# An Affective and Adaptive E-Learning System: A Machine Learning Based Approach

Lopa Mandal, Neelabjo Mukherjee, Samar Bhattacharya, Pramatha Nath Basu

**ABSTRACT-** E-learning has become a useful tool in today's education used widely by independent learners, corporate organizations and educational institutions. However e-learning systems, in most cases falter because unlike a conventional teacher-student setup, e-learning environments cannot detect student moods and emotions. This often leaves way students are left on their own, with no guiding or motivating force channelizing their process of learning, increasing the dropout rates in such systems. The present work proposes a novel approach to analyze learners' emotions using machine learning technique with no expensive equipment or questionnaire involved in the detection process. Hereby, the system on its own acts like a conventional teacher, which can predict a learner's learning state and mood based on his actions and teaches accordingly. Here using that learning state, the learner's emotion is instantly deduced by using Barry Kort's spiral learning model, providing an idea of a learner's emotional state at any given point of the learning process, which can then be used to improve the emotional state of the learner wherever required.

**Index Terms-** Emotion detection, Affective E-learning, Machine Learning, Regression Analysis, Kort's Spiral Learning model, Adaptive LMS, ITS.

## 1 INTRODUCTION

E-learning has emerged as a powerful tool in modern education enabling students to learn on the go, often in a self paced environment as opposed to conventional education. In fact certain scholars have actually gone ahead to propose that e-learning is a growing challenge to campus based educational activities [1]. A large number of students may view learning as a means of gaining knowledge but studies have proved that a chunk of students have shifted to viewing education to a more positive and constructive activity [2]. This consequently makes online learning a viable option since students are assumed to be self motivated. Along with this comes the assumption that students are self motivated and can guide their own learning process [3]. In this context it has to be mentioned that although e-learning has been applied on campus, in universities or schools as a complimentary part of the course, e-learning is still most beneficial in distance learning scenarios. The lack of interest is often very evident in such systems with increasingly high number of dropouts [4], which definitely proves that most students cannot guide their own learning process without the presence of a guiding force.

Herein studies and surveys conducted on various groups of learners undergoing e-learning have detected that affect or emotional state plays a vital role in the process [5]. Cognition or the mental state of an individual has a direct effect on his emotions and vice versa. It is the reason why individuals trigger response to external stimuli, like for instance increased blood pressure in tense situations, tear gland secretions when unhappy, goose-bumps when eerie and so on. In fact not only surveys but theoretical studies conducted by psychologists have stressed on the importance of affect in learning [6].

Conventional teachers have often stressed on how a positive mood facilitates creativity and better problem solving as opposed to a negative mood which has an exactly opposite effect on the learning process [7]. It is stated that a learner is able to give his best only when he is in a balanced state of mind without being too excited or depressed. A depressed learner is more a demotivated learner whose mental state hinders the basic processes of memory retrieval, rational behavior or decision making ability. At the same time, while positivity is a sign of higher motivation, excitement often leads to impulsive decisions or over-confidence which is equally harmful.

- *Lopa Mandal, Department of Information Technology, Institute of Engineering & Management, Kolkata, India. E-mail: mandal.lopa @gmail.com*
- *Neelabjo Mukherjee, Department of Information Technology, Institute of Engineering & Management, Kolkata, India. E-mail: neelabjo93@gmail.com*
- *Samar Bhattacharya, Jadavpur University, Kolkata, India E-mail: samar_bhattacharya@ee.jdvu.ac.in*
- *Pramatha Nath Basu, Jadavpur University, Kolkata, India E-mail: basupn@yahoo.co.in*

The proposed system is designed to address, exactly these drawbacks in the various e-learning systems of the day so as to encourage learners to persist and continue with the educational process as opposed to dropping out of a course in the mid-way. While a teacher or a course instructor quite naturally gauges the thought process, emotional state and response of the learner, it is not possible for an e-learning system to emulate unless it is modified to make it adaptable to the needs of the specific learner.

So the effectiveness of e-learning or the factors deeming it ineffective forms a very important part of our study.

