (very small in magnitude) fluctuations from ionic movement of neurons within the

brain [2]. Depending on brain activities different magnitude and frequency of signals are generated from brain. The amplitude of the EEG signals ranges between 10 - 200  $\mu$ V with a frequency falling in the range 0.5 - 40Hz. EEG waveform is classified into five different frequency bands (alpha, beta, theta, delta, and gamma bands) [3]. Delta ( $\delta$ ) waves (0.5 - 4Hz) are the slowest EEG waves, normally detected during the deep and unconscious sleep. Theta ( $\theta$ ) waves (4 - 8Hz) are observed during some states of sleep and quiet focus. Alpha ( $\alpha$ ) band (8 - 14Hz) originates during periods of relaxation with eyes closed but still awake. Beta ( $\beta$ ) band (14 - 30Hz) originates during normal consciousness and active concentration. Finally, Gamma ( $\gamma$ ) waves (over 30Hz) are known to have stronger electrical signals in response to visual stimulation. Fig.1 shows the five frequency bands of EEG signal. Different acquisition protocols have been tested for human recognition tasks such as relaxation with eyes closed, EEG recordings based on visual stimuli, and performing mental tasks. In this paper we analyze the eye movement activities and corresponding signals generated from the brain.

Waves	Frequency Bands (HZ)	Behavior Trait
Delta	0.3-4	Deep Sleep
Theta	4-8	Deep Meditation
Alpha	8-13	Eye Closed, awake
Beta	10-30	Eyes opened, thinking
Gamma	30 and above	Unifying consciousness

Figure 1: Five Frequency Band of EEG Signal

The brain-wave signals are extracted, and signal processed from BCI devices. The processed signal is transferred to the computer via Bluetooth, or any medium and feature selection processed of obtained discrete signal is handled with MATLAB. Figure 2 shows the proposed block diagram of the system.

The eyeball acts as a dipole with a positive pole oriented anteriorly (cornea) and a negative pole oriented posteriorly (retina) [4]. When the eyeball rotates about its axis, it generates a large amplitude electric signal which is detectable by any electrodes near the eye known as Electrooculogram [5]. Figure 3 shows, when the eyeball rotates closer to FP1 electrode and produces a positive deflection. Similarly, when the eyeball rotates downwards the positive pole (cornea) becomes far away from Fp1 (Closest to the reference electrode) produce

