

## Research Article

### Pattern Classification of EEG Signals on Different States of Cognition Using Linear and Nonlinear Classifiers

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**Abstract:** There is a need to analyze and interpret the EEG data obtained from the brain which has its importance in various fields and applications. In this study we have acquired the EEG signal from the subjects while performing different tasks and then use pattern classification to differentiate the various tasks. Artifacts in the EEG signal are removed in the preprocessing stage. Features extracted from EEG datasets of various subjects were used as input to the neural network for training, validation and classification. Nearest neighbor and feed forward Neural Networks were used for classification and their results were compared.

**Keywords:** Classification, EEG, feed forward neural networks, nearest neighbour classifier, pattern classification

## INTRODUCTION

The human brain is vital and has very important structures that all play a very important role. When people hear about the brain alone, they need to remember that it is the energy of the human body. It commands everything from the ability to process thoughts to physiological functions. There are many reasons why the brain is unique. One of those reasons is because it also contains billions of neural responses that work together to finish many activities in the body. The spinal cord is actually what brings information up to the brain and messages and orders back down. Here we propose to use multilayer neural networks (Culpepper and Keller, 2003) to train and classify segments of 12-channel Electro-Encephalogram (EEG) data into one of five classes corresponding to five cognitive tasks performed by a subject. Independent Component Analysis (ICA) was used to segregate obvious artifact EEG components from other sources, associated with EEG data. In this study (Osaka, 1984; Palaniappan and Raveendran, 2001), it is proposed to use neural networks for pattern classification of different tasks performed by the subjects.

Arulmozhi (2011) they used classification of tasks are simulated through matlab with neural networks tool box type. Bai *et al.* (2007) detecting artifacts produced in EEG data by muscle activity, eye blinks and electrical noise is a common and important problem in EEG research Left and right hand movement imagery can modify the neural activity in the primary sensory motor areas in a very similar way as observable with a real executed movement, leading to the special changes

of EEG components such as event-related de-synchronization/synchronization. Hema *et al.* (2008) Brain computer interfaces are designed to rehabilitate people with neural disorders to communicate or control devices. This paper proposes a novel algorithm to classify mental task signals using a particle swarm optimization training procedure for recurrent neural networks Khare *et al.* (2010) they proposed a classification algorithm of different mental activities for EEG application. Müller-Putz *et al.* (2005) proposed Brain computer interface applications for steady state evoked potentials can be used for classification algorithms. Srinivasan (2007), his volume provides a comprehensive overview of the nature of attentional and visual processes involved in language comprehension Zhu and Wang (2004) they used discrimination between right and left hand movement by taking imaginary Event related potentials for EEG applications.

EEG toolbox is very efficient for removing artifacts from EEG signals an open source toolbox for analysis Journal of Neuroscience Methods 134 (Delorme and Makeig, 2004). It can remove artifacts due to line noise, environmental artifacts and ocular artifacts, including much other type of artifacts. Hence we found to it to be useful for removing artifacts from EEG signal before using it for training in neural networks In this study, Friedman *et al.* (1997) evaluated approaches for inducing classifiers from data, based on the theory of learning Bayesian networks. These networks are factored representations of probability distributions that generalize the naive Bayesian classifier and explicitly represent statements about

independence In this study the author A neural network with enough elements (called neurons) can classify any data with arbitrary accuracy. In this study, Palaniappan and Raveendran (2001) used Cognitive task can be predicted under spectral analysis using auto regressive models. In this study Friedman *et al.* (1997) introduces the naive Bayes classifier which greatly simplifies learning by assuming that features are independent given class. Although independence is generally a poor assumption, in practice naive Bayes often competes well with more sophisticated classifiers. The EEG signal measured with the help of electrodes on the scalp consists of summation of thousands of neurons fired simultaneously. As a consequence, the magnitude of the EEG signal is less dependent on the total neural activity of the brain. The focus is instead on how synchronous that activity is. Features are extracted for five mental tasks using wavelet transform. In this study the author (Keswani and Bajaj, 2014) used Classification of Mental Task EEG signals is mainly used for brain computer interface related applications. In this study the author (Osaka, 1984) activity is analyzed based on alpha frequency and task difficulty is chosen for comparison. Computer interfaces are designed to rehabilitate people with neural disorders to communicate or control devices. Especially the research is going on in ERP study analysis all the above methods helps for analysis of EEG signals in Cognitive state analogy.