The main research question driving the present work is how to incorporate the empathizing capability of a conventional teacher within a e-learning system without involving any expensive specialized hardware to detect biophysical signals or extensive paraphernalia that could cause boredom and lack of interest towards the system.

The proposed system hence uses statistical and machine learning approach to serve the stated purpose.

## 2 Existing Work

The relation between emotion and learning has been documented in various models of learning documented by leading scholars like Russell, Sundström and Kort. The Sundström model states that, making a learner fully absorbed and involved in a system is possible if the system is dynamic and can establish a connection with the learner. Sundstorm describes the process of communicating the system akin to getting engaged in a loop, which he calls the affective loop. According to him getting involved in the system through the affective loop is possible only through an affective interaction with the system [8]. In this context one must mention that affective interactions with a system or affective computing has been formally defined by Picard as "the computing that relates to, arises from, or deliberately influences emotions" [9].

This form of computing has been subsequently incorporated in many learning management systems .With respect to this, the basic emotions experienced by a learner during his course of study and interaction with the system has been documented by Russell where he mentions interest, excitement, happiness, stress, tension, depression and fatigue as some of the basic emotions faced by the learner [10]. Kort, by his spiral learning model (Fig. 1) demonstrates how a learner's emotional state undergoes change along with progress in the stages of learning [11]. Shen and his fellow scholars analyzed this by detecting learner's emotion through biophysical signals and also explored the use of emotional feedback to enhance student learning. A very significant contribution of their study is that emotion aware systems perform better by 91% when compared to non-emotion aware systems [12].

Different methods available in the literature for detection of emotion are use of biophysical signals, speech signals, facial expressions, machine learning techniques applied on learners' preferences and behaviors in the systems, different text based method, virtual reality etc. The former methods though give better accuracy, are quite expensive and cumbersome and are less practical to implement in a large scale e-learning environment, whereas, the methods like machine learning, text based methods and virtual reality are less cumbersome and are more suitable in such scenario. So the present work focuses more on these types of emotion detection methods.

Incorporating intelligent agents is another method which has been used to recognize and address learner emotions. In one such system selection of a sequence of colors has been used to predict a learner's emotional state [13].This is carried out by performing a prior experiment and the application of ID3 algorithm on its results to obtain a decision tree providing emotional states and their corresponding color sequences. The emotion detection procedure of this process has recorded an accuracy of about 57.6% .Thereafter the agent influences the learner's emotion based on the situation encountered by using a combination of images and music.

Learning system designed by Neji et al. has used agent based emotion detection where six emotional states, viz. "happiness, sadness, surprise, fear, anger and disgust" have been identified through facial expressions [14].

Farman Khan et al. have proposed the detection of affective states on the basis of a student's behavior displayed in the learning management system [15]. Here behavior analysis is carried out on the basis of system variables like student performance, involvement, number of attempts to sole course segments etc.

With the advent of social networking sites, their increasing popularity and the huge amount of time spent and opinions stated in the form of comments and messages in networking sites researchers in the field have been increasingly using this resource for more sentiment analysis and applying it to e-learning. One such method is the extraction of sentiment polarity through messages typed by a particular user on Facebook. This method uses an application called SentBuk which classifies the messages through lexical analysis and machine learning and further uses this data in the domain of adaptive e-learning [16] .Another approach that has been used in this method is based on Latent Dirichlet Allocation (LDA).In this method a graph of terms is extracted from a set of documents belonging to the same subject or area of knowledge [17].This graph consisting of weighted word pairs can be used for classification and has been tested on e-learning platforms.

LDA as mentioned in this context is a generative model where observation sets can be explained by unobserved groups to explain the similarity in parts of data. As an example observations are words collected into documents it posits that a document is like a mixture of topics, and each words creation is attributable to one of the topics.

