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A COGNITIVE E-LEARNING SYSTEM USING AROUSAL VALENCE EMOTIONAL MODEL

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ABSTRACT

This paper proposes an approach to connote the basic human emotion to learner's emotion for e learning. The emotions are captured from the EEG signals and are processed at various levels to classify them. This paper uses arousal-valence model to recognize the learner's emotion. In addition, we introduce a cognitive system -Adaptive Control of Thought—Rational – (ACT–R) to dynamically monitor the learner's emotion. This dynamic cognitive learning environment brings the learner's mood to active listening mood through an external stimulus. This enables the learner to improvise their in-depth knowledge about the learning content and kindle their interest towards the subject. In general, this method is similar to the conventional classroom teaching where the teacher modulates the content delivery method depending on the mood of student.

Keyword: *EEG, Cognitive Architecture - ACT-R, Intelligent Learning Environment, E-learning*

1. INTRODUCTION

For the learner, active learning is always influenced by many parameters like teaching methodology, their interest towards the subject, attentiveness, motivation, and emotions[1]. In addition, learner characteristics like skills, ability, cognitive and learning practice and permissible conditions also contribute to active learning [2, 3]. Emotion recognition is possible through facial expression, gestures or bodily movements, and speech recognition. However, there exists a need to capture the emotions as in the pedagogical teaching environment the learner can control or disguise their emotions. The learner can pretend to be an active listener. So the capturing of the learner's emotions through bio-signals seems to be the right methodology. Many studies on emotion recognition have been done in the past few decades. The focus of these researches was only on the processing of human emotion. However, there was no suggestion for the continuous monitoring of the learner's emotion and dynamic change through an external stimulus, when the learner is found in an inactive mood. Therefore, we introduce ACT–R cognitive system that understands the mood of the learner and dynamically changes the content and delivery method in order to control the e-learner's emotion and conscious behavior towards learning. ACT-R is a hybrid architecture used to handle intelligent learning environment.

E-learning environment prevails in every area of study. Learning content in the form of audio and video makes an interesting learning environment. However, there exist areas of concern like the duration of study, learner's state of mind and monotonous learning content that can distract e-learner's emotion. Hence, an e-learning environment needs to be very interesting and intelligent. Therefore, bio signals are the right choice to reflect the human emotion. Here, we discuss various bio-signals like the respiratory system, EDA, EMG, ECG, and EEG signal which reflect the human emotions.

Respiratory system: This system [4] continuously monitors the human respiration activity. It measures respiration rate (RF) and the Relative breadth of the Amplitude (RA) or the

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depth of the amplitude. Different sensors are available to measure RF and RA. By continuously monitoring the variation in the RF--either an increase or a decrease in RF--either undesirable or desirable emotions can be noticed. For instance, when RF decreases, the resulting emotions are relaxation, bliss and when it increases, the emotions expressed are anger and anxiety [5].

Electro dermal Activity (EDA) - EDA signal [6] captured from the human body surface. It describes the functionality of the autonomic nervous system, also called galvanic skin response (GSR). This system constantly captures the electrical activity of the skin temperature (SKT). The SKT variation reflects the human emotion. Normalized GSR is calculated as

$$Normalized_{GSR} = \frac{(Original_{GSR} - Relax_{GSR})}{Relax_{GSR}}$$

EDA signal reflects the learner's emotion like excitement, stress, interest, and attention.

Electromyogram (EMG) – Muscular system – This system calibrates the skin's ability to conduct electricity. From this electrical variation, we evaluate the speed and amplitude of the electricity and generate into the time field analysis [7]. By analyzing the changes between speed and amplitude, we can predict the learner's emotion. The emotions are fear, anger, relaxation, excitement, and joy.

Electrocardiogram (ECG) – Cardiovascular system – This system captures the electrical function of our Heart and gives our Heart rate (HR) as output. From this HR, we can derive Blood Volume Pulse **(**BVP) and Heart rate Variability (HRV) [8]. By carefully analyzing the difference between HRV and BVP, we can detect the emotions like joy, sadness, fear, and anger.