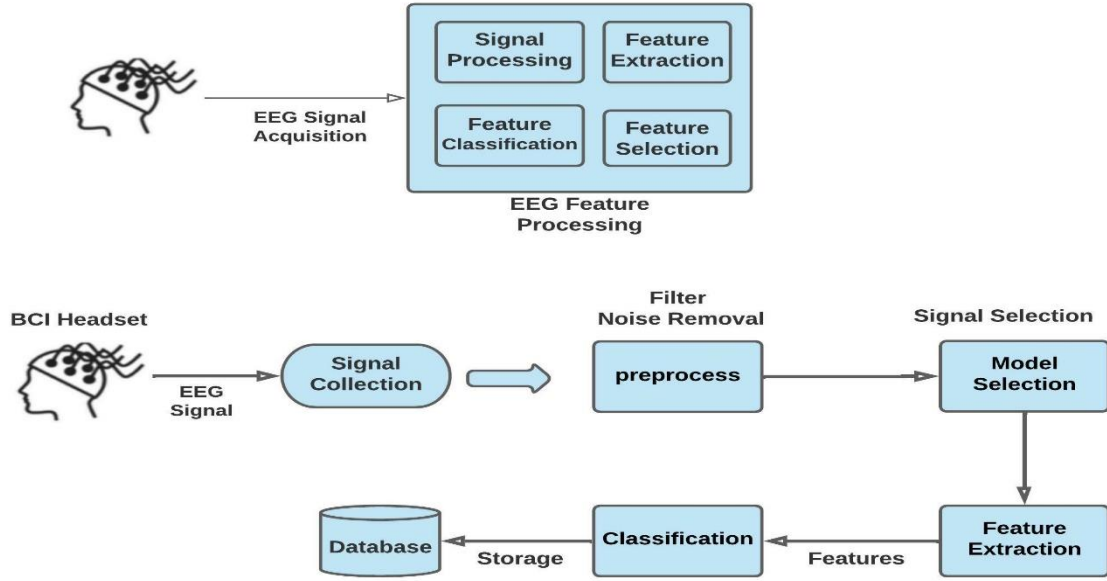


Figure 2: Overview of Brain-waves Eye Blink Detection System

negative deflection. This is like what happens when the eye blinks. When the eyelid closes, the Cornea becomes closer to Fp1 and a positive deflection is produced. But when the eyelid opens the cornea rotate away from Fp1 and a negative deflection is produced as shown in figure 3.

## II. LITERATURE REVIEW

The field of neuroscience is skyrocketing and its application ranges from cure of brain disease to controlling machines. Various works has been done in this field, different methods for signal acquisition is used. Multiple feature selection algorithms and classifier has been tested.

### A. Eye Blink Detection Using Summation of Derivative within a Window (SDW)

The An eye blink artifact is formed with a gradual increase and decrease generally within 100 and 500ms [6], whereas the EEG signals cover wider frequency ranges (0.5–50 Hz and above). When a sliding window is set to be large enough to cover multiple ripples of an EEG waveform, the summation of the first-order derivatives of the raw signal within the sliding window will filter out the ripples. When the sliding window size is set to be approximately half the width of the target eye blink wave and the window slides along the time axis, the filter output (the summation of the first-order derivatives within a sliding window) can distinctly extract the presence of the target wave while suppressing other ripples with smaller periods than the target wave. This novel method can predict the eye blink accurately than the conventional methods [6] [7].

## III. PROPOSED SYSTEM

Any human brain interface system consists of mainly four primary modules: data acquisition, pre-processing, feature extraction and classifier module. The followings are the techniques and methodology used in this research experiment. MATLAB and Python are the tools which were used to analyze and verify the results. Different classifications techniques were implemented in the python to find the accuracy.

### A. Data Acquisition

Data acquisition is a critical process, and one should acquire data that is free from external and internal artifacts. Bio-potentials collection methods can be classified into three categories: invasive, semi-invasive, and non-invasive [9]. The most invasive technique is called deep brain recording. In this case, a microelectrode is placed inside the skull and signals can be recorded from very well-defined locations. For semi-invasive little to no surgery is required to implant in the desired location. For non-invasive no surgery is required, simply it can be put in the skull readily and fast. The source of bio-potentials (neuron) is far in the case of non-invasive electrodes, this technique is more prone to error and signal loss. However, with the use of wet electrodes and active amplifiers they have been used accept in different neuroscience activities nowadays. The following are the different types of electrodes used in the EEG data acquisition methods:

Electrodes	Characteristics
Wet Electrodes	<ul style="list-style-type: none"> <li>• Electrodes made of silver/silver chloride</li> <li>• Less impedance with conductive gel</li> <li>• Gel dries quickly and needs to be replaced</li> </ul>
Dry Electrode	<ul style="list-style-type: none"> <li>• Single metal usually stainless steel used</li> <li>• Cleaner, quicker to setup and remove</li> </ul>
Active Electrode	<ul style="list-style-type: none"> <li>• Have a pre-amplification module</li> <li>• Conductive material between skin and electrode</li> <li>• Capture, process and amplify the signal</li> </ul>
Passive Electrode	<ul style="list-style-type: none"> <li>• Same as active electrode without pre-amplification module</li> <li>• Conductive gel is used</li> </ul>

In our case, Emotive Headset and OPENBCI headwear is used. Each headset consists of an ear clip with electrodes. Both headsets have EEG electrodes placed at FP1 position and the

