IoT based Students Interaction Framework using Attention-Scoring Assessment in eLearning

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Abstract

Students' interaction and collaboration using Internet of Things (IoT) based infrastructure is a convenient way. Measuring student attention is an essential part of educational assessment. As new learning styles develop, new tools and assessment methods are also needed. The focus in this paper is to develop IoT based interaction framework and analysis of the student experience of electronic learning (eLearning). The learning behaviors of students attending remote video lectures are assessed by logging their behavior and analyzing the resulting multimedia data using machine learning algorithms. An attention-scoring algorithm, its workflow, and the mathematical formulation for the smart assessment of the student learning experience are established. This setup has a data collection module, which can be reproduced by implementing the algorithm in any modern programming language. Number of faces, eyes, and status of eyes are extracted from video stream taken from a webcam using this module. The extracted information is saved in a dataset for further analysis. The analysis of the dataset produces interesting results for student learning assessments. Modern learning management systems can integrate the developed tool to take student learning behaviors into account when assessing electronic learning strategies.

Keywords: Internet of Things (IoT), interaction in eLearning, learning behavior, learning management system (LMS), visual attention, IoT services

Introduction

In this paper, we have presented Internet of Things (IoT) based interaction framework using data collection workflow and an algorithm for attention scoring. This was applied to students attending video lectures comprising an electronic learning component of their studies. Most learning, business, entertainment, and correspondence are now happening over the web, and the measurement of information is rising due to the data available for processing as a result. It has driven the development of systems for assembling smaller packets of information from this corpus of big data. Multimedia data analysis for eLearning assessment is a new field of research. It is used to improve the selection of learning opportunities and to refine educational practices to better fit student needs [1]. Analysts and designers of internet learning frameworks have started to investigate practically identical methods for extracting knowledge from student experiences on the internet. Internet-based learning frameworks are used in online courses or intuitive learning situations. Online courses are offered through a course administration framework, such as Sakai (https://sakaiproject.org), Moodle (https://moodle.org), Blackboard (http://anz.blackboard.com/sites/international/globalmaster/), or learning platforms like DreamBox Learning (http://www.dreambox.com) and Knewton (https://www.knewton.com). Cases of effective learning in different situations include those from Kaplan (http://www.kaptest.com), Khan Academy (https://www.khanacademy.org), and Agile Mind (http://www.agilemind.com). At this point, internet-learning frameworks use available information to change or adapt according to the behavior of the student, resulting in varied learning situations for individual students.

When learning, the behavior displayed by students is frequently indicative of the students' cognitive activity, and this behavior can be used as an intermediary measurement of engagement. This method relies on the same types of learning information utilized as a part of student learning prediction. In addition to different measurements, for example, the amount of time a student spends on the web, whether a student has finished a course, recorded changes in the classroom or the school's connection, participation, and lateness, are used to predict the learning experience. Considering a student's level of learning as induced by his/her interaction with the framework and other such sources of information, such as sanctioned test scores, is also useful. Student activity can be analyzed with a setup comprising video camera. computer, and the multimedia data can be analyzed using machine learning techniques [2, 3]. This setup facilitates students to interact with each other using IoT based infrastructure and services [4, 5].

The learning analytics can give instructors a mechanism to support their goals through an iterative procedure improving the efficacy of their courses [6]. The learning analytics toolkit empowers educators to investigate student characteristics and conduct. This toolkit’s primary purpose is to process extensive information sets in microseconds, keeping in mind that the ultimate aim is to help both educators and students to think about innovative upgraded demonstration and learning situations, and to recognize opportunities for action and change [7]. The use of intelligent algorithms to automate the process makes this investigating more effective.

Machine learning is a field dealing with smart algorithms. Machine learning methods involve information mining, managing unstructured information, discovering samples and symmetries in the information, and separating semantically significant data. Attention scoring is an essential and integral part of the interactive assessment of the student learning experience [8]. The activities of the students in the eLearning environment can be effectively modeled and measured, and this paper proposes a method for assessing the learning experience using a measurement of student attention based on the observation of the face and eyes. The proposed methodology is an attention-scoring model (ASM) described later in the paper.

The paper is organized into six principal sections. The next section presents a review of the relevant scholarship to date. Web and learning analytics are discussed to highlight the importance of data in the eLearning domain. Section 3 describes IoT based interaction in eLearning using proposed ASM [8], including the workflow, the model, the algorithm, and the mathematical formulation. The workflow and algorithm are presented using diagrammatic and pseudo code based approaches. The mathematical formulation of the model is elaborated in sub-section 3.2. Section 4 analyzes the scoring data using linear and generalized linear models. Section 5, presents the results achieved by applying different test methods to the data collected using the ASM and some further discussion. Section 6 offers some conclusions and outlines directions for future research.