However, the fewer number of basic human emotions is detected from by Respiratory system, EDA, EMG, and ECG signal. But EEG (Electro Encephalo Gram) signals which are brain wave signals that accurately reflect the learner's emotion and allow us to reflect new emotion from the combination of two different emotions like disappointment from sadness and surprise. Hence, this proposed system uses EEG signals and classifies learner's emotion using arousal - valence classification model.

2. RELATED WORK

Electroencephalogram (EEG) – This signal captures the current state of the brain and projects the leaner's emotion. The signal accurately predicts the emotion, providing a reliability of 90%. This signal is a very frugal but a highly sensitive one that can detect internal changes of our Brain Activity and resolution of this EEG signal is very high. Many studies in the area of emotion recognition through EEG signal' have been carried out and reported. However, these works concentrated only on capturing the leaner's emotion in a pedagogical teaching environment [9]. A need has arisen to capture and classify the emotion of an e-learner. The proposed system predicts the actual emotional state of the learner and dynamically monitors the learner's emotion using an EEG signal. On recognizing an inattentive state on the part of the learner, an external stimulus brings the e-learner to active listening mood. Brain is a collection of neurons. When we think or try to do anything, immediately the rhythmic signals get activated by the combination of electrical potential value among the brain waves. EEG sensors can measure these. Then the observed brain wave signals are divided into multiple bands based on the frequency of the brain waves. The bands represent the mental state of our brain. Then these bands and the respective human emotion are pigeonholed as shown in the table below [10].

Table1: EEG Signal Mental State

EEG Band	Frequency Range (HZ)	Mental state
Delta Band (δ)	0 to 3 HZ	Deep sleep state
Theta Band (θ)	4HZ to 7HZ	Drowsiness or mediation
Alpha band (α)	8HZ to 12 HZ	Awake
Beta Band (β)	13HZ to 30HZ	Actual thinking or concentration
Gamma band	36HZ to 40HZ	Noise signal

EEG Signal

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$$V(T) = \sum_{n=1}^{N} An\ Sin(2\pi fnt - \emptyset n)$$

Here Ø – phase, f – Frequency and A Amplitude

3. EMOTION RECOGNITION DESIGN FRAMEWORK

The EEG (Electroencephalogram) signals of the e-learner are captured through micro EEG devices. The captured bio-signals are then processed into multiple sequential steps as given below: Preprocessing- we make use of the Surface Laplacian (SL) filter for removing the noises and artifacts from EEG signal [11]. The computational model of SL is given as

$$Xnew = X(t) - \frac{1}{N\sum_{i=1}^{NE} Xi(t)}$$

Here X(t) – Raw EEG signal, X_{new} – Noise free signal, N – total number of neighborhood electrode. Feature extraction – The process of extracting statistical feature of EEG signal and representing the features in the form of time domain and frequency domain wavelets. Many techniques are available to extract the features from EEG signal:

1.Wavelet transform (WT), 2. Fast Fourier transform (FFT), 3. Hilbert Huang transform, and 4. Principal component analysis (PCA). Many researchers have found that the first two techniques produce better results than the other ones. In this study, we employ an FFT method for feature extraction. First, the electrical form of our brain waves is preprocessed. These noise free wave signals are represented as frequency domain signals. Then the frequency domain signal is segmented into specific band frequency and the unwanted frequency band signal is set to zero [12]. The extracted feature was selected using sequential forward selection method.