Other text based approaches include collection of a dataset from various instances with parameters like visited pages and messages considered and classified into positive, negative and neutral sentiment categories based upon the usage of keywords and phrases [18].Surveys have also been conducted wherein twelve essays written by a particular student have been analyzed and the text has been subsequently used to detect emotional pattern observed during the learning process [19].Sentiment analysis of text has been usually used to classify positive or negative orientation but work has also been done to use finer semantic distinctions where emotions in the form of appraisal groups like “very good” have been extracted ,wherein approval groups have been represented by using attribute values and state of art accuracy has turned out to be quite high [20].Opinion mining approaches have also featured joint extraction of entities and relations in the context of opinion recognition and analysis where entities have been identified as expression and source of opinions and a relation is one which connects these two [21].This approach has been enabled through linear programming.

Another approach has been the sentence level opinion detection in which opinion bearing and non opinion word collections were first developed, followed by finding their synonyms and antonyms using WorldNet [22].These synonyms where further considered to be opinion bearing and the antonyms non-opinion bearing. An equation is further used which considers the target word, its synonym or antonym given by WorldNet and the category in which they fall, i.e., opinion bearing or non-opinion bearing. Through this equation words are classified and further opinion bearing sentences deduced. This is also a useful approach for sentiment analysis whose use can be extended to e-learning system without the involvement of any elaborate paraphernalia.

The Kort’s model as mentioned before relates emotional experiences of the learner with respect to his learning state. Kort used biological signals to recognize emotions as per learning stage and came up with the spiral learning model.

The processes of using biophysical signals are not only expensive and cumbersome but also are not feasible in a large scale distance learning scenario.

Sandanayake et. al. subsequently used multiple regression analysis technique to measure the learning state of the learner and used Kort’s model to map learning state with emotions detected through an separate Achievement Emotion Questionnaire (AEQ). The use of AEQ is time taking and may cause boredom and lack of interest to the learners to answer correctly, making the system ineffective [23].

## 3 Aim of The Research

The research question driving this work required a method to detect learning state and from learning state, the learner’s emotional state, that would not involve any questionnaire, or equipment that would be cumbersome and could distract a learner and cause any form of disinterest.

This led to the investigation of various methods used in the emotion detection process that has been discussed before. The investigation led to a finding that learning level of a learner is directly related to the change in emotions which have been validated by Kort in the spiral learning model []. As per the spiral learning model emotions have been mapped with learning stage. This makes it evident that finding a learner’s learning level can automatically lead to the discovery of his emotion.

But two main problems were faced in the research at this point. First, a suitable method was required to find the learning level of each learner. Second, it was difficult to fathom whether the same emotions would apply to learners from different educational backgrounds, with varying stages of learning.

The first problem was solved by using a learning state detection method using multiple regression analysis and interpolation to deduce a learner’s level of learning. And the second problem was solved through a survey conducted on 31 learners with varying educational backgrounds who responded to a questionnaire that gauged how they feel at various stages of their learning. It was found that most of the learners responded to the questions, in accordance to the Kort’s model which proved the system to be a workable one.

## 4 Kort’s Spiral Learning Model

The Kort’s spiral learning model demonstrates how a learner’s emotional state undergoes change along with progress in the stages of learning [11]. The model explains how the learner moves along the spiral with the advancement of a particular course and subsequently undergoes changes in the emotional state. At quadrant 1, refer Fig. 1. , the learner starts from scratch. At this point of time the learner is curious and awestruck by the material but at the same time it does not really puzzle him. As and when he progresses to quadrant 2, the learning of new concepts lead him to a state of confusion. He is puzzled and somewhat overwhelmed by the array of new concepts that he is starting to imbibe. The learner consequently wants to solve this situation and more often than not he fails and falls into quadrant 3, which is known as the quadrant of unlearning. Here, he feels frustrated and tries to discard all misconceptions. Once the misconceptions are removed, the learner progresses to quadrant 4 and with the development of new ideas he is propelled back to the first quadrant.