Literature Review

We humans are surrounded by many of the objects arranged in the form of different network settings, which we call them as Internet of Things (IoT) [9]. This type of arrangement of devices in the connected scenario leads us towards ubiquitous computing and smarter learning setupts. The authors of [10] found that gaming practices, for example, clicking until the system gives a right answer and progressing inside of the educational program, were firmly connected with a reduction in learning for students with below normal scholastic accomplishment levels. Accordingly, they adjusted the framework to identify and react to these students and furnish them with additional activities. This produced a significant improvement in learning [10]. Web-learning frameworks mine the students' data to recognize student practices linked with learning [11]. The authors discussed a Blackboard Vista-upheld course and discovered variables that connected with the student's most recent grade. The authors demonstrate that motivation is the principal variable influencing the execution of tasks by online students, confirming its significance as a source of instructive efficiency [12]. The author of [13] states that student experience, as measured by the ability to keep up, is vital for organizations offering online courses [12].

Instructive Information Mining (IIM) [14] is another research field concerned with creating and applying automated techniques to recognize substantial accumulations of instructive information. The goal of IIM is to better understand how students learn and to recognize the settings in which the teachers figure out how to enhance useful results and to clarify and add information to learning material. This can be done using data compatibility and IoT based interacting devices [15]. IIM is an interdisciplinary field, which combines systems and procedures for software engineering, instruction design, and machine learning [16]. Online learning management systems are developed using web technologies and offer various functionalities to students and teachers. Interactive and graphic representations of the statistical results produced using different tools help students to visualize the results so that they can take full advantage of them and adapt as necessary.

Web Data Analytics

This utilization of web data investigates online conduct by using instruments that log and report web page visits, the location of the user, and the links that were navigated. This type of web investigation is used to understand and enhance how individuals use the web. However, now organizations have developed strategies to track increasingly complex client interactions with their sites [17, 18]. Through the web social activities, for example, bookmarking popular destinations, presenting on blogs or Twitter, and commenting on stories, can be traced and analyzed. Two areas that are relevant to the utilization of enormous information on learning are IMM and learning assessment [19-22]. For the most part, IMM searches for new samples of data and develops new calculations and new models, while learning research applies known models to instructional frameworks [23, 24]. Advancements in systems for various levels of information mining and extensive information display have been critical for mining educational information [19]. Big data does not have a consistent size; any number allocated to characterize it would change as processing innovations advance to handle more information. [25-27]. The research on machine learning has yielded strategies for information mining that find new and conceivably valuable data in unstructured information [28].

Learning Analytics

Learning investigation refers to the transformation of an extensive variety of information, delivered by the teacher and accumulated for the benefit of the students, with the goal of evaluating academic advancement, anticipating future performance, and identifying potential issues [29, 30]. The objective of learning investigation is to empower instructors and schools to tailor instructive opportunities to each student's needs and capacity [18]. In contrast to IIM, learning investigation has for the most part not addressed the advancement of new computational strategies for information assessment, but instead addresses the use of known routines and models to answer critical inquiries that influence student learning and learning frameworks [6, 19, 31]. The objectives of learning investigation is to empower instructors and schools to tailor instructive opportunities to every student [19]. Web analytics for knowledge extraction in eLearning is necessary and essential for the next generation of learning management systems. New and innovative learning approaches require new pedagogical and assessment methods [8, 32] to be formulated and used to measure and improve the process efficiently.