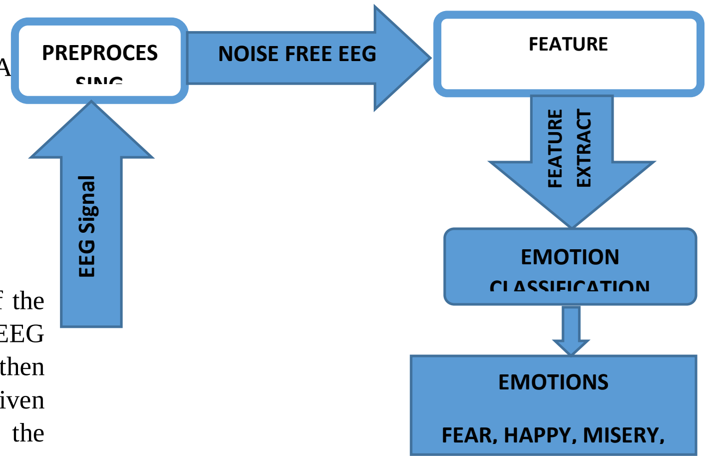

Fig1. EEG Signal Processing

Emotion classification –In this study, we use Arousal-Valence two dimensional emotion specification model. Using this model, the emotions are widely classified into six basic human emotions: 1.Fear, 2. Happy, 3. Misery 4. Sad, 5. Satisfied, and 6. Sleeping. This model also supports grouping the basic emotions that result in the recognition of additional human emotions.

Emotions can be represented in two ways--Discrete approach and Dimensional approach. Here discrete approach represents core emotions, which are happy, sad, disgust, anger, curiosity, and surprise. The dimensional approach represents these core emotions in a better way using Arousal – Valence Classification model. Here we use two axes to represent human emotions, namely Valence axis and arousal axis [13]. This study uses Arousal – Valence classification model to represent the e-learner's emotion. The emotion of the i-th segment ei, was calculated by

$$ei = \sqrt{ai^2 + vi^2}$$

Where Ai = arousal, Vi = valence

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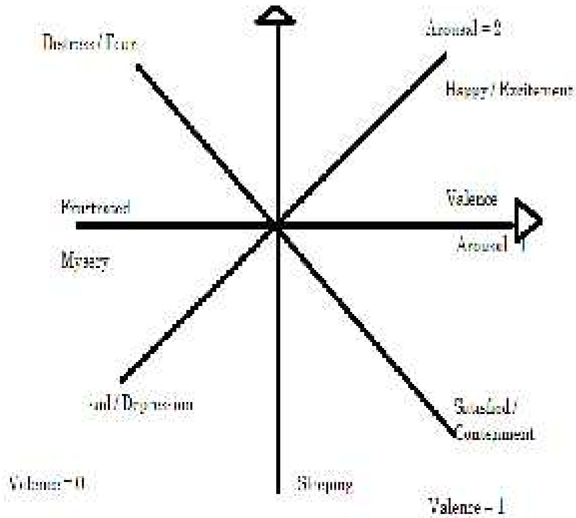

Fig2. Arousal Valence Emotional Model

Table2: Eeg Signal Mental State Mapping Based On The Arousal And Valence Value

Arousal Value	Valence Value	Human emotion
2	1	Excitement
1	1	Satisfied/ Contentment
0	1	Happy
2	-1	Fear
1	-1	misery
0	-1	Depression
0	0	Sleeping

Then we use Support Vector Method (SVM) for emotion classification with valence and arousal data. Many researchers have found that the Support vector Machine method is the best approach to classify the data into more emotion modes [15, 16]. Because of this reputed approach, we use SVM to analyze a set of data and reflect the emotion. The main objective of SVM is to identify the hyper plane with the highest margin. The difference between any set of hyper planes for a pattern

$$\mathbf{Y} = |g(\mathbf{y})| / ||\mathbf{a}||.$$

Here with the assumption of the positive margin b exists.

$$z_k\, g(\mathbf{y}_k) / ||\mathbf{a}|| \geq b,$$

$k = 1, \ldots, n$;
here, to find the weight vector which maximizes b and zk is the class of k-th pattern, b is margin and $g(\mathbf{y})$ is a linear discriminant in an augmented $\mathbf{y}$ space $g(\mathbf{y}) = \mathbf{a}^T\mathbf{y}$

