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Classification of Visually Evoked Potential for Color Perception Using Soft Computing Techniques

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ABSTRACT: We offer a novel approach to predict the colour path utilising soft computing techniques and electroencephalogram in this study (EEG). To eliminate the effect of artefacts, the EEG response of distinct brain lobes to a colour stimulus is first recorded, and the collected EEG signals are filtered using an active band pass filter. Second, a moving window is set over the EEG data, and a short-term Fourier transform is used to extract the power in each window, with the ultimate goal of determining the time-point (the centre of one specific window) on the EEG signal with the highest power. After that, the filtered data is sent into a neural network to train it. The obtained dataset is then sent into the neural network, which predicts and classifies the results.

KEYWORDS: Electroencephalography, Brain-Computer Interface, Convolutional Neural Network

I. INTRODUCTION

The Brain Computer Interface (BCI) is a computer-based system that collects, analyses, and converts brain signals into commands that are sent to an output device to perform a desired activity. BCI research began at the University of California in 1970. Hans Berger's contributions to human brain research and electrical activity are intimately linked to the creation of brain computer interfaces and electroencephalography (EEG). Berger was inspired by Richard Canton's discovery of electrical signals in animal brains in 1857.

The perception of colour is a human sense. Cone cells come in three different kinds, each of which is responsible for one of the primary colours. The electrical responses are transmitted to the optic nerve, which then sends the information to the visual brain for interpretation of the stimuli. Distinct colour stimulations cause different responses in different brain networks. Electroencephalography is being used to measure brainimpulses in this experiment.The goal of this study uses electroencephalographyand softcomputing approaches to anticipate the signalling pathways inthe brain for various colour stimulations. Electroencephalography is used to collect brain impulses, which are then fed into a neural network to anticipate and identify colour pathways.

II. LITERTURE SURVEY

[1].A Review on the Use of Deep Learning for Visual Decoding and Reconstruction from Brain Activity Madison Van Horn, Informatics Forum, University of Edinburgh, Edinburgh, UK, EH8 9AB: - We will expound on the role of the architectures that offer the ability to recreate and improve images because this review will only focus on the decoder and reconstruction process of perceived images. The architecture of the model is critical in demonstrating that newly created images are aesthetically similar to the original image. Deep learning has clearly grown in importance in the fields of neuroscience and machine learning, allowing for the reconstruction of observed images from brain activity.

[2]."Decoding signals from Electroencephalography Measured in brain signals" by Jasper E. Hajonides, Anna C. Nobre, Freek van

Ede, and Mark G. Stokes:- have conducted this experiment and demonstrated that they could track visual colour processing using EEG patterns on Linear Discriminant Analysis. All of the participants had normal vision and completed 900 treks. They employed EEG pre-processing data, which was analysed using Field Trip with the OHBA Software Library in MATLAB 2017a. (P7, P5, P3, P1, Pz, P2, P4, P6, P8, PO7, PO3, PO4, PO8, POz, O1, Oz, O2) are the electrodes. The EEG data revealed 17 posterior electrodes between 300 and 1000 milliseconds following the stimulation. They discovered that colour signified grey 12/12 colours and could be deciphered using a p.05 threshold (min = 2.440; max = 6.175).

[3]."Using electrocorticographic signals, real-time detection and differentiation of visual perception" -C Kapeller, H Ogawa, W G Coon, and K Kamada: The ventral temporal cortex comprises specialised regions that handle visual input, according to the research. The spatial and temporal dynamics of ECoG responses to varied types and colours presented to four human volunteers were studied in this study. The subjects' ECoG signals were recorded while they were shown colourful and greyscale versions of seven different visual stimuli, resulting in 14 different discrimination classes. Faces, black screens displayed on a monitor, or natural sceneries (i.e., the face of an experimenter, natural photographs of faces) were all classified asynchronously by a real-time system. Discrimination performance was one of the outcome metrics in all of the experiments.

[4]. Statistical Characteristics of EEG Color Stimulus Responses" Ismail Jouny, Daniel Zakzewski, and Yib Choung Yu [2014]: - The statistical aspects of the retrieved EEG signatures are highlighted in this research, as well as prospective classification algorithms that may be suitable for this application. Eight distinct colours were used in the preliminary calibration test. On a 60-inch TV screen, the colours were exhibited in a random order for 15 seconds. A white screen was presented for 5 seconds in between test colours. For a single test instance, data was collected from a person across ten trials. Each of the 14 sensors collected 18840 samples in a single session. 128 Hz is the sampling rate. The first 5 seconds were cut to avoid possible distortion caused by retina correction.