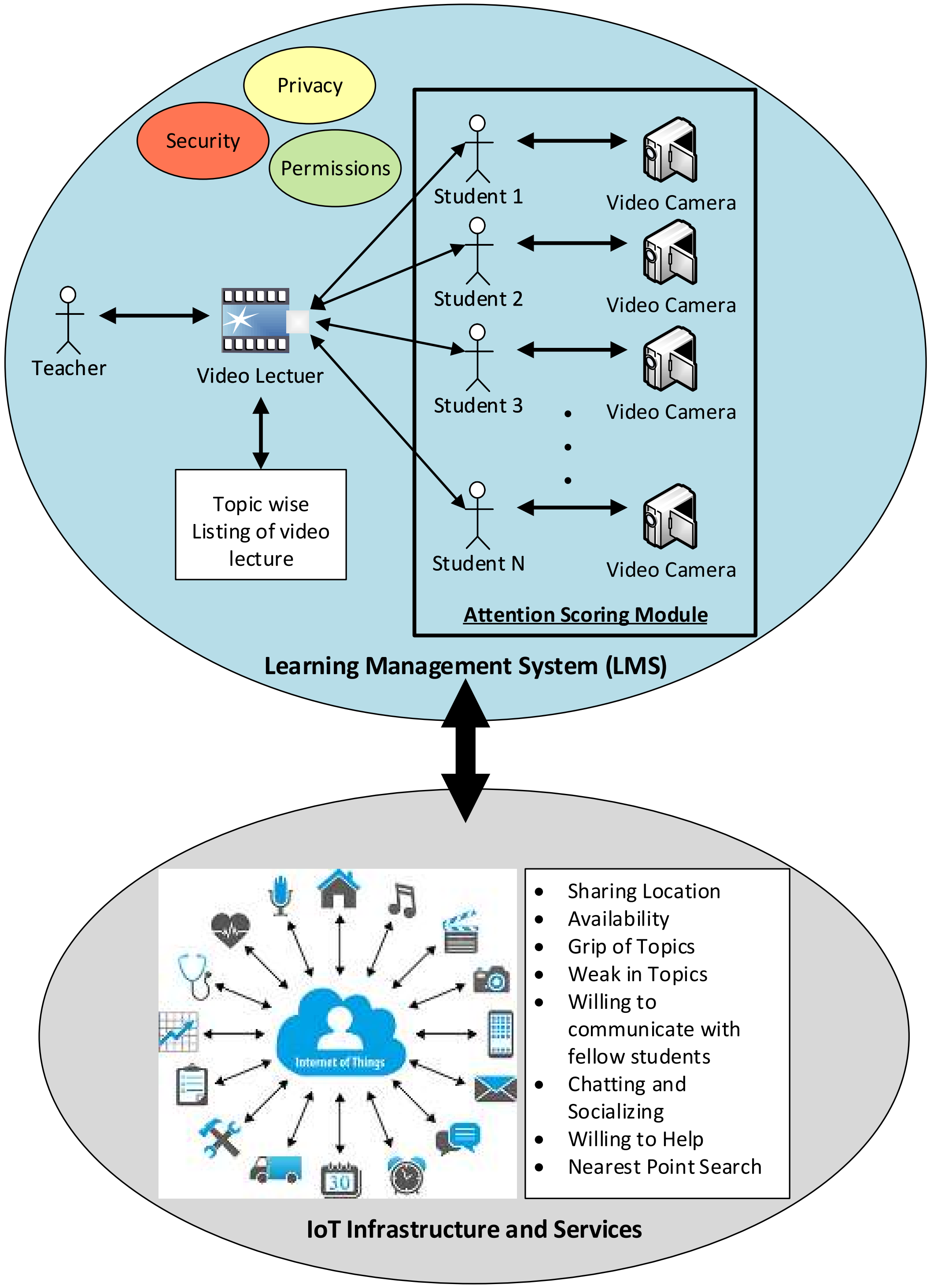

Fig 1. IoT based Interaction and Collaboration of Students in eLearning

Attention measurement plays a critical part in improving the student learning experience as well as teaching performance [33, 34]. An ASM [8] for this process is proposed here.

IoT based Interaction in eLearning

Students' interaction and collaboration in IoT based infrastructure is convenient. Students setup their details through learning management system (LMS) and allow fellows to interact with them as per choice and need for the discussion on any selected topic. Students share their location, availability and other contact details using LMS. Attention scoring module assesses attention of the student in the video lecture. This process is done using Algorithm 1. Topic wise analysis of students' attentiveness provides information to other students using LMS. The system provides interaction opportunities based on their grip or weakness on the topics as shown in **Fig 1**.

Attention-Scoring Model

Online learning offers a several advantages over traditional classroom-based learning [35]. The number of students that can take the class is not constrained by the size of a physical classroom. Learning management systems (LMS) are web-based and are a platform on which to fabricate and convey modules and courses. Open-source versions include Sakai (https://lms.brocku.ca/portal/), ILIAS (http://www.ilias.de/docu/ilias.php?baseClass=ilrepositorygui&reloadpublic=1&cmd=frameset&ref_id=1) and Moodle.