4. COGNITIVE SYSTEM

ACT-R is a hybrid cognitive architecture. In the real world applications, this architecture has the capability to integrate knowledge of human cognition into the computational models. Hence, the proposed system uses this architecture to make the e-learning environment more intelligent. This is achieved by additionally incorporating learner's emotion captured through EEG signal to identify learner's performance and mood diversion. ACT – R [17] acts as an interface between the e-learner and the learning environment. This architecture consists of two types of knowledge structures such as chunks and productions. Chunks are used to represent declarative knowledge while productions are used to represent procedural knowledge [25]. The availability and applicability of symbolic knowledge can be ascertained by the parameters defined in order to predict the performance of ACT – R [18]. Activation of chunk i is given by

$$A_i = B_i + \sum W_j S_{ji},$$

where

B_i = Base – level activation of chunk i.
W_j= Activation spread from linked chunks j.
Log likelihood of i occurring

$$B_i = \log \left[\frac{\Pr(i)}{\Pr(\text{not } i)} \right]$$

Log likelihood of i occurring with j

$$S_{ji} = \log \left[\frac{\Pr(j|i)}{\Pr(j|\text{not } i)} \right]$$

5. PROPOSED SYSTEM

In pedagogical environment, the tutor identifies the leaner's mood through facial expression and gesture. Learner's facial expressions or gestures reflect their inattentive mood. Which can be converted into attentive through external stimuli. The stimulus like a question and answer session helps tutors to bring learners to active mood [14]. However, in an e-learning environment, the absence of a physical tutor lets go a learner's

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mood unidentified. Hence, the proposed system captures the emotion of the learner using an EEG signal. This signal is incorporated into ACT-R architecture to provide a better e-learning environment under such circumstances. Unlike questions raised by the tutor in pedagogical environment, in e learning, we create a bundle of external stimuli related to current learning material for the e-learner. This stimuli change the emotional status of e-learner by triggering it whenever necessary.

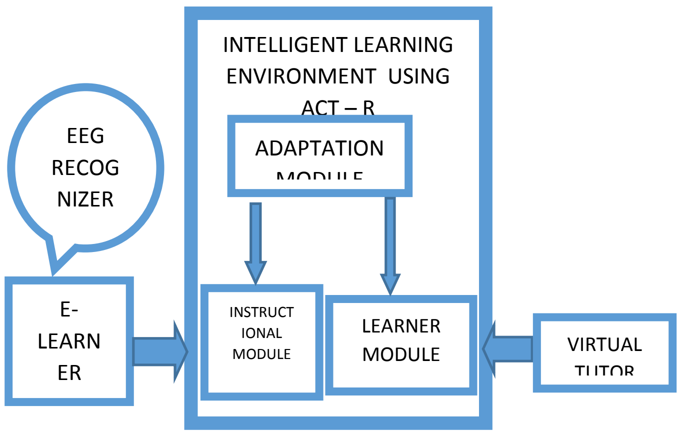

Fig3. Proposed E-Learning Environment

In our proposed system, we employ three modules to observe learner's emotional behavior. 1. Learner module, 2. Instructional module, and 3. Adaptation module.

Learner module – This module gets the learner's mood from EEG recognizer. We use EEG measuring headset with the trademark of emotive [19] to reflect the e-learner's mood. It has the learner details like, learner profile, learner's knowledge, performance, mood disruption, learner's conscious listening duration and area of interest. It acts as learner's history feedback module which is coordinated by Adaptive module. If learner's emotion is distressed, distracted or depressed, we attempt to divert the learner's mood to focused or attentive mood. This can be achieved by activating the external stimuli. These stimuli may be an audio or video content relevant to our learning material, quiz i.e., multiple-choice question, or any presentation clip for 5 minutes. When the learner sees the different form of learning content, it may result in an automatic mood diversion.

Instructional Module – This module holds the learning material and its corresponding stimulus. We have taken a subject like System Software and prepared the e-learning material for this subject. In addition, we prepared various stimuli related to this subject.

Adaptive Module–We enhance the proposed learning environment by embracing Adaptive module to make a learning environment as an intelligent learning one by taking care of learner module and instructional module in order to control the learner's behavior towards learning. The adaptive modu0le not only provides the learning content from instructional module but also chooses an appropriate stimulus based on the learner's mood and triggers it.

