Raw EEG based visual learners classification using LSTM

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Abstract

The idea of this study is to analyse the learning styles of students using Raw Electroencephalography (EEG) signals. The aim is to differentiate raw EEG patterns of visual and non-visual learners. Thirty-four students were recruited to participate to this study. The EEG of the students were recorded from 128 scalp sites during performing a learning tasks. The Long short-term memory (LSTM) algorithm was implemented as a classifier. The results showed 87.5% classification accuracy.

Keywords: Raw EEG, LSTM, learning style, visual learner.

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1. Introduction

It is interesting to know how people differ in their learning capabilities. Broadly categorizing as quick learners and slow learners, which is also dependent on the understanding of the topic (Truong, 2016). This study is conducted for classification of non-visual learner and visual learners considering the brain patterns extracted from the Electroencephalography (EEG) recorded during learning new topic.

Electroencephalography (EEG) is used to measure brain signals over time. It has different frequency bands observing different brain regions. Each brain region has different duties.

The main focus of existing works is to see how EEG can differentiate between different individuals information processing (Ahn et al, 2010). In learning, information processing is a very broad term. The more precise terms are learning style, cognitive style (Mayer et al, 2003) and thinking style. Analysis of which, can help in identification of cognitive load. The existing studies uses the concepts of neuroscience educational, psychology, technology, computational methods and statistics to distinguish non-visual learners from visual learners (Abid et al, 2016).

Machine learning is widely used along with EEG for many learning studies. For instance using EEG to distinguish low impulsive and high impulsive individuals while learning new instrument (De Pascalis et al, 2010). EEG coherence and power features were extracted from 30 scalp sites. The authors found that low impulsive learners have higher theta on parietal region and lower value on frontal region. They have lower beta power in Centro-parietal region and higher beta power on temporal region. Non-Learners (Low impulsive individuals) have less coherence for frontal-parietal as compare to learners (high impulsive individuals). The results show the significance of a frontal-parietal region in learning and memory. It highlights the importance of the learning process and learning ability and how it varies from person to person.

Another study predicts the learners' answers from their emotional dimensions and brain waves (FRASSON, 2009). Twenty-four participants participated in the experiment. They were asked to read thirty-five questions for the first time, which they were supposed to answer the next day. Measuring the brain waves tells the participant emotional state when they know the answer as compared to when they do not know the answer.

A work was also done in increasing attention of normal college student (Rasey et al, 1995). Subjects are divided into learners and non-learners using feedback practicing standards. The subjects were divided into learner and non-learner based on their scores in Intermediate visual and auditory (IVA) attention test. The participants of this study who were diagnosed with attention deficit disorder based on IVA test. Were provided with EEG biofeedback to enhance beta activity while lowering the alpha and theta activity. The activity involves intermediate visual and auditory continuous performance test. The results showed the significant improvement in learners however non-learners show no improvement.

Apart from these, many studies were done on reward and learning relationships describing how reward enhances learning. (O'Rourke, 2014), (Schroder et al, 2014), (Dweck, 2012), (Akioka and Gilmore, 2013), (Ryan and Deci, 2017).

In this study, we present a method for differentiating visual learners from non-visual learners based on the raw EEG signals and employed the long short-term memory (LSTM) for classification purposes. The idea is to use deep learning technique, which can be applied directly on the data without extracting features and cleaning data. The advantage is robustness and time efficiency. Out of many available deep-learning classifiers we use LSTM because it works best for time-series data (Amin et al, 2015). We attempted to explore the brain neuronal behavior of the visual learners as compared to non-visual learners when the new information is presented to the students.

The rest of paper is organized as follows: section 2 provides the material and methods, section 3 explains the results and is followed by the discussion in section 4 and the conclusion in section 5

2. Materials and Methods

This study presents a framework, which will use the concepts of educational psychology, neurosciences, technology, statistics, and computational methods to identify the learning style of a student. We use 2D-based educational tools on learning processes.

2.1. Block Diagram

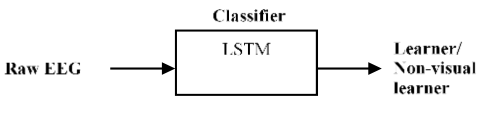

Figure 1. Block diagram of the system.

2.2. Experimental Procedure (Raw EEG)

Subjects: Data is collected from thirty-four healthy participants in the form of an experiment with written consent (age range [18-28], male and female, undergraduate and graduate). Before conducting the experiment, the study is presented in front of an ethical committee for approval (Amin et al, 2015). Here, healthy subjects mean that the subject is free from any neurological disorders or any other learning disabilities. The subjects have normal to corrected normal vision.
Following are the exclusion criteria:

1. Subject who has background knowledge of the learning topic.

2. Subject having any neurological disorder.
3. Subject who are not undergraduate student.
4. Subject who does not have engineering background.