## 5 Proposed System Architecture

The overall system can be broadly divided into two modules, namely the course module and the emotion detection module. Each module can be further divided into sub parts and each part of the system contributes substantially towards the entire learning management system. The learner in the system first enters the course module and browses through the content at hand. The emotion detection module runs separately and the results obtained through this module play the main role in making the system affective. According to the results in one module the next module is also modified. For instance, the results obtained through the system variables collected from the course module are what influences the results of the learner in the emotion detection module. The overall system architecture is depicted in Fig. 2

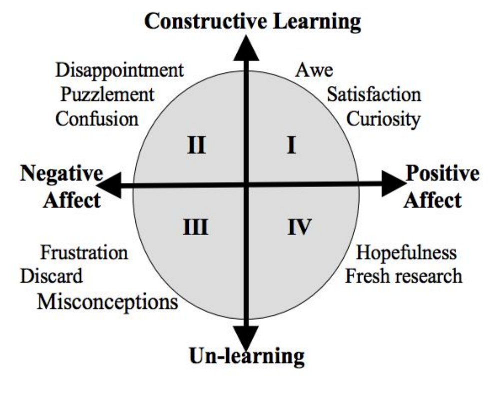


Fig. 1. Kort's Spiral Learning model [11]

### 5.1 Course Module

The course module consists of various components of a course in the proposed LMS. Fig. 2 clearly depicts the various steps to be followed to complete a course.
Once users log in, they move on to the next sub part of the course module. The join course module basically enlists the user name in the course database. Hence, the user is now ready to proceed with the course. On the start of the course, the user has to clear a pre assessment test which tests the existing knowledge of the learner. Then the user proceeds to the main course contents. The present system consists of several lecture videos on varied subjects. The learner can browse through the video contents at their own pace. This time taken by the learner is however recorded by the system and it is further used in the emotion detection module to adjudge the learning level of the learner as well as their emotional state. Every video lecture in the system is followed by a quiz. The quiz performance of a learner is also recorded and used as a factor for calculating the emotional state of the user.

### 5.2. Emotion detection module

#### 5.2.1. System variables used in the process of emotion detection:

i) Time spent in LMS: -
According to the research performed by leading scholars one of the [24] important factors when it comes to gauging the learning state of the student are the time that he spends inside the LMS. For instance if a person spends four hours to complete a 15 minute course model then he has been either procrastinating or spending his time browsing other websites or involved in some other activity as opposed to absorbing himself in the pursuit of learning.
As a result his learning state would also be much less compared to the learning state of any of his peers or compatriots who spend optimal time to complete a course. Similarly if a person finishes a course in a short span of time and also scores well in his pre-assessment test it is easily understood that his concepts are strong and he doesn't require any extra effort to grasp the given course material.
Therefore this becomes a very significant factor in the pursuit of predicting the current level of learning of a particular student.
ii) Time breaks: -
The next variable that we need to collect in the database, for the functioning of the LMS is the time breaks between successive course modules undertaken by the user. Time breaks elucidate the kind of motivation or focus exhibited by a learner .For instance if a learner enjoys the course material and is motivated then he should be ideally working at a stretch and finish the four videos in one single sitting with minimal breaks. Some students may generally have the habit of taking short ten minute breaks in between studying to reinstate their interest. In that case if they however have good scores in the quizzes or post less doubts it would signify that they have a good learning level in spite of the breaks taken.
Therefore it is an important variable whose value is one of the main factors that we have used to detect how much the student has learnt and how effectively.
iii) Average score in quizzes:-
In the LMS we have basically used a pre-assessment test before the beginning of the entire course so as to test the existing knowledge of the learner. This assessment comprises of five MCQ type questions which have a positive mark for every correct answer while a wrong answer is not scored. Accordingly after the submission of the assessment test a percentage mark, based on the score is stored in the system.
This is followed up with a post assessment test following the same structure at the end of every individual module in the course. In other words as soon as a video lecture is

completed the learner is supposed to switch on to an assessment test, which when finished he is supposed to attempt the next module in the course.
There is also another test at the end of all the modules to test the overall level of understanding of the learner.
All the scores of these tests are further averaged to come up with a final score which is fed inside the regression analysis equation to obtain the learning state of the user.

iv) Percentage of comments posted in forum:-
As mentioned before the LMS comprises of a doubt forum where every learner can post their queries based on the videos or any doubts whatsoever.
In this context to detect the learning state one more important variable required in the regression analysis process is the percentage of comments made in the doubt forum.
Doubts reflect whether the learner is at an advanced stage of learning where he doesn't need to clarify existing concepts or whether he is still at a preliminary stage of learning where he needs help from the course instructor or his peers at every step to progress to the next level. In the system we have basically calculated the percentage of comments made by an user A in the forum and used this figure consequently in the regression analysis process.