Here, we use ACT-R –architecture to handle the psychological refractory period (PRP)[20, 24] of the e-learner. This PRP is known as the period of time in which the response for the second stimulus is significantly slowed due to the ongoing process of the first stimulus. (This delayed response required to deviate the attention exhibits a negative effect in various fields of study). In this proposed system, we use this idea to handle the e-learner's mood. For example, EEG system recognizes that the learner is in the sleeping state which calls first stimulus, so immediately the adaptive module is ready to trigger the external stimuli to bring the learner mood to active listening mood called second stimulus. But, surprisingly, the learner gets into active mood without getting any external trigger. So obviously, the second stimulus significantly gets slowed and there is no necessity to trigger the external stimuli. To handle this cognitive situation, we use ACT-R architecture for dynamically monitoring the e-learner behavior.

Arousal – Valence model classifies the human emotions using an emotional parameter such as arousal and valence value [21]. These identified emotions are indicative of the learner's mood. For instance, a learner who is in a happy and excited mood is not in a preoccupied state of mind. We feel that this may enable them to focus on the learning content. Hence, human emotion-happy/ excitement can be mapped as focused

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mood. However, the performance and interest towards the subject can be known by conducting skill test to the learner.

Similarly, a depressed state of mind is preoccupied and distracts the learner. Correspondingly, the human emotion shown in the above model can be mapped into the learner's mood by using the arousal and valence value. We observed the arousal and valence axis position and the various emotions from fig.3. With these data we framed a table, which reflects the learner's mood while learning **[table2].**

Table3: EEG Signal Mental State Mapping To E-Learner Emotional State

Arousal Value	Valence Value	Human emotion	Learner's Mood
2	1	Excitement	Focused Mood
1	1	Satisfied/ Contentment	Attentive Mood
0	1	Happy	Listening Mood
2	-1	Fear	Distress Mood
1	-1	misery	Distraction mood
0	-1	Depression	Depression Mood
0	0	Sleeping	Sleeping mode

Here, we use SAM form [22] (self-assessment manikin). This form will give two results based on the learner's response towards the external stimuli, i.e., active listening mood and active mood. If it is active listening mood, the e-learning progression can be improved. If it is an active mood, then the virtual teacher has to give an overview of the previous learning content to enable the learner to have a better understanding about the learning content. The learner's behavior is continuously monitored by the cognitive system ACT- R, so that their interest towards the subject can be improved and their knowledge enhanced [23].

6. EXPERIMENTAL RESULTS AND ANALYSIS

Using conventional classroom teaching methodology, we have taught System Software subject to 20 students. Here we observed the mood and performance of those students. The facial expression and gestures of the learners were taken as the criteria to see if they got distracted or not and accordingly, the faculty member had adopted different methods to keep the learning mood. The outcome of this process was recorded in terms of marks obtained by the learners. The learner gave his best performance when he or she was focused and attentive. The performance observation was done by conducting surprise objective based test, question-answer session and feedback about the learning process like content of delivery and method of delivery.

The same subject was taken with the proposed system. Here we prepared the e-learning content for the subject of System Software and all the related stimuli like audio clip, video clip, presentation clip, few questionnaires slide and attractive pop up was created for the same subject. We were observing the learner mood from EEG signal and the active behaviour of the learner was recorded. Here we used the same performance testing towards learning and it was recorded like cognitive teaching.

Next, we observed the performance of the learner during conventional teaching and the proposed system by conducting various test like written test, oral test and quiz based test related to the subject. In conventional teaching, more number of students were involved in learning, so the observation of the student behavior became a little bit difficult for those tutors who have less experience. However, in the proposed system, the virtual tutor was concentrating on individual learner behavior. So this system could obtain the data that nearly 70% of the students were listening while learning and the remaining 30% of the student got distracted.