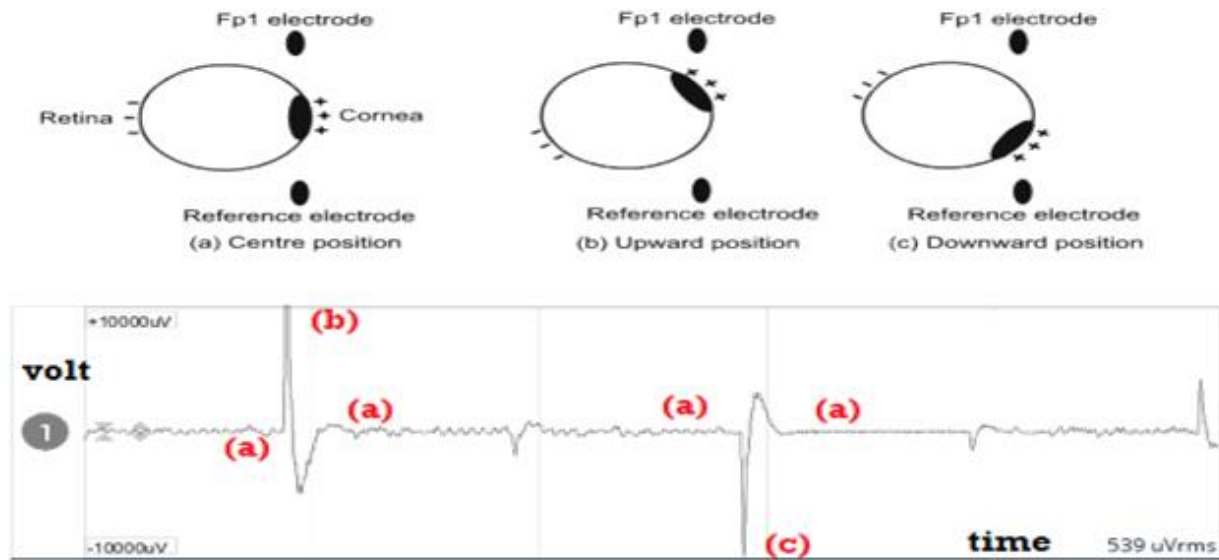


Fig 3: The dipole model of eyeball with waveform of EEG signal when the cornea in the center (a), rotating upwards(b), downwards (c)

electrodes are made of dry electrodes; however, wet electrodes can also be used. The raw EEG signal was collected from one subject (me) and 6-8 trials of EEG signal were collected. The subject will be asked to make 8-12 eye blinks in each trial. Data will be collected each week. MATLAB software will be used for recording the EEG data from both headsets and further processing. can also be used. The raw EEG signal was collected from one subject (me) and 6-8 trails of EEG signal was collected. The subject will be asked to make 8-12 eye blinks in each trail. Data will be collected each week. MATLAB software will be used for recording the EEG data from both headsets and further processing.

### B. Signal Preprocessing

Now, we have raw data from the headset which needs to be further processed. Extracting discriminative characteristics from EEG recordings may be a challenging task, due to the significant presence of artifacts in the acquired data [10]. Different physiologic artifacts like Alternating Current Artifact, Electrode Artifacts, Movements in Recording Environment, Interference of Other equipment, Electrocardiogram (ECG), Skin Artifact are present in the EEG signals [11].

Various techniques can be used to remove such artifacts. Some of the methods are discussed below:

**Artifacts Avoidance:** By placing the EEG cap correctly in the subject and using non-hairy part to implant electrode improve the EEG signal. It is not an algorithm to be applied but it is a technical preparation for acquisition a high-quality record before signal filtering from physiologic artifacts.

**Linear Filtering:** Linear filtering is commonly used for removing artifacts located in certain signals that do not have any overlapped frequency bands with the frequency of the brain signals. Low- pass filtering and high-pass filtering are the most noticeable examples for linear filtering algorithms [12]. High-pass filter is commonly used to remove the EOG artifacts as the EOG artifacts consist of low frequency components. Low-pass filter may remove most of EMG

artifacts as most of EMG components have high frequency values.