In this study the objective of the study involves Neural networks Classifier and Nearest neighbor Classifiers are considered for analysis of EEG data for classification of Tasks.

Roschke and Aldenhoff (1992), in order to perform a nonlinear dimensional analysis of the sleep Electroencephalogram (EEG), here application is used with algorithm proposed by Grassberger and Procaccia to calculate the correlation dimension for different sleep stages. Skarda and Freeman (1987), nonlinear analysis is used for finding chaos in the brain (Wang *et al.*, 2007) feature exact ration of mental task is carried out by using brain computer interface with nonlinear analysis. Yang *et al.* (2012), here Ann concept and genetic algorithm is used for classification and channel selection is effectively used. Zhou *et al.* (2008), in order to characterize the non-Gaussian information contained within the EEG signals, a new feature extraction method based on bi spectrum is proposed and applied to the classification of right and left motor imagery for developing EEG-based brain-computer interface systems.

## METHODOLOGY

**Data acquisition:** Simple EEG activity can be recorded with two electrodes. a frontal electrode on the forehead and an occipital electrode on the scalp at the back of the head. A third (ground or earth) electrode is also attached to reduce electrical interference (Fig. 1). This

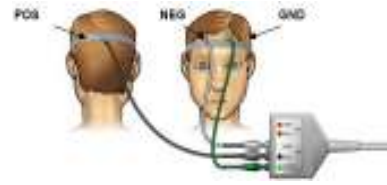


Fig. 1: EEG acquisition

can be performed with an AD Instruments single or dual bio amplifier and Power Lab data acquisition system. Single or dual channel EEG recordings may be useful for the simple recording and identification of alpha activity in conscious subjects or specific waveforms representative of the sleeping subject.

Multiple channel EEG recordings are used for the identification of neurological functioning and/or abnormalities and require multiple recording electrodes placed in an array over the head. Good subject preparation and application techniques are essential to ensure high quality, low noise recordings of EEG/ECOG. Excessively high skin impedances (due to inadequate preparation) will cause signal artifacts that can interfere with EEG/ECOG recordings.

A total of 8 channels were used. Channels 1-4 were used to acquire Delta, Theta, Alpha and Beta waves respectively (Fig. 2). Channel 5 gave a Combined EEG from channels 1-4. Channels 6-9 were used to acquire EEG from Frontal, Temporal, Parietal and Occipital Lobes respectively. The voltage range for the Delta, Theta, Alpha, Beta and Combined EEG was 0-10 V. The Voltage range for the EEG from Frontal, Temporal and Occipital lobes was 0-50 mV. The Voltage range for the EEG from Parietal lobe was 0-100 mV.

The EEG data was acquired using AD Instruments Power Lab equipment and Lab Chart software.

**Protocol design:** Initially, the subject was asked to lie down and the cap is applied. The subject was instructed to be in the normal state of mind for about 2 min. The EEG signal was acquired in the normal state for 2 min. Then, the subject was asked to perform different tasks containing baseline task, figure rotation, letter task, math task and visual counting. The same procedure was repeated for all the subjects for several numbers of days.

The following 5 tasks were performed by the subjects.

**Baseline Task (BLT):** Preceding the stimulus program, the subject was asked not to perform a specific mental task, but to relax as much as possible, make as few movements as possible and think of nothing in particular. This task is considered a baseline task for alpha wave production and was used as a control measure of the EEG.

**Letter Task (LT):** The subject was asked to rehearse the English alphabets a to z continuously in mind without moving their lips or vocalizing them.