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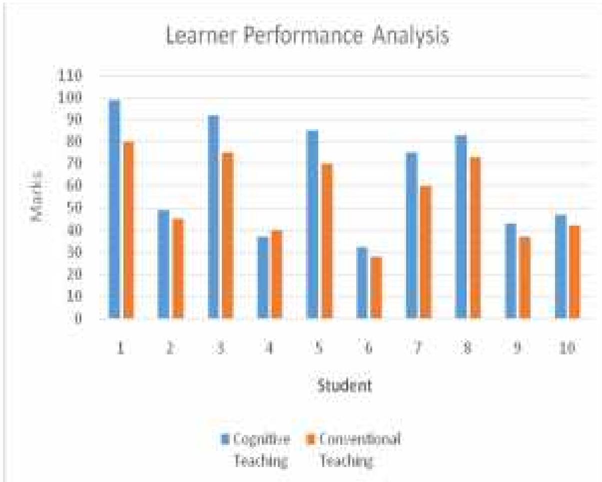

Fig 4. Learner Performance Analysis In Cognitive Teaching And Conventional Teaching Based On Their Written Test Performance

The figure 4 depicts the performance of the learner in conventional teaching and cognitive teaching. Now we repeated test for the understanding capability of the learner by conducting oral test and the progress was recorded. The same methodology was applied to the proposed system in the form of raising quiz question and the progress was recorded. In cognitive teaching, the performance was increased by nearly 20% compared with the cognitive teaching.

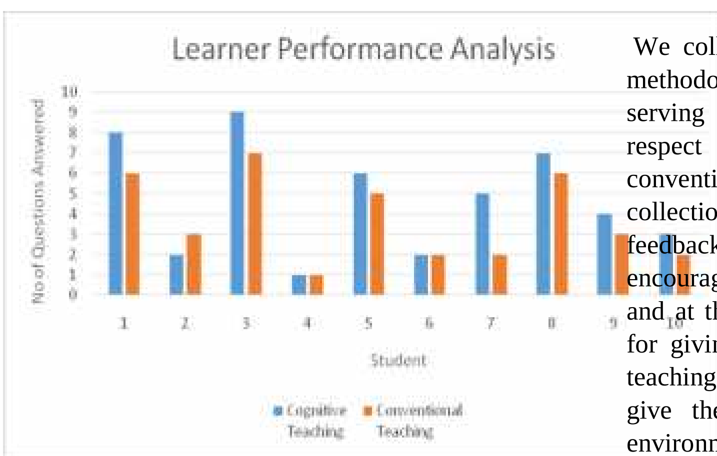

Fig 5. Learner Performance Analysis In Cognitive Teaching And Conventional Teaching Based On Their Question Answer Test Performance

Then we observed the time taken by ~~of~~ the learner to understand the learning concept. Obviously, the pedagogical teaching system is always the best system. It takes less time to understand the concept. But today's life pattern forces us to go in for e-learning system. So the proposed system was effective in giving a better e-learning system like pedagogical system. The basic concepts could be taught in one hour by adopting the conventional teaching besides getting the feedback. But in e-learning, the process consumed two hours.

Fig 6 Depicts The Time Taken By The Learner In Conventional Teaching And Cognitive Teaching For The E-Learner.

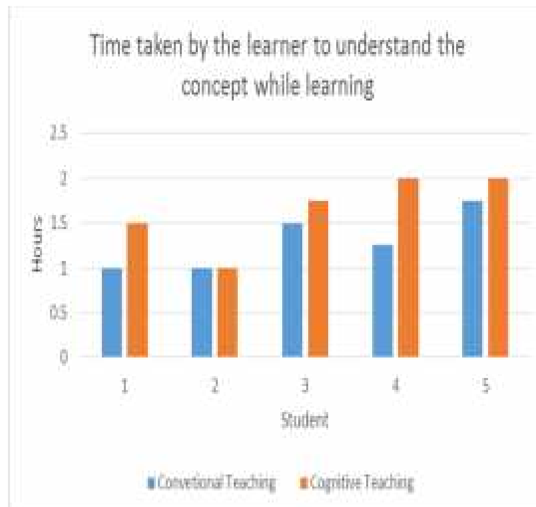

Fig. 6 Time Taken By The Learner To Understand The Concept While Learning

We collected the feedback about the teaching methodology and delivery of learning content by serving questionnaires to the learner with respect to both the learning environments. In conventional teaching, face to face feedback collection lead both positive and negative feedback, i.e., face to face learning environment encourages the learner to give better feedback and at the same time causes fear and hesitation for giving negative feedback. But in cognitive teaching, it allows the learner to feel free and give the exact feedback about the learning environment. By collecting this feedback, we can make the necessary rectification towards learning. This feedback is based on the course content, the teacher's teaching methodology, and the delivery of the learning content.