Besides this, some other types of filtering like Cauchy Based Filter, Linear Adaptive Filter, Quantum Neural Network-Based filter can be used [12]. In this paper, I highlighted the various artifacts and their removal techniques. The subject is prescribed to make an eyeblink every **2.5 seconds** and the waveform was recorded. However, in this research experiment, I have used filter designing modules of MATLAB to filter the data and to make it noise-free.

### C. Feature Extraction

Feature extraction is a process of dimensionality reduction by which an initial set of raw data is reduced to more manageable groups for processing. A characteristic of these large data sets has many variables that require a lot of computing resources to process. The eye blinks were extracted from EEG using the following criterion. Eye blink has the largest amplitude in EEG signal so can be detect easily [11][12]. Also, the amplitude of these peaks will be significantly higher compared to the rhythmic brain activity. An eye-blink signal can be detected by its positive and negative peak occurrences. The below figure 4 represents typical eye blink instances.

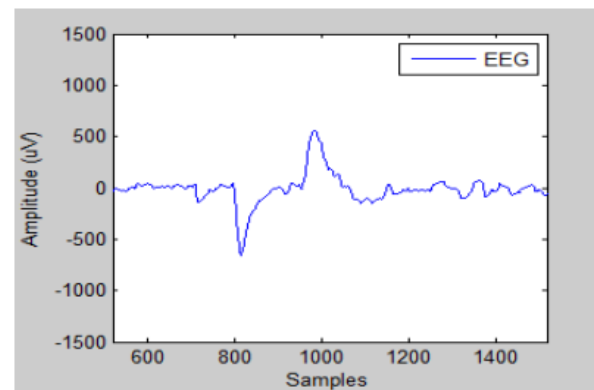


Figure 4. Eyeblink Signal

The EEG signal is stochastic, and each set of samples is called realizations or sample functions ( $x(t)$ ). The expectance

( $\mu$ ) is the mean of the realizations and is called first-order central momentum. The second-order central momentum is the variance of the realizations. The square root of the variance is the standard deviation ( $\sigma$ ), which measures the spread or dispersion around the mean of the realizations. The kurtosis, also called fourth-order central momentum, characterizes the relative flat or peak of the signal distribution, and is defined in equation below, which was modified to refer to a non-Gaussian distribution. The kurtosis coefficient of an event is significantly high when there is an eyes-open, eyes-close or an eye blink [13]. The other spurious signals generated by patient movement, event like switching ON/OFF a plug etc. have a small value for kurtosis coefficient. Hence eye events can be detected by kurtosis coefficient.

$$Kurtosis = E\left[\frac{x(t) - \mu}{\sigma}\right]^4$$

By examining it was found that the positive peak of eye blink is always greater than 0.3 and the negative one is smaller than -0.3 (after normalization) [11]. The eye blink signals are characterized by high value of kurtosis coefficient, normally above the value 3 [11][13]. MATLAB was used to detect the peak and to analyze and determine whether the signal is eye blink or not. Only useful data was analyzed and passed into different techniques like Independent Component Analysis (ICA) and Machine Learning Algorithms to determine the signal a blink or not. However, ICA is a common technique to remove eye blink artifacts from EEG.

#### D. Classification

The design of classifier is a hot topic in EEG data processing and applications. Traditional methods for EEG classifier design face the challenge caused by high dimension of EEG data sets, thus the classification result may have large deviations. Small sample size problem of EEG could lead to the overfitting phenomenon, which limits the application of traditional classifier. In this research, I have applied different binary classifications like Random Forest Classifier, Gradient Boosting, and Logistic Algorithms to determine whether the EEG signal is associated with eye blink or not. The detailed explanation of these techniques is discussed in the following sections.

### IV. EXPERIMENTAL SETUP AND RESULTS

EEG signals were extracted from the brain using BCI devices and transferred to the computer using Bluetooth. All the filtering, noise removal was carried out using MATLAB, ICA component analysis using BCILAB, a MATLAB module for EEG signal processing, and Machine Learning Algorithms was implemented using python programming language.