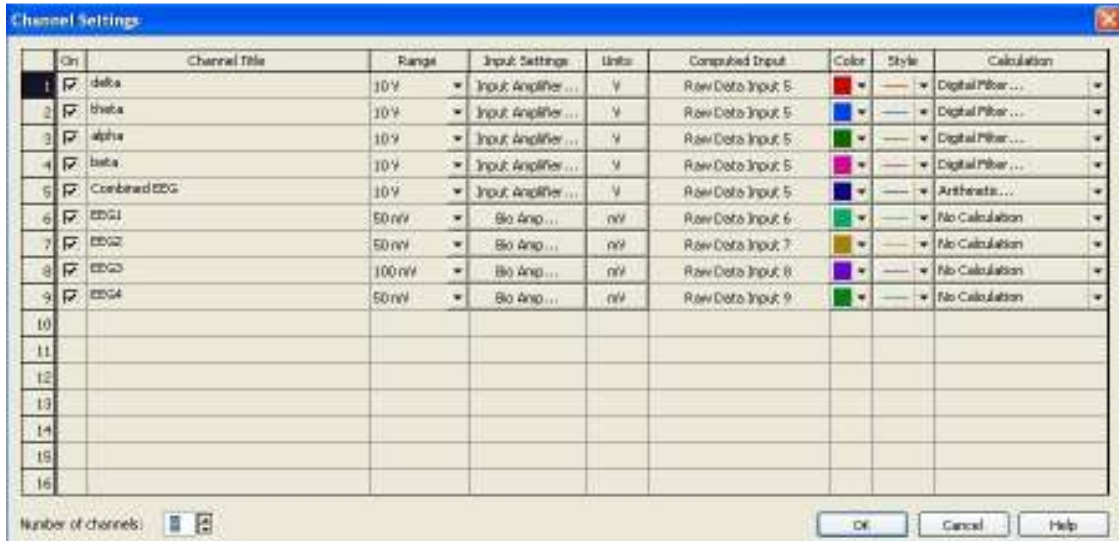


Fig. 2: Channel settings for data acquisition

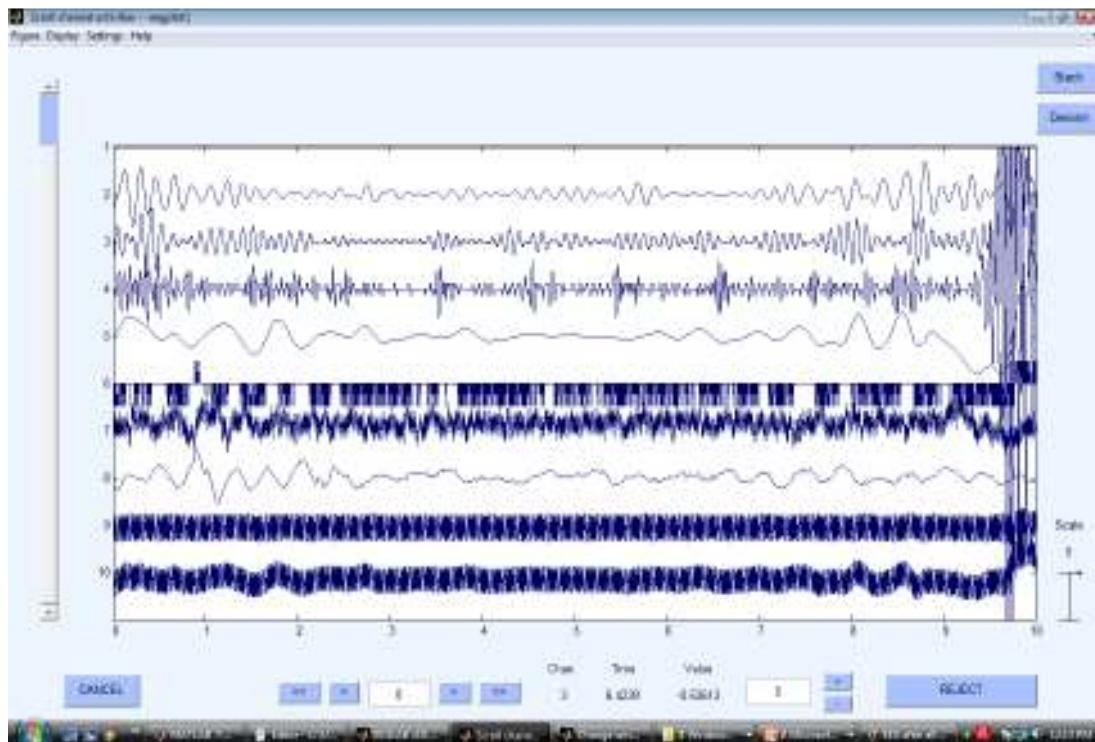


Fig. 3: EEG signal with ocular artifacts

**Math Task (MT):** The subject was asked to perform nontrivial multiplication problems, such as 89 times 67 and to solve them without vocalizing or making any physical movements. The problems were designed so that they could not be solved in the time allowed.

**Geometric Figure Rotation Task (GFRT):** The subject was shown images of three-dimensional figures (rendered and shaded) and asked to visualize them rotating about an axis.

**Visual Counting Task (VCT):** The subject was asked to imagine an image of black Roman numerals on a white background and asked to visualize similar numerals being written onto a blackboard, one after another, sequentially in ascending order, the previous numeral being erased before the next being written.