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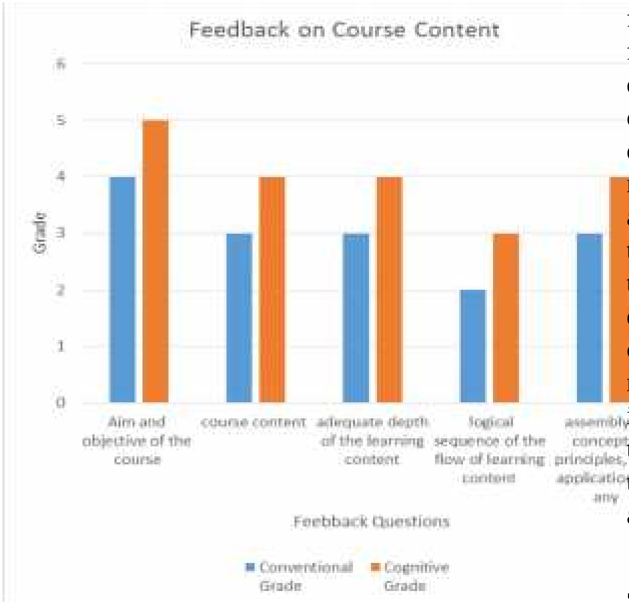

Fig.7 Feedback On Course Content

The feedback questionnaire on course content: We prepared a set of questions for both convention teaching and cognitive teaching. We assigned a range of grade values to the possible responses to the questions. We collected the grades from the learner for both the teaching methodologies. Fig 5 depicts the feedback report on the course content. We collected a better feedback in the e-learning environment than conventional teaching.

In the proposed cognitive learning environment, we prepared the learning material for the same subject. We generated various stimuli related to the subject. The on time emotion of the learner was collected using emotive headset and it was classified using arousal – valence emotion model. The captured emotion was one of the basic human emotions and it was mapped to the learner's emotion. We compared the obtained emotion with the emotion listed in Table2. If the emotion is distracted emotion like Distress mood, Distraction mood, Depression mood, and Sleeping mood then the adaptive module triggers the external stimuli from the instructional module for 5 minutes.

When we triggered an external stimuli, the mood was diverted i.e., very attentive and the performance increased up to 85%. This system could achieve 20% performance improvement for 60 learners. If we try the same methodology for more number of learners, we can obtain drastic improvement towards conscious listening of e-learner. The learner module maintains the details of the learner history feedback. It plays a major role in helping the student to make an appropriate choice of the subject. It also helps the system to trigger external stimuli based on the previous history of their mood distraction data set. This data set includes the learner's conscious listening duration and the frequency of mood distraction. Hence the proposed cognitive intelligent learning environment could impress the learner, improve their performance, enhance the learner's knowledge towards the subject, and avoid mood desperation.

7. CONCLUSION

In this paper, we discussed the learner's emotion recognition using bio – signals like EDA, EEG, etc. We used the EEG signal to recognize the learner's emotion in e learning environment. EEG signals are less aggressive and economical. Hence, they ~~it~~ enable the system to capture the activities of human brain. This paper also provides a detailed description of valance – arousal emotion model to express the e-learner's emotions. We used external stimuli related to the learning content to divert unfocused e-learner to conscious listening mood. The activities were dynamically monitored by ACT-R cognitive system to handle PRP time. All said, some issues such as time constraint and accuracy need to be discussed with respect to ~~in~~ using EEG signal. In future, we plan to improve and resolve EEG signal issues. This will enable the system to measure learner emotion accurately. We can extend its functionality to various e-learning courses; accordingly more external stimuli can be added to make the proposed e-learning environment more interactive and interesting.

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