The OPEN BCI headband device was used to record 142 occurrences of eyeblink instances from a single individual (Male, 27 Years Old). With the use of a timer, the individual was instructed to blink every 2.5 seconds, and many trial were performed to collect data. The raw signals were treated with the butterworth filter. The high frequency signals were removed using the filter since eyeblink signals are low frequency signals (less than 30 HZ) [14]. Different techniques

for identifying eyeblink, such as the base value method, ICA, and Machine Learning algorithms, were used after the filtered signals were normalized within range of [-1, +1]. The methods are described in detail further down.

#### A. Normalization and Base Value Method

Eyeblink signals are characterized by high amplitude compared to the rest of the signals [11] [12] [13]. EEG signals are normalized in the range of [+1, -1]. After normalization, the base value of  $\pm 0.3$  and  $\pm 0.4$  v is considered as eye blink and the accuracy of the system is found considering each base value. Those signals which have a base value greater than +0.3, +0.4 and less than -0.3, -0.4 are considered as eye blink. All these normalizations, and identification was done in MATLAB. Eyeblink were recorded every 2.5 seconds. Actual class were calculated based on that time.

Actual Class	Based on eyeblink instances recorded every 2.5s.
True Positive (TP)	Actual eyeblink predicted true by base value method
False Positive (FP)	Actual eyeblink predicted false by base value method
False Negative (FN)	No eyeblink predicted as true by base value method
True Negative (TN)	No eyeblink predicted as false by base value method. In this scenario there will be infinite number of TN cases in every trial. The TN number in both cases is not considered.

The confusion matrix for both thresholds as described below.

Case I: At first, consider the threshold for  $\pm 0.4$  V as an eyeblink.

Actual Class	Predicted Class	
	Blink	No-Blink
Blink	64 (TP)	50(FP)
No-Blink	28 (FN)	-(TN)

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN} = 0.450$$

Case II: Consider the threshold for  $\pm 0.3$  V as an eyeblink.

Actual Class	Predicted Class	
	Blink	No-Blink
Blink	71	44
No-Blink	27	-

$$Accuracy = 0.500$$

#### B. Independent Component Analysis (ICA)

The algorithm was implemented in the MATLAB programming language with the addition of a FastICA toolbox from EEGLAB [14] provided by the EEGLAB Organization at the University of California, San Diego. Some of the functions of the FastICA toolbox [15] were removed or modified to decrease the computation time. In addition, default

parameters for non-linearity, orthogonalization, stopping criteria, kurtosis were changed to suit the application and improve the performance of the algorithm. The goal was to produce a fast algorithm by having a computation time shorter than the time length of the signal imported. A GUI was created to make a “user-friendly” interface for a more effective demonstration of the algorithm and results. The complete process of the algorithm is described in the following diagram

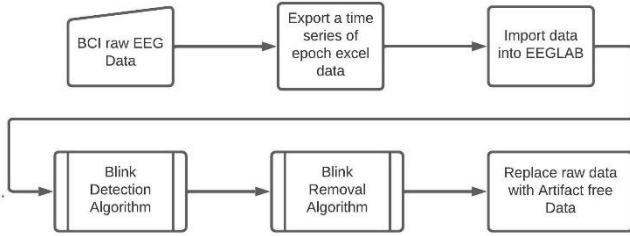


Fig: Flow Chart of the Complete Algorithm

ICA is commonly to remove eye blink artifacts from the EEG signals. I have used the same technique to find the instances ICA considered the signal as an eyeblink. the predefined function **runica** in the EEGLAB to remove the eye blinking artifacts in the EEG data.

The overall accuracy of the algorithm was **0.405**.

### C. Machine Learning Algorithms

The sample rate of the OPENBCI hardware is 200 HZ. Every 5 millisecond the EEG signal voltage is recorded by the hardware. Suppose 30 seconds of EEG signal is recorded while making an eyeblink every 2.5 seconds.