**Artifact removal:** Contamination of EEG activity by eye movements, blinks, cardiac signals and muscle and line noise is a serious problem for EEG interpretation

and analysis. One way of dealing with this problem is to simply reject segments of EEG with unacceptable amounts of noise. However, this may result in an unacceptable amount of data loss. Fortunately, there are other, algorithmic alternatives to discarding data.

EEGLAB is an interactive MATLAB toolbox for processing continuous and event-related EEG, MEG and other electrophysiological data incorporating, artifact rejection, event-related statistics and several useful modes of visualization of the averaged and single-trial data. EEGLAB allows the user to reject many such artifacts in an efficient and user-friendly manner.

Figure 3 shows the EEG signal with ocular artifacts and Fig. 4 shows the signal after the removal of the artifacts. It is ridded of artifacts and there is a boundary defined in red to separate the signal indicating that some part of the signal was removed in that region. This red line region is not shown where the ocular artifact was removed as that part of the signal was the end of the EEG signal.

**Feature extraction:** Once the data is preprocessed and the artifacts are removed, features must be extracted. The features extracted from the data are Mean, Standard deviation and Variance.

**Mean:** The mean  $\mu$  of a random process is defined as the average value of the all its sample functions and is given by:

$$\mu = \frac{1}{N} \sum_{i=1}^N x_i$$

**Standard deviation:** Standard Deviation (represented by the symbol  $\sigma$ ) shows how much variation or "dispersion" exists from the average (mean, or expected value). A low standard deviation indicates that the data points tend to be very close to the mean, whereas high standard deviation indicates that the data points are spread out over a large range of values:

$$\sigma = 1/N \sum (x_i - \mu)^2$$

**Variance:** The variance is a measure of how far a set of numbers is spread out. It is one of several descriptors of a probability distribution, describing how far the numbers lie from the mean (expected value). In particular, the variance is one of the moments of a distribution.

If a random variable X has the expected value (mean)  $\mu = E[X]$ , then the variance of X is given by:

$$\text{Var}(X) = E[(X - \mu)^2]$$

That is, the variance is the expected value of the squared difference between the variable's realization and the variable's mean. This definition encompasses random variables that are discrete, continuous, or neither (or mixed).

**Classification:** An artificial neural network is a computational simulation of a biological neural network. We have compared two classifiers: One is using feed forward Neural Network and the other one is nearest neighbor classifier to discriminate various Cognitive activities. All two classifier were fed with the same dimensional feature data under identical conditions.