Tasks: Subjects were asked to learn and retain contents which are displayed to them through 2D tools.

Procedure:

1. Before starting the experiment, Participants were asked to fill the questionnaire, certifying they were healthy (to minimize the effects of non-experimental variables).
2. To identify the uniform IQ level of the participants. They were asked to perform an intelligence task. Raven's advanced progressive matrix (RAMP) intelligence test is a used to measure the intelligence of the students.
3. At first EEG data was recorded without performing any task with eyes closed and eyes open condition.
4. 2D contents were then shown to the participants, which they must learn. Where EEG data is collected during the learning task.
5. The data is collected in three learning sessions called as Learning session one (learning 1), Learning session two (learning 2), Learning session three (Learning 3) and two retrieval sessions called as Recall 1 and Recall 2.

The selected format of the test is multiple choice question (MCQ) type. MCQ is the best choice for EEG recording. Because this type of test has reduced artifact as compared to other methods such as oral and written test in which other areas of the brain are active because of the sensory movement which induces artifacts. Following was the format of the test. The participants were shown the video of 8-minutes duration referred to science concepts. The contents of animation were: 1) "Human skull and its structure", 2) "Brain anatomy and functions", 3) "Brain disorder (Alzheimer disease)". The subjects had verified that they have no background knowledge of the animation's contents.

Based on the video a total of 20 questions were asked. Each multi-choice questions (MCQ) comprises of missing information with four choices, out of which one was the correct answer. The subjects had limited time to answer the (MCQs). The questions were designed using standard rules for preparing multiple choice question test. The test is designed with the help of a field expert. Students were instructed, to be honest as there was no grading involved. Based on their results, the participants were grouped in visual and visual learners. The grouping was later used as ground truth for the classification using the patterns of EEG recorded while they were answering the test.

2.3. Long short-term memory (LSTM)

(i) LSTM as a classifier

LSTM can be used for classification as it is just a standard neural network that takes an input, in addition to input from that time step, a hidden state from the previous time step. So, just as a NN can be used for classification so can an LSTM. LSTM works best for time series data. That is the reason we choose it among all other deep learning techniques.

(ii) LSTM working Principle

Traditional neural networks do not have persistence that's the shortcoming in them. Recurrent neural network addresses this problem. Having loops in them making the information persist. The problem of RNN is long-term dependencies. The Long-Short Term Memory networks are special type of RNN. The idea here is to learn long-term dependencies. It remembers information for long period of time by default. LSTM's has a chain like structure same as RNN but instead of having one layer they have four layers. The LSTM does have the ability to remove or add information to the cell state carefully regulated by gate structures. Here the LSTM based deep Learning model has been proposed for the classification of visual learner and non-visual learner states using brain waves. The technique that has been used is one-hot encoding. The implementation is done using tensor flow. The accuracy of the model is calculated from confusion matrix for batch size 8. Figure 2 shows the LSTM architecture.

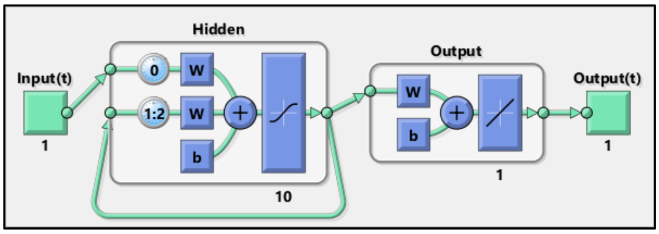

Figure 2. The LSTM architecture

3. Results

The behavioral data is analyzed to measure the performance of the visual learners and non-visual learners. For learning, the correct responses and reaction times are computed for each participant. The reaction time shows the mental speed of information retrieval and is measured from the point where the MCQ is displayed until the participant presses a button for the selection of an answer. The percentage of correct responses per participant was then used to measure his/her learning performance. The total number of trials available per subject was 34 subjects X 20 MCQ = 680 trials. To assess the learning ability RAMP score is used. The subjects are divided into two equal groups using median score (Amin et al, 2015). Based on the median score, the subjects who scored equal or above the median are considered as visual learners and those who scored less than the median are considered as non-visual learners. To classify the visual learner and non-visual learner, we analyze the retrieval task; the first retrieval task is recorded thirty minutes after the learning task (Recall session one).

To evaluate the model performance, the accuracy, sensitivity (true positive rate), and specificity (true negative rate) parameters are computed, and the receiver operating characteristic (ROC) curve is obtained. To calculate the accuracy, sensitivity, and specificity, the confusion matrix is first computed. A confusion matrix is used to describe the performance of a classification model on a set of data with known true values.