### 5.2.2. Overall learning state detection of the learner in the system using Multiple Regression Analysis

In the system, the overall learning state of a learner is computed using Multiple Regression Analysis. Here the learning state has been considered as the dependent variable Y which is dependent on the system variables like Time spent in the LMS, Time breaks between successive course modules, Average marks scored in the quiz and the Percentage of comments posted by a particular learner in the comments forum.
As mentioned before,
$Y_i = a_0 + a_1 X_{1i} + a_2 X_{2i} + a_3 X_{3i} + a_4 X_{4i} + e_i$
Now in the system,
Y = learning state of the learner
$X_1, X_2, \ldots\ldots X_n$ = Identified observable parameters
$a_0$ = Intercept
$a_1$ - $a_4$: Slope coefficients for $X_1$ –$X_4$
$e_i$ = Error term for ith observation
Further,
$x_1$ = Average Marks obtained in quiz
$x_2$ = Percentage of comments made in forum
$x_3$ = Time spent in the LMS
$x_4$ = Average Time spent between two successive course modules.

In the regression analysis procedure, the dependent variable is the one that is predicted on the basis of its relationship with the other parameters mentioned.
In the model we have used the parameters to predict the learning state of the learner. In this context one has to mention that the relationship between the learning state and the various parameters or in the other words the slopes denoted by coefficients $a_1$-$a_4$ has been deduced on the basis of an assumption.
The assumption lies in considering the progress of a learner, as his learning state so as to deduce the coefficients. In the experiment a course of 4 modules has been taken and considered that if a learner has completed the entire course successfully, his learning state is 100% and if he has not progressed with the completion of even the first module his learning state is 0%.Similarly for completion of the first module his learning state is 25%, for the second module it is 50% and for the third module, out of the four in the course it is 75%.
The data used for the deduction of the learning state is based on this assumption and hereby using R code, namely the lm function with Y as the learning state, and the rest of the data based on the other attributes mentioned, the equation has been used to deduce the coefficients in the equation.
For any new learner entering the system, the system simply collects the values of the various variables and using these values in the deduced equation the learning state of the new learner is calculated.

### 5.2.3. Module wise Learning Level detection of the learner in each course module using Interpolation

As mentioned above, using multiple regression analysis the learning state of the learner is obtained.
But the main objective of the system was to detect the learning state of the learner as well as his emotional state. For understanding the emotional state, the progress of the learner in each module is to be deduced as the emotional states are repeated in each module from starting to end of that particular module. For this purpose, it is to be known, which module the learner is learning at a particular point of time.
In this regard, from the regression analysis equation the learning state is first deduced as a percentage .This is done in the following way. If the overall learning state deduced from regression analysis is say x% then we first find out, which module the learner lies in. As in the experiment a course of 4 modules has been taken, the classification is given accordingly in Table 1. For example if the learning state of a learner is 39 percent in this case, then the learner is in module 2.
Now, after obtaining the module number, the progress of the learner in that module is calculated as shown in the algorithm described in section 5.2.4.
Now, how to map a learner's learning level n a particular module, with his emotional state?
This very question is answered by the Kort's Model.
According to the spiral model a learner in his initial stage experiences awe, satisfaction and curiosity. When he

progresses to stage 2 he is usually disappointed, puzzled or confused. In the third stage, the learner is frustrated and discards all his misconceptions while in the final stage the learner returns back to being hopeful and continuing fresh research.