Total samples in 30 seconds =  $30 \times 200 = 6000$  samples

Average time of eyeblink = 0.15 seconds

Number of samples in an eyeblink =  $0.15 \times 200 = 30$  samples

Number of eye blink in 30 seconds =  $\frac{30}{2.5} = 12$  times

Total samples for 12 eyeblinks =  $12 \times 30 = 360$  samples

For ML models, the learning data is obtained by labeling the corresponding 30 samples of data every 2.5 seconds as 1.

The eyeblink is represented by this label. For non-eyeblink, the remaining corresponding samples column are set to 0. Now we have three columns of data sets: the first column contains data samples from hardware, the second column contains the eyeblink label (generated by the user), and the third column contains the timestamp. Once the ML model has been trained with these learning datasets, the new dataset can be used to predict whether or not the signal is an eyeblink.

Output set is defined in which the eye blink events are marked as ‘1’ and non-eye blink events as ‘0’. The processed EEG signal with the labels was passed into the ML algorithms to predict whether the signal is an eyeblink or not. Let’s consider the target Y (blink or no-blink) best on the given input X (spike in the voltage signal). Since this is a classification task that has only 2 outputs: 0 for no blink and 1 for blink. Some of the most common machine learning algorithms are implemented as follows.

### I. Random Forest Classifier

RFC classifier is based on the classic technique of the decision tree. Since this task is a binary classification, decision trees are supposed to be yield better results [16]. RFC is an ensembling learning method for classification and regression which operates by creating multiple forests of decision trees at training time. Many parameters were tuned to increase the accuracy of the model and max\_depth of 9 which is the maximum depth of a tree was implemented. Several criteria like gini, entropy was changed, however, it did not impact the results.

The final accuracy of the model was **0.681**.

### II. Gradient Boosting

Gradient Boosting utilizes the concept of boosting. In this approach, the algorithm tries to boost the weak classifier and when the weak classifier gets combined with the best classifier it minimizes the overall prediction error [17]. N\_estimators of 100 were implemented which indicates the number of boosting stages to perform. Similarly, a learning rate of 1 is the rate at which the contribution of each tree gets shrank. Similarly, max\_depth of 1 was the most effective in our model. Max\_depth limits the number of nodes of each tree. Usually boosting approach yields better results, however, in this case, the accuracy was **0.665** which is even lower than RFC.

### III. Logistic Regression

The logistic regression with normalization to reduce the overfitting of the algorithms was implemented but 11 and 12 normalization had little to no impact on our final accuracy. The predicted accuracy of the model was **0.662**.

## V. CONCLUSIONS AND FUTURE DIRECTIONS

Basic threshold, ICA, and Machine Learning Algorithms were implemented to determine the EEG signal is an eyeblink or not. Basic threshold, ICA has low accuracy as compared to ML algorithms. Basic Logistic algorithms were tested. The advanced decision tree-based algorithm such as RFC and GB were implemented, however, these two algorithms were not able to yield a significant increase in accuracy in comparison to logistic regression. This can be down to the fact that our data sets are severally limited in terms of features which is making it hard for ML algorithms to generalize well with data sets. In this project, we have a limited number of electrodes. However, if we use EEG channels of 64 or 128 (number of electrodes) then we have multiple features making Machine Learning Algorithms have high accuracies.

EEG signal processing and application are applied to more and more fields. In this paper, I have highlighted the following perspectives. (1) EEG signal acquisition methods using different electrodes with their characteristics. (2) Some noise, artifacts are highlighted and their removal from signals are discussed. In fact, I have presented many ways to remove noise and artifacts in an EEG signal in an efficient way. (3) Eye blinking effect on EEG signals is discussed and a promising way to detect eye blinking signals is applied. I have placed an



emphasis on the detection of eye blinking signals using different techniques and algorithms. In summary, the study on Brain Signals is still in its infancy. Through various research has been done in this area but much more to achieve. There is always space for better development of products and the use of algorithms.

Brain-Computer Interface should not only be limited to analysis of brain activities rather BCI devices must be sophisticated to find the cure of mental diseases. There should be works done in the field of translating neural signals to text using a Brain-Computer Interface. Brain waves also can be used as a secure identification tool in this digital world. However, with every innovation there comes the risk. BCI hardware and software are subjected to risk; anyone can get in this system and simulate the brain, get unauthorized data. Also, invasive BCIs are risky since it requires neurosurgery.