[5]."EEG signal decoding reveals non-uniformities in colour neural geometry" - Check out ORCID's profile Lindsay N, Tushar Chauhan, Ivana Jakovljev Color opponency asserts that colour perception is formed by contrasting two chromatic mechanisms, red vs green (RG) and yellow versus blue (YB) (YB). Red, green, blue, and yellow are the four distinct colours. We show that during a 100-300 ms window from stimulus start, electroencephalographic (EEG) responses carry substantial information about isoluminant distinct colours. Their reciprocal distance in a nominally uniform perceptual colour space does not totally predict the efficiency of hue decoding. Instead, key non-uniformities are visible in the encoding space, implying that anisotropies in neurometric hue-spaces are likely to represent perceptual distinct colours.

[6].Byoung-Kxong, Mina.b. Hyun-Seok, "Electrophysiological Decoding of Spatial and Color

Processing in Human Prefrontal Cortex." Robert T. Knigh: Kimo Wonjun Koa. - The PFC is critical for goal-directed cognition, but its representational code is still a mystery, with decoding attempts failing. separating task-relevant variables from PFC variables Here, we used a regularised linear model. With 87 percent decoding accuracy, they were able to identify a mentalrotation job from a color-perception task using discriminant analysis on human scalp EEG data. Dorsal and ventral The primary traits distinguishing the two were ventral regions in the lateral PFC. A BramAmp DC amplifier was used to record the EEG. A reference electrode was implanted on the tip of the nose, and a series of processing steps was used to extract signals from 15 BAs using IDF bandpass filtering.

[7].“The influence of Object-Color Knowledge on Emerging Object Representations in the Brain”. Lina Teichmann, Genevieve L. Quek, Amanda K. Robinson, Tijl Grootswagers, Thomas A. Carlson and Anina N. Rich: - The ability of the human visual system to perceive complex objects quickly and accurately is critical. To recognise an object, we must combine incoming visual information like colour and form into coherent brain representations and integrate them with our prior knowledge of the environment. The characteristic colour of various objects is a key element for recognition; for example, a banana is normally yellow. We investigated how object-color information impacts emerging object representations across time using multivariate pattern analysis on time-resolved neuroimaging (MEG) data. Our findings from 20 The typicality of

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object-color combinations influences object representations, although not at the first stages of object and colour processing, according to the participants (11 female). We show evidence that colour decoding for atypical object-color combinations peaks later than for normal object-color combinations, illustrating the interaction between incoming object features and stored object knowledge. These findings add to our understanding of how visual information is combined with previous conceptual object knowledge.

[8] "A Neuroelectrical Brain Imaging Study on the Perception of Figurative Paintings against Only their Colour or Shape Contents "Anton G. Maglione, Ambra Brizi Giovanni, Vecchiato, Dario Rossi, Arianna Trettel, Enrica Modica and Fabio Babiloni; - This trial involved 16 healthy volunteers (7males and 9 females; average age 38.3 6 years old). All of the subjects had a bachelor's degree in artfrom a university. All subjects agreed to participate in the

study willingly and supplied written informed consent in accordance with the Declaration of Helsinki from 1975, as amended in 2000. The proper ethics committee of the University of Rome Sapienza has approved the research initiative related to this study. The identical research project was also authorised by the IRCCS Fondazione Santa Lucia's ethics committee. The real EEG recordings were made at the IRCCS Fondazione Santa Lucia.

[9] "Feature selection algorithm for evoked EEG signal due to RGB colors" Eman T. Alharbi; Saim Rasheed; Seyed M. Buhari: -

The efficiency of a single trial classification is a critical step toward online EEG signal classification. The Empirical Mode Decomposition (EMD) approach is used to evaluate signals, and the final decomposition is used in the feature extraction stage. Furthermore, we offer a new feature selection approach that focuses on identifying the best features by analysing the behaviour of EEG components that occur as a result of the injected colour. The results of utilising all extracted features, the results of using the selected features by the suggested technique, and the results of using the selected features by the recursive feature elimination algorithm, which is employed by similar studies, were compared. As the classification accuracies grow, the suggested approach is proven with all of the tested feature extraction methods. The categorization procedure employs the Support Vector Machine (SVM). We discovered that employing colour as a stimulus takes only 0.23 seconds to execute, which is significantly shorter time than any other stimulus offered in previous studies, such as imagery and spelling words.Target Mean and EMD residual are the best feature extraction methods that yield the highest classification accuracy and may be employed with real-time BCI systems since their accuracies are high and computation time is low.