TABLE 1.
LEARNING STATE IN REGRESSION ANALYSIS VS. LOCATION OF LEARNER IN THE SYSTEM

| Learning state from regression analysis | Location of the learner in the system |
|---|---|
| 0-25 | Module-1 |
| 25-50 | Module-2 |
| 50-75 | Module-3 |
| 75-100 | Module-4 |

So, in the system on deducing the learner's learning level in a specific module, Kort's learning spiral model is used to deduce his emotional state.

#### 5.2.4. The overall process is explained with the proposed algorithm, given below.

Step 1: The learning state(X) is deduced through Regression Analysis.

Step 2: The learning state is mapped with progress in the course modules. (Herein as per Table 1, the learner's location in the course module is deduced.)

Step 3: As per the location of the learner in the course module the learner's learning level in that course module is calculated by the equation using the interpolation technique as:
Learning Level (L) = X (Learning State) – Lower Limit of the Particular Learning State Interval.

Step 4: Deduction of learning level percentage

Learning Level Percentage (Lp) = (Learning Level (L) / Length of the Learning Level Interval (25))* 100.

Step 5:- The learning level percentage (Lp) is now to be mapped with the stage in Kort's Model. (This mapping in shown in Table 2.)

For example,
Let Learning State= 39.
This means the learner is in module 2. (Since 25<39<50)
Now interpolation technique has been used to find the amount of progress made by the learner in module 2.
Learning Level= 39 - 25 = 14. (25 is the lower level of Learning State Interval 25-50)
Learning Level Percentage = (14 / 25) * 100 = 56
Thus, the learner has completed 56% of module 2.

Therefore, his/her emotion is Frustration, Misconception, Discarded.

TABLE 2.
LEARNING LEVEL VS EMOTIONAL STATE

| Learning Level Percentage(Lp) | Stage in Kort's Model | Emotional State |
|---|---|---|
| 0-25 | I | Awe<br>Satisfaction<br>Curiosity |
| 25-50 | II | Disappointed,<br>Puzzled<br>Confused |
| 50-75 | III | Frustrated<br>Discards<br>misconceptions |
| 75-100 | IV | Hopeful<br>Fresh Research |

## 6. RESULTS

The proposed algorithm was validated through a survey conducted on e-learners from varying educational backgrounds who responded on their emotions experienced during various stages of their learning. The educational background of most of the learners is B.Tech while the rest come from various backgrounds like B-Schools, medical colleges and law schools. The results are as follows:

Question 1: (For validating the 1st quadrant emotions of Kort's Model)

How do you feel when you start off with learning something? (Refer Table 3. for the result)

TABLE 3.
SURVEY RESULTS FOR VALIDATING THE 1ST QUADRANT EMOTIONS OF KORT'S MODEL

| Emotions | Percentage Response |
|---|---|
| Awe, Satisfaction, Curiosity | 51.6 |
| Disappointment, Puzzled, Confusion | 9.67 |
| Frustration, Misconception | 3.2 |
| Hopeful, Enthusiastic for fresh research | 35.5 |

Question 2: (For validating the 2nd quadrant emotions of Kort's Model)
How do you feel when 25-50% of your course is complete? (Refer Table 4. for the result)

TABLE 4.
SURVEY RESULTS FOR VALIDATING THE 2ND QUADRANT EMOTIONS OF KORT'S MODEL

| Emotions | Percentage Response |
|---|---|
| Awe, Satisfaction, Curiosity | 22.6 |
| Disappointment, Puzzled, Confusion | 29 |
| Frustration, Misconception | 16.1 |
| Hopeful, Enthusiastic for fresh research | 32.3 |

Question 3: (For validating the 3rd quadrant emotions of Kort's Model)

How do you feel when 50-75% of your course is complete ? (Refer Table 5. for the result)

TABLE 5.
SURVEY RESULTS FOR VALIDATING THE 3RD QUADRANT EMOTIONS OF KORT'S MODEL

| Emotions | Percentage Response |
|---|---|
| Awe, Satisfaction, Curiosity | 29 |
| Disappointment, Puzzled, Confusion | 9.7 |
| Frustration, Misconception | 35.5 |
| Hopeful, Enthusiastic for fresh research | 25.8 |

