

# Brain Workload Evaluation Using Neural Networks

Rishabh Yadav, Prashant Bajpai, Jayesh Behera, Varsha Wangikar  
Student, Student, Professor  
IT Department,  
K.C College of Engineering, Thane, India

**Abstract :** In this paper, we have put forward a system which will detect workload of brain. Different classification algorithms will evaluate the real time workload of a person. User will perform certain task at the same time frequency from the brain will be gathered. On the basis of trained data and classification algorithm will help system to determine the workload of the person. A 2d brain image will be final hard copy report of the person. System will help various individual and organization to know the work related load of a person and to reduce the stress level thereby increasing productivity.

**IndexTerms - EEG machine, Neural networks, Brain image**

## I. INTRODUCTION

To measure workload of brain currently there is no perfect method. Organization like security-forces need to classify people on their mental alertness and fitness. If test is conducted to decide whether someone is fit or not for certain position then it will give overall workload of that person. To measure real time workload of brain or how someone reacts to certain situation or task there is need for a system which will represent actual workload of brain. The brain is divided in parts and these parts work in coordination and perform different functions of brain. More specifically, it is divided into five major regions, namely, telencephalon, diencephalon or interbrain, mesencephalon (hindbrain/medulla oblongata), metencephalon and mesencephalon. By measuring parameters from different regions of brain we can evaluate how brain is reacting to the situation. To measure these parameters EEG machine can be used. By giving a situation or task, which is similar-to-real-one-will-help-in-depicting-the-workload of a person and while he will be performing the task parameters will be calculated by EEG machine. A 2D image of brain will feature the workload report of that person to that situation. This report will help in selection of person on their mental alertness and fitness.

## II. LITERATURE SURVEY

### 2.1 CT scan (Neuroscience)

This technique takes advantage of the fact that X-rays reflect the relative density of the tissue through which they pass. If a narrow X-ray beam is passed through the same object at many different angles, it is possible to use computational techniques to construct a visual image of the brain.

Problems: Prolonged or repeated exposure to ionizing radiation can cause tissue damage. Thus, as with x-rays, CT scans are used sparingly. Additionally, only structural information about the brain can be gathered. This is perfect for identifying problematic brain tissue, but gives us little insight into how the brain functions during cognition

### 2.2 PET (Neuroscience)

Positron Emission Tomography - This involves introducing a low activity, short-lasting radioactive label to compounds like glucose or oxygen in the brain. The radioactive labels decay in a characteristic way, giving off sub-atomic particles (positrons). By surrounding the subject's head with a detector array, connected to a suitable computer, it is possible to build up images of the brain showing different levels of radioactivity, and therefore, cortical activity.

Problems: Expense, inaccessibility, lack of temporal (40 seconds) and spatial (1 cm) resolution

### 2.3 fMRI (Neuroscience)

Functional Magnetic Resonance Imaging - This measures changes in oxygen levels in the brain which is an indicator of blood flow, a property of cortical activity. The amount of oxygen carried in the blood affects the blood's magnetic properties. fMRI can detect functionally induced changes in blood oxygenation with a spatial resolution of about 2mm.

Problems: fMRI is expensive, and has poor temporal resolution (whole brain images can typically only be collected every 2 seconds).

### 2.4 Mental workload evaluation with frontal EEG using SVM

Using a wireless single channel EEG device, we investigated the feasibility of using short-term frontal EEG as a means to evaluate the dynamic changes of mental workload. Frontal EEG signals were recorded from twenty healthy subjects performing four cognitive and motor tasks, including arithmetic operation, finger tapping, mental rotation and lexical decision task. Our findings revealed

that theta activity is the common EEG feature that increases with difficulty across four tasks. Meanwhile, with a short-time analysis window, the level of mental workload could be classified from EEG features with 65%–75% accuracy across subjects using a SVM model.

## 2.5 Different deep learning architectures

Table No 01. different deep learning architectures

Description	Key Points
<p><b>Deep Belief Network</b></p> <ul style="list-style-type: none"> <li>Proposed in [10] is a composition of RBM where each sub-network's hidden layer serves as the visible layer for the next</li> <li>Has undirected connections just at the top two layers</li> <li>Allows unsupervised and supervised training of the network</li> </ul>	<p><b>Pros:</b></p> <ul style="list-style-type: none"> <li>Proposes a layer-by-layer greedy learning strategy to initialize the network</li> <li>Inferences tractable maximizing the likelihood directly</li> </ul> <p><b>Cons:</b></p> <ul style="list-style-type: none"> <li>Training procedure is computationally expensive due to the initialization process and sampling</li> </ul>
<p><b>Deep Boltzmann machine</b></p> <ul style="list-style-type: none"> <li>Proposed in [11] is another approach based on the Boltzmann family</li> <li>Possesses undirected connections (conditionally independent) between all layers of the network</li> <li>Uses a stochastic maximum likelihood [12] algorithm to maximize the lower bound of the likelihood</li> </ul>	<p><b>Pros:</b></p> <ul style="list-style-type: none"> <li>Incorporates top-down feedback for a more robust inference with ambiguous inputs</li> </ul> <p><b>Cons:</b></p> <ul style="list-style-type: none"> <li>Time complexity for the inferences is higher than DBN</li> <li>Optimization of the parameters is not practical for larger datasets</li> </ul>
<p><b>Recurrent neural network</b></p> <ul style="list-style-type: none"> <li>Proposed in [13] is a NN capable of analyzing stream of data</li> <li>Useful in applications where the output depends on the previous computations</li> <li>Shares the same weights across all steps</li> </ul>	<p><b>Pros:</b></p> <ul style="list-style-type: none"> <li>can memorize sequential events</li> <li>can model time dependencies</li> <li>has shown great success in many natural language processing applications</li> </ul> <p><b>Cons:</b></p> <ul style="list-style-type: none"> <li>learning issues are frequent due to the vanishing gradient and exploding gradient problems</li> </ul>