The proposed model i.e. attention-scoring model (ASM) incorporates an accepted model. This model can detect student movement from fundamental behavioral information, i.e., the students' connections with a teacher [36]. The video camera monitors the students' activities while watching recorded lectures. A large amount of academic content is being generated in the medium of video, making it a good candidate for multimedia big data. The video sequence of the student's activity is analyzed with the help of EmguCV (http://www.emgu.com/wiki/index.php/Main_Page), a library used for building computer vision applications. On the back end, OpenCV (http://opencv.org/) is used. Image frames are processed in a sequential order. Each image undergoes analysis to detect the face, the eyes, and the state of the eyes, i.e., whether the eye is open or closed as shown in Fig 2. The process starts with the video camera or webcam by taking video stream of the student, and the subsequent steps are:

Step 1: Image frames are extracted from the video stream.

Step 2: Face is detected in each frame and image segment is cropped.

Step 3: Eyes are sought for and cropped out of the face image if found.

Step 4: State of the eyes is classified as either opened or closed.

Step 5: Scores and other information extracted during step 2 to 4 are saved.

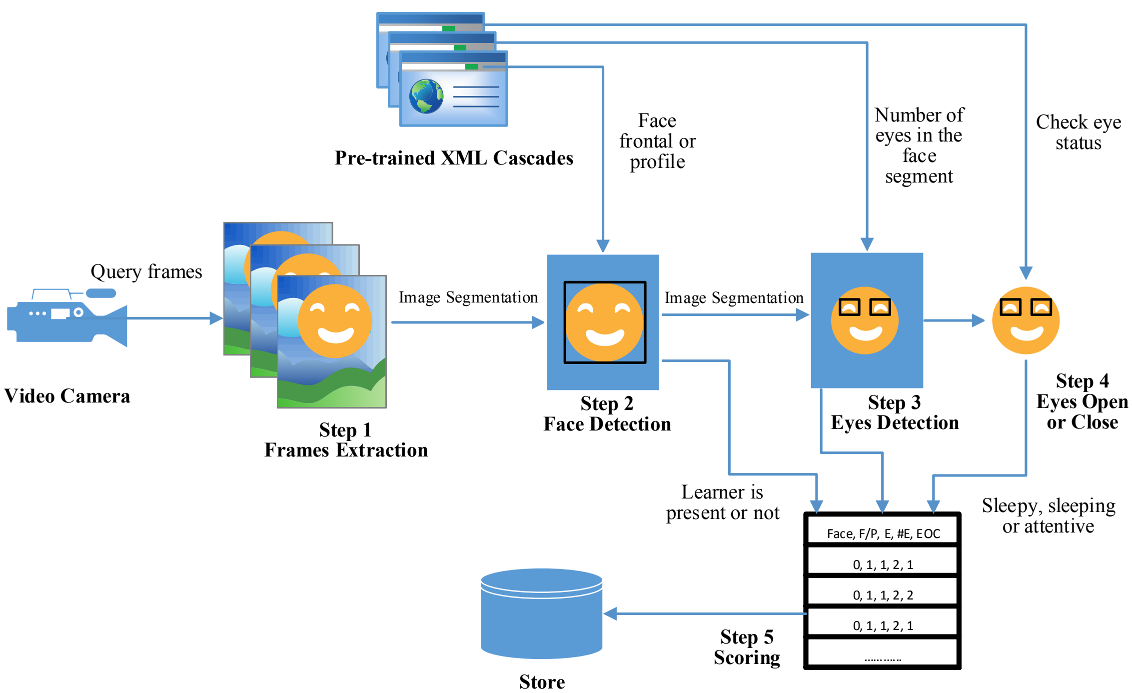

Fig 2. ASM workflow. The data collection module used to monitor and collect the data for student attentiveness using a webcam.

The image is not processed further if a face is not detected in the image. If a face is detected, the image is processed and the score is calculated using the ASM Scoring Algorithm. This algorithm is applied to a sequence of images or a video stream. One by one, the frames are extracted from the video stream. Each frame is searched for multi-scale faces. After detection, the face detection score is saved to the log file, the face portion of the image is cropped, and all faces in that particular frame are kept in a generic array. Then one face image is taken from that array and is searched for eyes. If eyes are identified, then that portion of the face image is cropped, the eye detection score is logged, and those are kept in a separate array. Now each eye image is taken from the collection of cropped images and checked to see whether the eyes are open or closed. Then the appropriate values are assigned to the log file. This score is saved for further processing and the validation of the results. Cronbach's alpha test is then applied using a SPSS software tool (http://www-01.ibm.com/software/analytics/spss/) to validate the dataset collected using the developed tool. The total numbers of items is 8 and the statistical reliability value is 0.852, which confirms that the dataset is valid. Our focus in developing the model is:

1. Predicting future learning behavior by making models that link essential data such as student learning information, inspiration, metacognition, and demeanor;
2. Discovering or enhancing models that describe the subject to be learned and ideal instructional delivery;
3. Studying the impact of the various types of pedagogical support; and
4. Advancing relevant information about learning and students through building computational models that fuse models representing the student, the space, and the teaching method [37].