III. PROPOSED METHODOLOGY

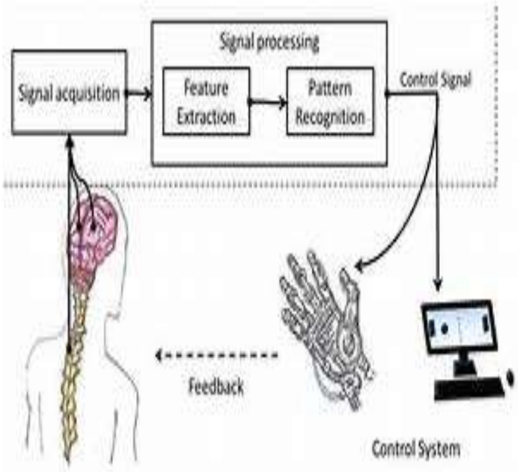

Figure. 0.1. BCI Stages

A. Signal Acquisition:

EEG signals are acquired from the scalp. EEG signals are acquired from electrodes arranged in a particular pattern or a montage. High-density EEG data were recorded using a 8-channel EEG electrode system with a sampling rate of 250 Hz. Most of EEG waves range from 0.5-500Hz(Delta, Theta, Alpha, Beta). The recording reference was at CZ (vertex of the head), and the impedances were kept below 20k. All analyses were performed using MATLAB 2018b. The Simulink toolbox of the MATLAB toolbox was used to automatically pre-process EEG data. It functions as a wrapper to execute currently known EEG pre-processing algorithms and provides objective uniform quality assessment for big investigations.Our preprocessing pipeline consisted of the following steps. First, 7 of the 8 electrodes is only included for further processing. The electrodes are placed in the Parietal lobe, Temporal lobe, Occipital Lobe because this the pathway where stimulations due to different colour stimulus occurs. The electrodes are placed CZ, OZ, O1, O2, POz, P3, PZ positions of the cap and signal is acquired.

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Figure.0.2.Realtimesignalacquisition of thesubject

Figure 0.3 Electrode placement

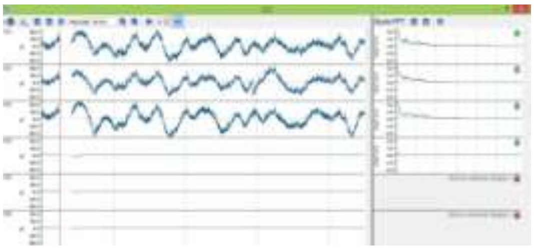

Figure 0.4 Raw EEG signal of the subject

B. PREPROCESSING

The EEG machines we use has only 8 electrodes. So we selected only 7 channels of the 8 for the next process (CZ, OZ, O1, O2, POz, P3, PZ). We apply Band pass filter which is inbuilt in the Simulink toolbox of MATLAB, which makes the pre-processing stage more easy and less time consuming. The filter is applied to all channels and the range is set to as less than 30Hz which filters all the flat lines, noise from the electrodes from other electronic circuits, wave peaks due to muscle movements like blinking of eyes. After the filter is applied the data is acquired in the form of values in the excel sheet. The acquired data is then used for the next steps feature extraction and classification.

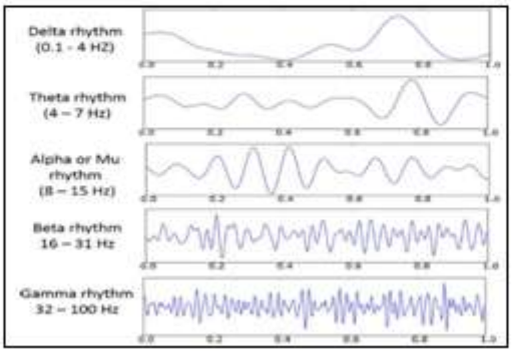

Figure.0.5 EEG Rhythms with frequencies

MultipleprotocolsarefollowedduringtheacquisitionoftheEEGsignalforthebetterclassification

Protocol 1:

During first protocol 8 electrode system is used for the purpose of signal recording. Electrodes are placed in CZ, OZ, O1, O2, POz, P3, PZ . This system produces more data for processing but it also provides more irrelevant data and noise which will be difficult for pre-processing. Five colours are chosen Red, Green, Blue, Brown and Yellow. The colours are displayed in continuous video. Each colour is displayed for a time period of 10 seconds with 5 seconds of blank screen in between. Signals of Five trials are taken. Each trial has break for 5 minutes.