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## Appendix I

The dataset for the experiment can be found:

[https://github.com/aamir095/eyeblink\\_dataset](https://github.com/aamir095/eyeblink_dataset)

### Algorithm to determine duration of Eye Blink:

```
%pkg load signal;
data=csvread("eeglab.csv");
% Time Stamp in Seconds
EEG=data(:,2);
%Filtering signal for 50Hz and 60z signals
[b, a] = butter(2,[40 70]/(200 / 2.0),
'stop');
EEG=filter(b,a,EEG);
time_stamp=data(:,1)/1000;
% Normalizing for zero mean value
EEG=EEG-mean(EEG);
% Normalizing for maximum unity magnitude
value
EEG=EEG/max(abs(EEG));
%plotting normalized EEG Signal
plot(time_stamp,EEG);
xlabel('time(s)');
ylabel('Normalized Amplitude')
hold on;

%finding blinkpoints peaks
blink_points=zeros(1,7830);
previous_signal=0;
for a=1:numel(EEG)
    signal=EEG(a);
    if ((previous_signal>-0.4) && (signal<-
0.4))
        blink_points(a)=-1;
    elseif ((previous_signal)<0.4 &&
(signal>0.4))
        blink_points(a)=1;
    end
    previous_signal=signal;
end

%Removing multiple peaks within single cycle
previous_value=0;
previous_value_index=1;
for a=1:numel(blink_points)
    value=blink_points(a);
    if(value~=0)
        if(value==previous_value)
            if((a-previous_value_index)<100)
                blink_points(previous_value_index)=0;
            end
        end
        previous_value=value;
        previous_value_index=a;
    end
end
```

%Calculating duration between peaks and multiplying it by 2 to get actual blink duration

```
peaks=find(blink_points~=0);
durations=zeros(1,17);
```

```
for a=1:numel(peaks)/2
    for index=peaks(2*a-1):peaks(2*a)
        blink_points(index)=1;
    end
    durations(a)=(time_stamp(peaks(2*a))-
time_stamp(peaks(2*a-1)))*2;
end
```

```
%Plotting Blink detection signal
plot(time_stamp,blink_points);
legend ("Normalized EEG Signal","Blink
Detection");
%legend (h, "location", "northeastoutside");
%set (h, "fontsize", 20);
length=numel(durations);
%Displaying Results
fprintf('Time duration for each bilnks are
\nSN \t Duration \n ');
%[(1:1:length) durations];
for i=1:15
    fprintf('%d Blink= %.3f
ms\n',i,durations(1,i)*1000);
end
```

Time duration for each bilnks are

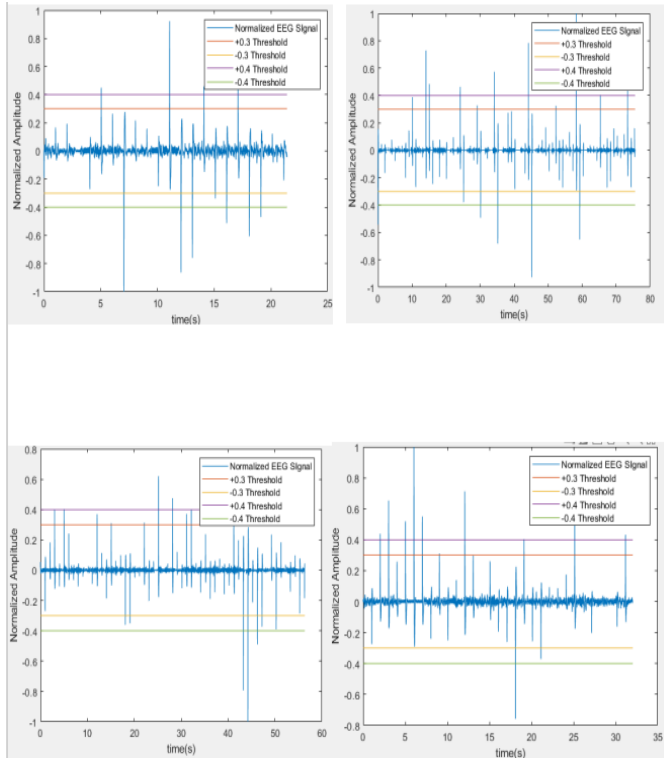
SN	Duration
1	Blink= 150.000 ms
2	Blink= 140.000 ms
3	Blink= 140.000 ms
4	Blink= 120.000 ms
5	Blink= 140.000 ms
6	Blink= 150.000 ms
7	Blink= 310.000 ms
8	Blink= 60.000 ms
9	Blink= 170.000 ms
10	Blink= 80.000 ms
11	Blink= 100.000 ms
12	Blink= 130.000 ms
13	Blink= 120.000 ms
14	Blink= 150.000 ms
15	Blink= 110.000 ms