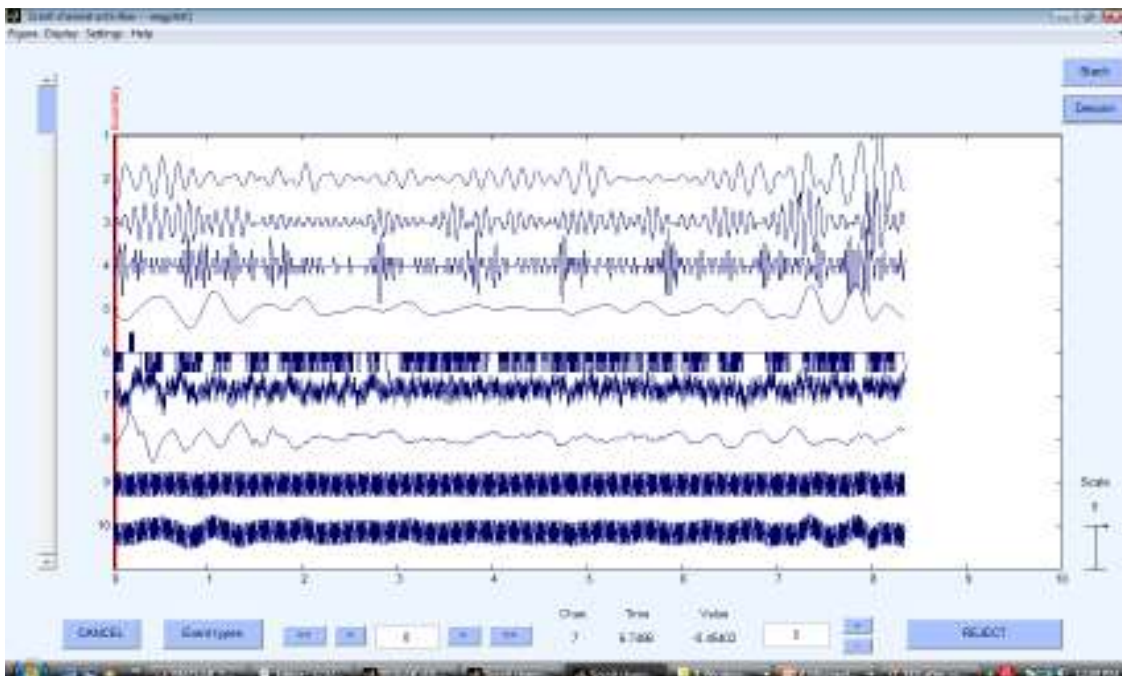


Fig. 4: EEG signal after artifacts were removed



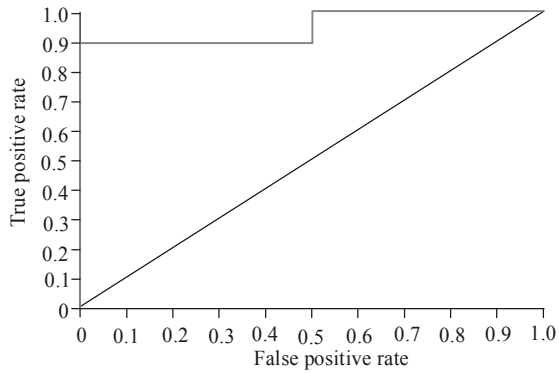


Fig. 5: ROC plot for baseline task with 25 hidden neuron

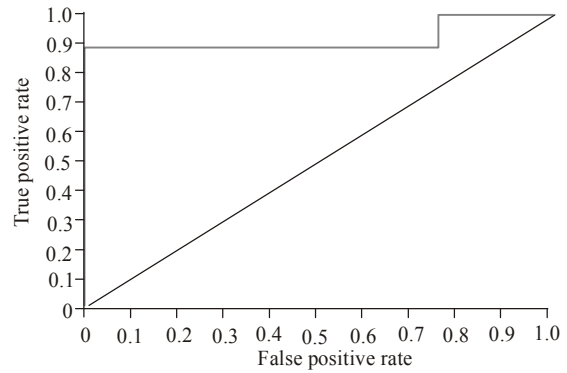


Fig. 8: ROC plot for baseline task with 5 hidden neurons

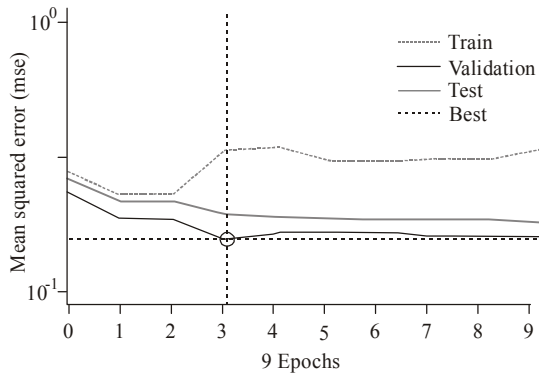


Fig. 6: Performance plot for baseline task with 25 hidden neurons

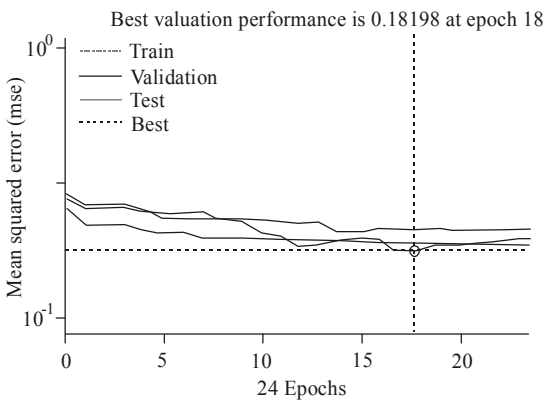


Fig. 7: Performance plot for baseline task with 5 hidden neurons

**Feed forward neural network classifier:** The feed forward neural network was the first and arguably most simple type of artificial neural network devised. In this network the information moves in only one direction—forward: From the input nodes data goes through the hidden nodes (if any) and to the output nodes. There are no cycles or loops in the network. Feed forward networks can be constructed from different types of units, e.g., binary McCulloch-Pitts neurons, the simplest example being the perceptron. Continuous neurons, frequently with sigmoidal activation, are used in the context of back propagation of error.