Protocol 2:

In second protocol the electrode placement is changed for better result and less noise. The electrodes are placed in the order CZ, O1, O2, O3, OZ, P2, POz. The electrodes are placed near the visual cortex for better result. The same colours are chosen for this protocol also. But the time period the colours displayed are reduced to 5 seconds. The colours are not displayed in a continuous video instead the image of the colour is displayed for 5 seconds. This produced less noise but still it produced irrelevant data , Which made pre-processing stage difficult.

Protocol 3:

In third protocol the same electrode placement is used, but 7 colours are chosen Red, Green, Blue, Brown, Yellow, Violet and Magenta. Each colour is displayed for a time period of 5 seconds. The images of the colour are displayed. Five trials are taken. For each trail there is a break of 5 minutes. Remote keyboard is used to operate the system for not disturbing the subject this yielded in better concentration of the subject which in turn produced better results.

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Protocol 4:

In fourth protocol the 7 electrode system is abandoned even though the noise were less in Protocol 3 still it produced more irrelevant data. For this protocol 3-channel electrode system is chosen. The electrode are placed in CZ, O1, O2, P4. The electrode are placed in occipital lobe for better result. Same 7 colours are chosen for this protocol also. The subject is seated in a room with no disturbances. Electrical appliances are turned off for concentration. Any electrical devices that may interfere is removed from the subject. The subject is left alone and not disturbed during the entire process. The system is operated remotely. First the base state of the subject is recorded without showing any image. This is helps us to find if there is any variation in the brain stimuli while seeing the colour images. Each colour is shown for a period of five seconds. There is a break in between each colour for 30 seconds. The colours are shown in random order for each trial. The signals are recorded and stored in an excel sheet.

C. Feature Extraction

Many aspects of EEG activity might be used as the categorization process's foundation. In the 0–30 Hz frequency range, we extract EEG features for each class using the Auto Regression feature extraction technique. Autoregression:

$$Y_t = \alpha + \beta_1 Y_{t-1} + \beta_2 Y_{t-2} + \cdots + \beta_p Y_{t-p} + \epsilon_t$$

The feature selection procedure is critical for boosting generalisation and reducing variability. time for training, adherence to system standards (such as running time and storage) as well as improving system interpretability. An exhaustive search for the best feature subset from all conceivable feature combinations,on the other hand, iscomputationally costly. Overcoming many feature selection strategies have beenproposed as a result of this. There iscurrently no rule for EEG Feature selection due to non stationary property.

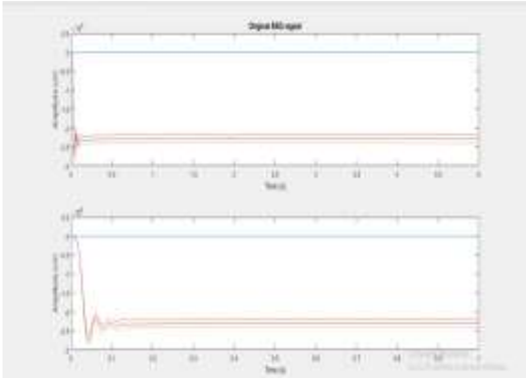


Figure.0.6.ExtractedFeatureWave

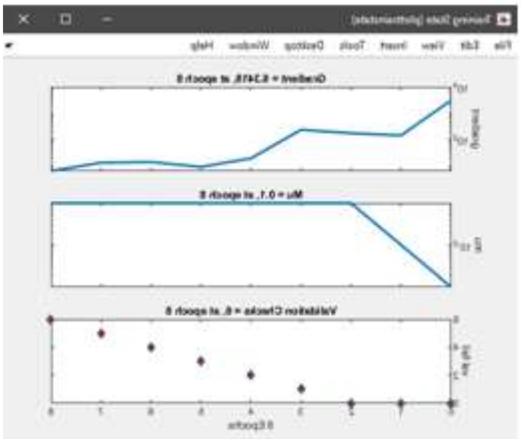
There are different traditional analysis methods such as the Fourier transform which does not provide a complete data because it depends on the use of frequency information only without considering the time domain information. The researches show that the combination of frequency-time domain information can provide more comprehensive set of features that improves the classification performance of EEG signal.