### III. METHODOLOGY

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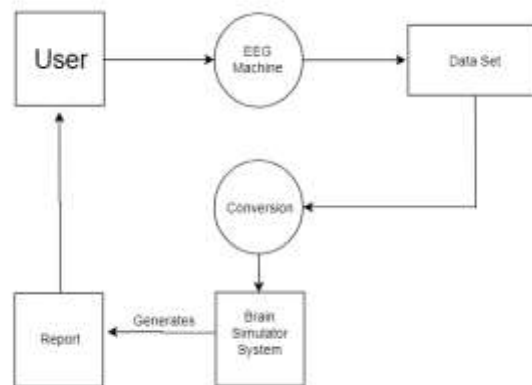
By giving a situation or task, which is similar-to-real-one-will-help-in-depcting-the-workload of a person and while he will be performing the task parameters will be calculated by EEG machine.

#### A. EEG Machine

System will be using EEG machine to take the input from the human Brain Using EEG 14 channel Cord. An EEG tracks and records brain wave patterns. Small flat metal discs called electrodes are attached to the scalp with wires. The electrodes analyze the electrical impulses in the brain and send signals to a computer that records the results.

The electrical impulses in an EEG recording look like wavy lines with peaks and valleys. EEG measures the electrical impulses in your brain by using several electrodes that are attached to your scalp.

Once the test begins, the electrodes send electrical impulse data from your brain to the recording machine. This machine converts the electrical impulses into visual patterns that appear on a screen. A computer saves these patterns in excel format.



(i) collection of data

## B. Algorithms used.

### a) SVM

“Support Vector Machine” (SVM) is a supervised machine learning algorithm which can be used for both classification and regression challenges. However, it is mostly used in classification problems. In this algorithm, we plot each data item as a point in  $n$ -dimensional space (where  $n$  is number of features you have) with the value of each feature being the value of a particular coordinate. Then, we perform classification by finding the hyper-plane that differentiate the two classes. In other words, given labeled training data (supervised learning), the algorithm outputs an optimal hyperplane which categorizes new examples.

### b) Stacked Auto encoder

A stacked auto encoder is a neural network consisting of multiple layers of sparse auto encoders in which the outputs of each layer are wired to the inputs of the successive layers. The auto encoder tries to learn an approximation to the identity function.

The DLN exploits the unsupervised pertaining technique with greedy layer wise training. The algorithm performs unsupervised pertaining one layer at a time, starting from the input layer to the output layer. The first sparse auto encoder (1st hidden layer) is trained on the raw inputs ( $x$ ) to learn primary features  $h(1)$  on the inputs. During pertaining process, all of weight and bias parameters have been learned to minimize the cost function. Next, the algorithm performs forward propagation by using the raw inputs into this trained sparse auto encoder to obtain the primary feature activations. For pertaining in the next hidden layer

### c) Radial basis function

In the field of mathematical modeling, a radial basis function network is an artificial neural network that uses radial basis functions as activation functions. The output of the network is a linear combination of radial basis functions of the inputs and neuron parameters. Radial basis function networks have many uses, including function approximation, time series prediction, classification, and system control. They were first formulated in a 1988 paper by Broom head and Lowe, both researchers at the Royal Signals and Radar Establishment.

### d) Linear Discriminant Analysis

Logistic regression is a classification algorithm traditionally limited to only two-class classification problems. If you have more than two classes then Linear Discriminant Analysis is the preferred linear classification technique.

## C. Display of Final result

A 2D image of brain will feature the workload report of person undergoing the test. Report will tell in how much workload the brain was while performing the simulating task.

## IV. CONCLUSION

Organization like security forces need a testing system which will evaluate brain workload so that candidate will be placed according to capability of both mental and physical.

Proposed system will help in evaluating real time workload of the candidate in a simulated environment. This system will be perfect combination of medical and IT technology for knowing hidden mental abilities of a candidate. System will change the selection process

of organization as it will be base on real time workload. The ultimate aim is to increase the workload capability and enhance the cognitive abilities by mathematically analyzing the results of the deep learning algorithms..

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