Question 4: (For validating the 4th quadrant emotions of Kort's Model)

How do you feel at the end of the course? (Refer Table 6. for the result)

TABLE 6.
SURVEY RESULTS FOR VALIDATING THE 4TH QUADRANT EMOTIONS OF KORT'S MODEL

| Emotions | Percentage Response |
|---|---|
| Awe, Satisfaction, Curiosity | 25.8 |
| Disappointment, Puzzled, Confusion | 3.2 |
| Frustration, Misconception | 3.2 |
| Hopeful, Enthusiastic for fresh research | 67.7 |

The results show that in three of the four stages, viz. 1st , 3rd and 4th (refer Table 3, Table 5, Table 6), except stage 2 (refer Table 4) , learner emotions are in sync with Kort's model, whereby it can be concluded that the system is workable in 75% of the cases.
After detecting their emotion using the above method, appropriate emotional plug-ins can be provided to support the learners emotionally [24].

## 7. CONCLUSION

The design of the system has incorporated two major factors which generally discourage learners from online learning. One of these factors is the lack of a personalization and the second is being ignorant of the learners' emotional state. The present system has developed a adaptive as well as affective system which can judge the emotional state of the learner and bring him back to a more balanced state of mind so that he can perform better. This has been accomplished in the system through machine learning (regression analysis ) as well as the learning to emotional state mapping theory deduced from Kort's Model. The survey results show that the proposed system is found to be workable in 75% of the cases.

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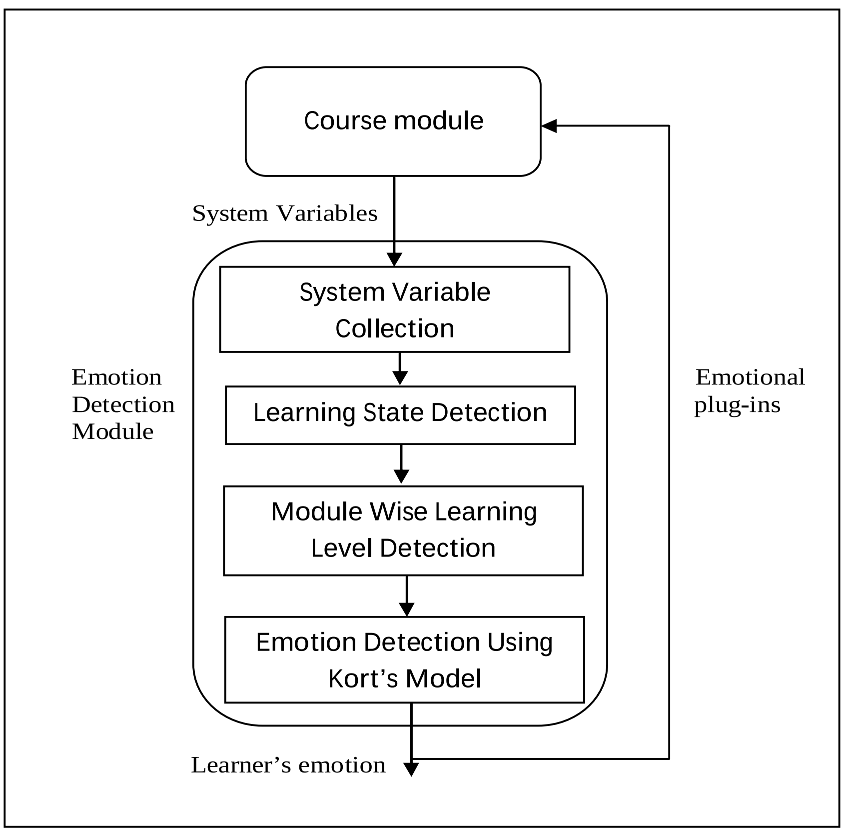


Fig. 2. The System Architecture