D. Classification

Artificial Neural Network

A neural network is a computational model based on the biological nervous system's neuron cell structure. The neural network can learn the data using a learning algorithm and a training set of data. The algorithm is a Feed Forward Neural Network. Error correction is accomplished using back propagation. The neural network generates a mapping between inputs and desired outputs from the training set using feed forward by changing the weighted connections within the network.

There are multiple layers, units per layer, network inputs, and network outputs in a neural network.



When the network is running, each hidden layer unit calculates the inputs and passes the result to

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the next Layer.The Laven berg-Marquardt optimization algorithm was used to create the feed-forward network.The approach involves updating the network and bias using damped least squares to minimise the error. To get greater performance and a nice gradient, the number of hidden layers is increased.

1. TestData

The feature extracted values are split into training data and test data for training and testing the neural network. Sixty percentage of the total feature extracted dataset is used for the training and forty percentage of the feature extracted dataset is used for the testing the feed forward neural network. The data are fed to the feed forward neural network and trained.

2. Classifier

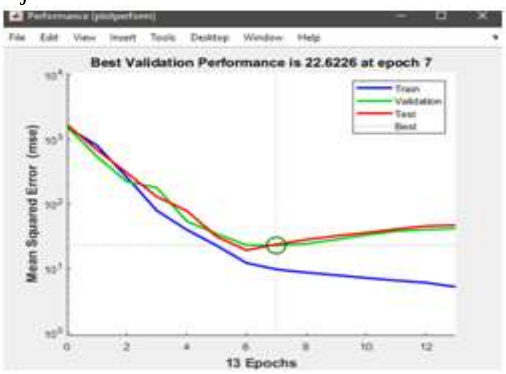
The test data is fed to the neural network. The number of hidden layer is adjusted after each training to get better performance and good gradient. For each subject total of 15 iterations of training and testing were done. For each iterations the number of hidden layer is increased starting from 1 hidden layer up to 15 hidden layers.

3. Output

The classifier after training gives the gradient and percentage accuracy for each classification. The results are compared and best suitable number of hidden layers are selected. For each subject error value is also calculated. After every iterations is completed the hidden layer which yielded maximum
accuracy is chosen for each subject and 10 trial is done.

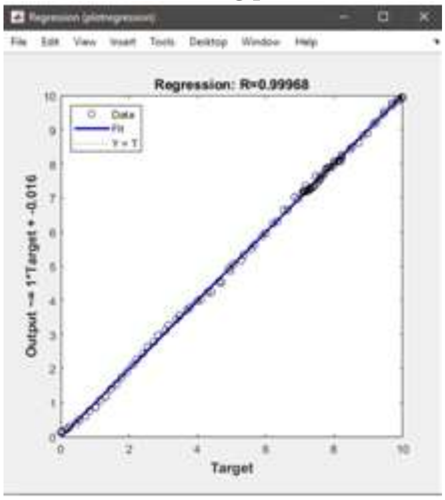
IV. RESULTS AND DISCUSSION:

Subject 1:

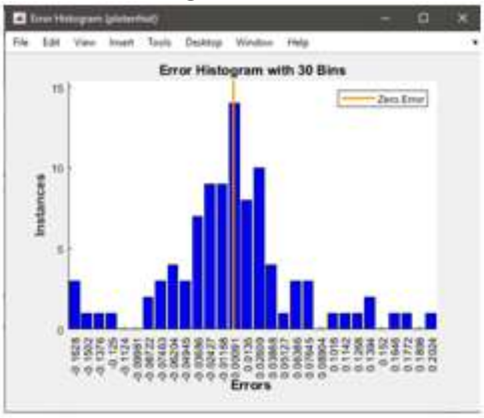


Performance Plot

Training plot



Regression Plot



Error plot

HL	Epoch	Accuracy
1	1000	43
2	1000	46
3	1000	46
4	112	96
5	597	96
6	1000	26
7	1000	93
8	158	96
9	1000	60
10	1000	96
11	1000	96
12	148	99
13	1000	60
14	437	97
15	1000	50
	Average	73.33333
	Min	26
	Max	97
	S.D	26.36195

HN	Epoch	Accuracy
14	595	90
14	1000	93
14	1000	56
14	450	97
14	334	96
14	111	96
14	637	96
14	560	96
14	127	97
14	232	99
	Average	91.6
	Min	56
	Max	99
	S.D	12.74711