Table 1 show the model accuracy along with precision and recall. Table 2 show the confusion matrix for the raw EEG obtained from different iterations, respectively. The dataset consists of 34 subjects. The data is divided using 75, 25 formulation. Here 75 % data is used for training and 25% data is used for testing. From Table 1(a) two predicted classes for the visual learner (L) and non-visual learner (NL). The classifier predicted 5 NLs and 1 Ls. However, there are actual 3 Ls and 5 NLs, where TP is a true positive, TN is true negative, FP is false positive, and FN is false negative. The TPs are the instances where the predicted visual learners are actual visual learners. The TNs are the instances where the predicted non-visual learners are actual non-visual learners. The FPs are when the visual non-learners are predicted as visual learners. The FNs are when the visual learners are predicted as non-visual learners.

From the confusion matrix shown in Table1 the accuracy, sensitivity, and specificity are calculated. Mathematically, the accuracy, precision, and recall parameters are shown in equations.

$$\boldsymbol{Accuracy} = \left(\frac{\boldsymbol{TP}+\boldsymbol{TN}}{\boldsymbol{TP}+\boldsymbol{TN}+\boldsymbol{FP}+\boldsymbol{FN}}\right)\times \mathbf{100}\%$$

$$\boldsymbol{Precision} = \left(\frac{\boldsymbol{TP}}{\boldsymbol{TP}+\boldsymbol{FP}}\right)\times \mathbf{100}\%$$

$$\boldsymbol{Recall} = \left(\frac{\boldsymbol{TP}}{\boldsymbol{TP}+\boldsymbol{FN}}\right)\times \mathbf{100}\%$$

Plotting the TP along the y-axis and the FP rate along the x-axis generates the ROC. Figure 3 shows the ROC curve of the LSTM classifier where backline represents visual Learner and green line represents non-visual learner, with area under the curve (AUC) values of 0.67 and 0.67 for both classes.

Table 1. Model evaluation

```
****************** model loaded *******************
8/8 [==============================] - 16s 2s/step

[info] loss=0.586, accuracy: 87.500%


              precision    recall  f1-score   support

           L       1.00      0.67      0.80         3
          NL       0.83      1.00      0.91         5

    accuracy                           0.88         8
   macro avg       0.92      0.83      0.85         8
weighted avg       0.90      0.88      0.87         8
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Table2. Confusion matrix

n= 8	Predicted (L)	Predicted (NL)
Actual (NL)	TN= 2	FP = 1
Actual (L)	FN = 0	TP = 5

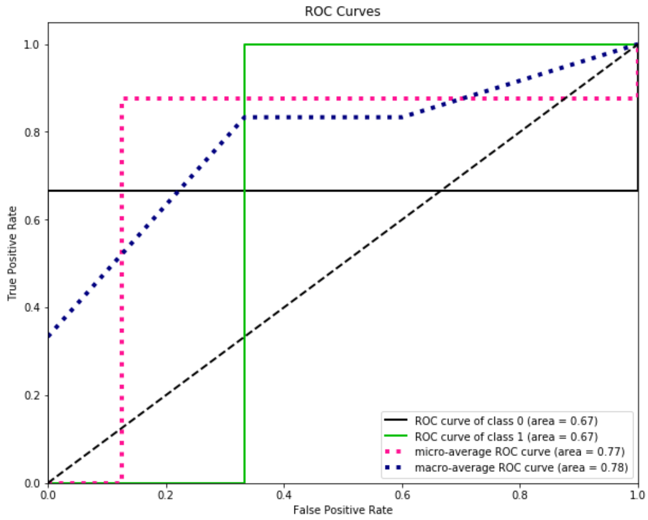

Figure 3. ROC curve of LSTM classifier

4. Discussion

In this study, visual learning styles were analyzed using EEG signals and Long short-term memory as a deep learning classifier. Participants were classified as visual or non-visual learners. The EEG signals were recorded during learning task, which make the outcome more transparent in a sense. Indeed, most existing learning theories such as Kolb, which is based on the accommodators, convergers, diverges and assimilators (Kolb, n.d.), The Index of learning (ILS) based on active/reflective, sensing/intuitive, visual/verbal, and sequential/global learning (Felder et al, 1988), use self-rating by participants. The self-rating may bring a bias as a learner might think he is a visual learner while in fact he/she is not. So, one of the ways to make things unbiased is recording the brain patterns during learning task to see the complete picture. This way of identifying learning style is unique and more reliable in a sense as it does not involve self-rating and is purely based on what the brain patterns has to say about the learning style.

5. Conclusion

In this work, we have proposed a brain-learning model for identifying visual learners and non-visual learners using raw EEG signals. To distinguish the visual learners from the non-visual learners, EEG is extracted from 128 scalp sites such as Frontal, Occipital and Parietal regions, which play active role during visual learning. The LSTM is used for classification. The classification accuracy was recorded as 87.5% for the visual learners and non-visual learners. From above results we concluded that LSTM alone could be used for the classification of raw EEG signals.

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