Before implementing the classifier algorithm on the data samples collected. The given set of data was first separated into two categories, training and test. The data can be divided in the ratio of 75:25, 70:30, 65:35 or 60:40 for training and validation purposes. The output of the classification depends mainly on the training and hence 70:30 was chosen over others. The data was trained using Pattern Recognition Toolbox in MATLAB.

The Neural Network is a two layer feed forward network, with a sigmoid hidden and output neurons. The network is trained using Scaled Conjugate Gradient back propagation (Fig. 5 to 8).

Here the training, the validation and the testing graphs are almost converging after some time, which indicates the training is satisfactory.

Since, the best efficiency in neural network for the given data is obtained for 25 hidden layers the results obtained in this case is used for comparison purposes.

**Nearest neighbour classifier:** Nearest Neighbor Search (NNS), also known as closest point search, similarity search. It is an optimization problem for finding closest (or most similar) points. Nearest neighbor search which returns the nearest neighbor of a query point in a set of points, is an important and widely studied problem in many fields and it has wide range of applications.

A major advantage of Nearest-Neighbor classification is that it tends to be very accurate given a large training set because similar points increase as the data set gets larger.

**Performance index:** The above study evaluated the performance of two classifiers for classification of different cognitive activities. Seventy percent of entire EEG data (five mental tasks with four subjects) was taken as training data. Remaining 30% of EEG data was taken as test data and the performances were recorded.

The following measures were used to assess the performance of the classifiers:

$$\text{sensitivity} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}}$$

Table 1: Output using feed forward neural networks classifier

Parameter	Task 1 (BLT) (%)	Task 2 (MT) (%)	Task 3 (LT) (%)	Task 4 (GFRT) (%)	Task 5 (VCT) (%)
Sensitivity	83	78	76	78	80
Specificity	50	0	0	0	0
Accuracy	80	64	65	70	80
Positive Predictive Value (PPV)	93	87	81	87	100

Table 2: Output using nearest neighbor classifier

Parameter	Task 1 (BLT) (%)	Task 2 (MT) (%)	Task 3 (LT) (%)	Task 4 (GFRT) (%)	Task 5 (VCT) (%)
Sensitivity	100	88	69	69	75
Specificity	100	0	0	0	0
Accuracy	100	80	55	55	60
Positive Predictive Value (PPV)	100	88	69	65	75

$$\text{specificity} = \frac{\text{True Negative}}{\text{True Negative} + \text{False Positive}}$$

$$\text{PPV} = \frac{\text{True Positive}}{\text{True positive} + \text{False Positive}}$$

$$\text{accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}}$$

## RESULTS AND DISCUSSION

Table 1 and 2 show the performance of the classifiers for each of the tasks using neural networks and nearest neighbor classifier respectively.

The performance of BLT and MT are better when using the nearest neighbor classifier. There is clearly distinguishable cognitive activity during these tasks and therefore a simple classifier like nearest neighbor can classify them. Whereas LT, GFRT and VCT perform better when a non-linear classifier like neural network is used. From the above results we can conclude that neural network classifier can effectively classify tasks which show small manifestation.

## CONCLUSION AND RECOMMENDATIONS

In future scope to use a 32 lead EEG data acquisition instrument for acquiring EEG data. It can be extended for more features from the EEG data obtained so as to improve the accuracy overall in pattern classification and it can also be used for different algorithm so that we can classify all the tasks at once. When we give an input the machine it should be able to classify the task from all the five tasks when collectively given. A predominant paradigm of research in cognitive neuroscience is EEG/ERP. The EEG/ERP has been extensively used in creativity research. EEG and ERP designs are useful in understanding the time domain analysis of cognitive processes and various analysis techniques including Spectral analysis, coherence analysis and other types of analysis have been used in creativity research employing EEG. The use of high density EEG systems along with the modern techniques for EEG signal analysis shows promise for the cognitive research advances and also identification of ADHD and dementia it can be applied as future study. We all know

kids who can't sit still, who never seem to listen, who don't follow instructions no matter how clearly you present them, or who blurt out inappropriate comments at inappropriate times. Sometimes these children are labeled as troublemakers, or criticized for being lazy and undisciplined. However, they may have ADD/ADHD. Attention Deficit Hyperactivity Disorder (ADHD) is a disorder that appears in early childhood. The above said analysis can help for patients who are undergoing the disorders such as ADHD, ADD patients.

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