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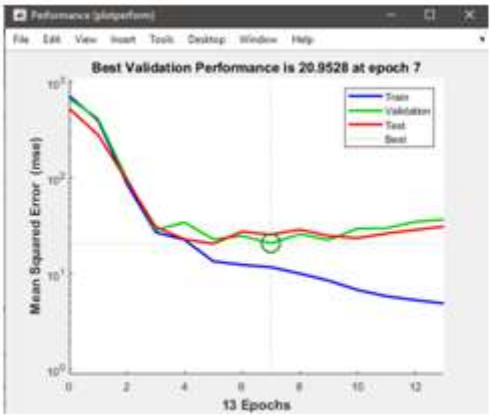
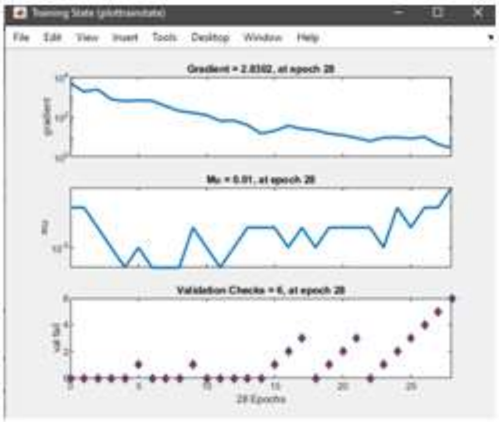
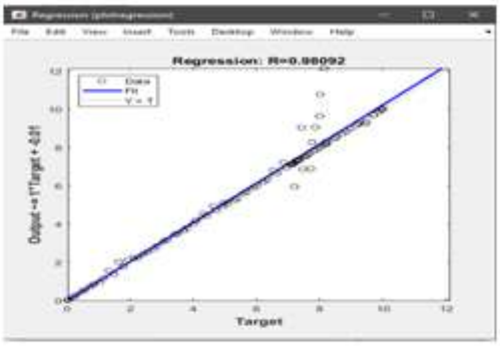
Subject 2:



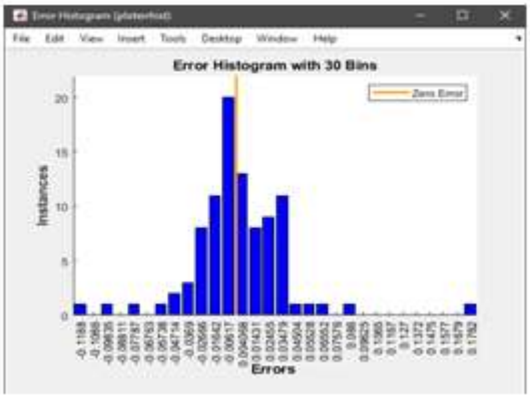
Performance plot



Training plot



Regression Plot

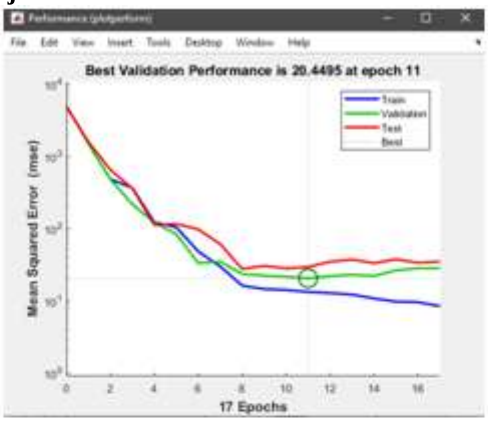


Error plot

HL	Epoch	Accuracy
1	1000	26
2	1000	33
3	1000	86
4	202	99
5	282	96
6	1000	83
7	1000	90
8	1000	60
9	1000	96
10	1000	56
11	126	96
12	316	99
13	1000	96
14	1000	91
15	1000	90
	Average	79.8
	Min	26
	Max	99
	S.D	34.21985

HN	Epoch	Accuracy
4	1000	90
4	1000	93
4	366	96
4	1000	93
4	1000	86
4	191	99
4	350	96
4	1000	93
4	1000	90
4	1000	90
	Average	92.6
	Min	86
	Max	99
	S.D	3.777124

Subject 3:



Performance plot

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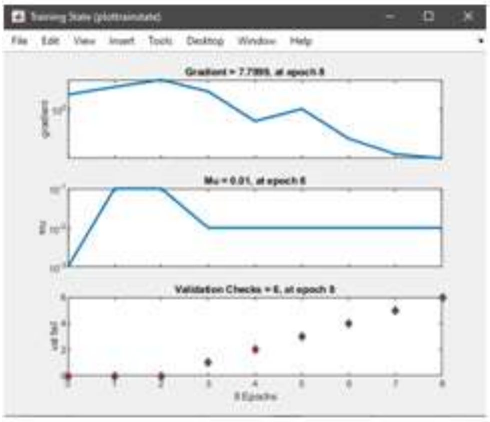
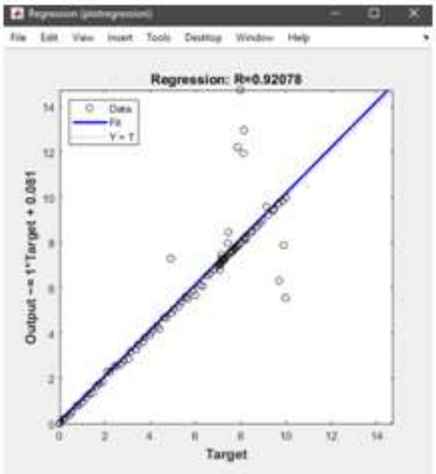


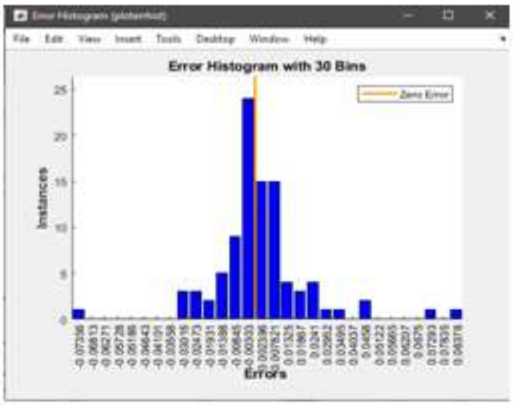
Training plot

HL	Epoch	Accuracy
1	1000	43
2	1000	53
3	1000	63
4	150	96
5	1000	90
6	237	100
7	1000	86
8	147	97
9	1000	93
10	207	99
11	222	97
12	1000	83
13	1000	90
14	249	96
15	160	97
	Average	85.53333
	Min	28
	Max	100
	S.D	17.893

HN	Epoch	Accuracy
6	1000	93
6	1000	96
6	1000	93
6	1000	93
6	237	100
6	1000	90
6	317	96
6	127	97
6	1000	90
6	1000	83
	Average	93.1
	Min	83
	Max	100
	S.D	4.72464

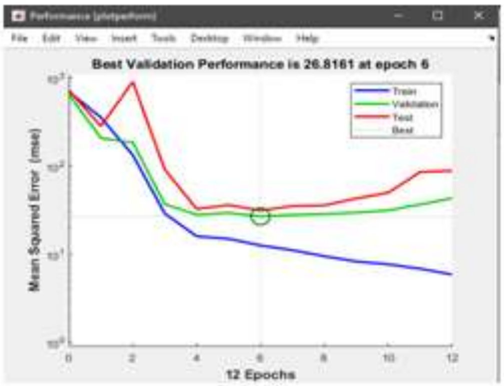


Regression Plot

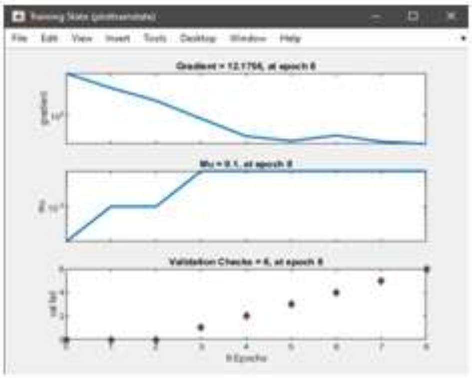


Error plot

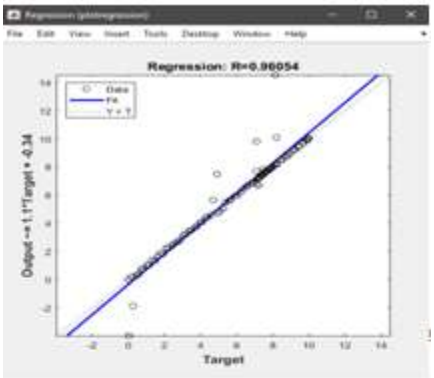
Subject 4:



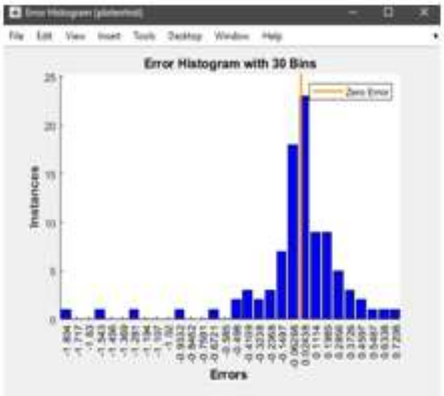
Performance plot



Training plot



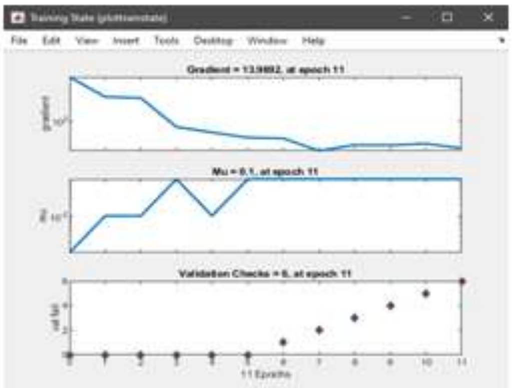
Regression Plot



Error plot

Subject 5:

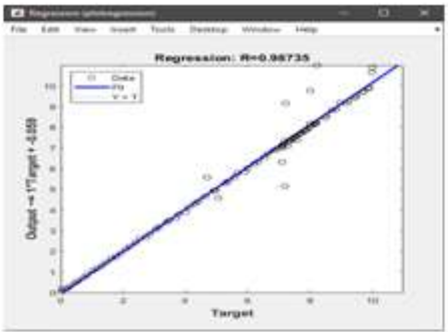
Performance plot



Training plot

HL	Epoch	Accuracy
1	1000	60
2	1000	73
3	721	100
4	1000	76
5	1000	99
6	185	99
7	170	97
8	498	96
9	235	98
10	1000	96
11	305	99
12	225	96
13	102	98
14	1000	96
15	1000	90
	Average	91.26667
	Min	60
	Max	100
	S.D	11.85909

HN	Epoch	Accuracy
3	448	96
3	1000	90
3	1000	86
3	450	99
3	1000	80
3	1000	73
3	414	96
3	277	96
3	1000	80
3	828	99
	Average	89.5
	Min	73
	Max	99
	S.D	9.264628



Regression plot

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Error plot

HL	Epoch	Accuracy
1	1000	63
2	1000	66
3	1000	95
4	1000	86
5	1000	93
6	1000	40
7	1000	95
8	1000	33
9	493	96
10	722	99
11	319	96
12	886	96
13	800	96
14	1000	86
15	202	99
	Average	82.33333
	Min	26
	Max	99
	S.D	21.60906

HN	Epoch	Accuracy
10	1000	96
10	212	96
10	500	99
10	518	96
10	1000	93
10	1000	86
10	1000	90
10	1000	76
10	1000	93
10	1000	86
	Average	91.1
	Min	76
	Max	99
	S.D	6.854844

The average and standard deviation for each subject is calculated.

Subject	HN	Average	Min	Max	S.D
1	14	91.6	56	99	12.74
2	4	92.6	86	99	3.77
3	6	93.1	83	100	4.72
4	3	89.5	73	99	9.26
5	10	91.1	76	99	6.85
	Average	91.58			
	Min	89.5			
	Max	93.1			
	S.D	1.406058			

The average accuracy of the neural network is 91.58%. Subject 3 has the highest accuracy of 93.1%. From this we can infer that subject 3 has concentrated more and the brain stimulation is high.

V. CONCLUSION

In this research, we proposed a feature selection algorithm for EEG signals by studying the ERPs components. The measurement statistic of our algorithm is based on the residual components itself which is computed using the regression of the generated peak. The investigated features are: Auto regression coefficient. In addition, we introduced a single trial classification to simulate the online classification and the classification results are compared from all methods within three cases. Our proposed algorithm outperforms the recursive algorithm and it is proved with all the investigated feature extraction methods. The time is much less than the time required by any other stimulus such as hand/foot imagination movement and spelling word. This result proves the main idea behind using colours in the next generation of BCI systems, which is based on introducing more efficient and speedy systems that are able to give response faster than any other time.

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