Fig: Duration of eye blink in milliseconds

## Appendix II

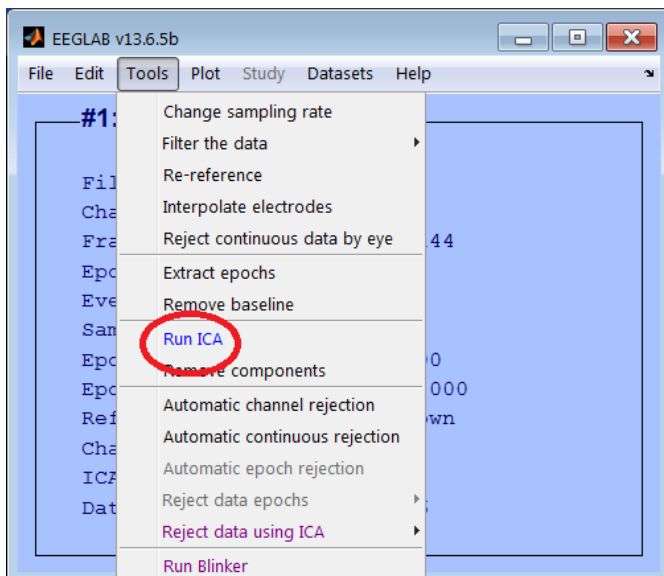
### For Base Value Method:

MATLAB is used to find the number of eye blinking instances for the threshold of 0.3 and 0.4 as shown in figure below.



### For ICA Decomposition:

EEGLAB, a MATLAB Toolbox is used.



### Machine Learning Algorithms:

```
import pandas as pd
```

```
import matplotlib.pyplot as plt
```

```
import numpy as np
```

```
df_data = pd.read_csv('data1.csv')
```

```
# print(df_data.head())
```

```
y = df_data.to_numpy()
```

```
x = np.linspace(0, 39.2, num = len(y))
```

```
#Label
```

```
label= np.ones(7829)
```

```
for i in range(7829):
```

```
    if i%600 <=200:
```

```
        label[i] = 0
```

```
# plt.figure(figsize=(12,8), dpi =180)
```

```
# plt.plot(x,label,'r')
```

```
#Machine Learning Part
```

```
#LG
```

```
from sklearn.linear_model import LogisticRegression
```

```
clf = LogisticRegression(random_state = 0).fit(y,label)
```

```
print(clf.score(y,label))
```

```
print(clf.predict )
```

```
#RFC
```

```
from sklearn.ensemble import RandomForestClassifier
```

```
clf = RandomForestClassifier(max_depth=9, random_state=0).fit(y,label)
```

```
print(clf.score(y,label))
```

```
print(clf.predict )
```

```
#GB
```

```
from sklearn.ensemble import GradientBoostingClassifier
```



```
clf = GradientBoostingClassifier(n_estimators=100,  
    learning_rate=1.0,max_depth=1, random_state=0).fit(y,label)  
print(clf.score(y,label))  
print(clf.predict )
```