Mathematical Formulation of ASM

ASM's mathematical formulation represents the formal working of the module. The face detection score is calculated as zero if no face is found and calculated as one for each face, as denoted by Eq. (1):

$$F(f) = y\begin{cases} 0 & \text{if no face} \\ \sum_{i=1}^{n} f_i & \text{on each face} \end{cases} \qquad \text{(1)}$$

Detection of the eyes is calculated in the same way, as denoted by Eq. (2):

$$E\left(f\right)=x\begin{cases}0 & \text{if no eye}\\ \sum_{i=1}^{n} e_i & \text{on each eye}\end{cases} \qquad \ldots\ldots\ldots\ldots\ldots\ldots (2)$$

Where *f* is a single frame captured through camera, T_s represents the total score of detection in a second, as denoted in Eq. (3):

$$T_s=\sum_{i=5}^{n}\left(E\left(f_i\right)+F\left(f_i\right)\right) \qquad \ldots\ldots\ldots\ldots\ldots\ldots (3)$$

T_s is the ideal case, whereas λ represents environmental factors affecting the results, as represented in Eq. (4):

$$T_s' \approx \lim_{x\to 1} \lambda_x T_s$$

$$\left(\frac{d}{dx}T_s\left(x\right)\right) \approx \left(\lambda_1 T_s\right) \qquad \ldots\ldots\ldots\ldots\ldots\ldots (4)$$

$\because \qquad 1$

When $\lambda=1$, $T_s'=T_s$ such that the effects of error-prone factors, like resources, time, processing, etc., are nullified. Then, using $v=\sum_{i=1}^{n}\left(x_i\right)$, a single image extracted from the video stream. It uses the ASM to collect the scoring data, so pre-trained XML cascades are used as sub-routines in the algorithm. This algorithm creates a strong predictor by combining weighted simple weak predictors in a linear fashion. One predictor is assigned to all the images, and this can be calculated by taking the inverse of the total number of positive candidate images. If we have N positive images and the weight of all the positive images is *w*, then we can define the predictor function using Eq. (5). A pseudo-code representation elaborates on the functioning of the model and helps to work out computational time complexity. The asymptotic time complexity of the ASM algorithm is $O\ (n^2)$.

Algorithm 1: A score-counting algorithm based on automated detections of faces and number of opened-closed eyes

Input: Video stream and image holders i.e. imgOriginal, faceOnly and faceWithEyes

Output: Scoring of each image

1. **Begin**
2. ***If*** *faceDetected = false* ***Then***
3. *Start the video capturing process*
4. ***While Loop*** *video sequence*
5. *imgOriginal = get an image/frame from the video sequence*
6. *Detect multiscale face image using cascade classifier*
7. ***For Loop*** *Rectangle rect in detectFace*
8. *Draw rectangle around face image*
9. *Copy imgOriginal to faceOnly*
10. *faceOnly.ROI = rect*
11. *faceDetected = true*
12. *Insert face detection score*
13. ***End For Loop***
14. *Crop and Copy face image*
15. *Detect multiscale eye image using cascade classifier*
16. ***Loop For*** *Rectangle eyeRect in detecteye*
17. *Draw rectangle around eye image*
18. ***If*** *(faceDetected == true)* ***then***
19. *Insert eye detection score*
20. ***Else***
21. *Append 0 score for the eye detection*
22. ***End If***
23. ***End For Loop***
24. *Crop and Copy Eye image*

25. *Detect EOC using cascade classifier*

26. ***Loop For*** *Rectangle EOC_Rect in detecteye*

27. *Draw rectangle around eye image*

28. ***If*** *(EOC == true)* ***then***

29. *Insert EOC score 1*

30. ***Else***

31. *Insert score 0*

32. ***End If***

33. ***End For Loop***

34. ***End While Loop***

35. *Return the Attention Score*

36. ***End***

Furthermore, ASM uses three different trained XML cascades. One is for frontal or profile face detection, one for eye detection, and the last one for determining whether the eyes are open. These cascades are used to calculate the score for each frame extracted from the video stream grabbed from the webcam. We calculate the score using Eq. (6):

$$h\left(x_i\right) = predict\left(\sum_{i=1}^{p} k_j h_j\left(x_i\right)\right) \qquad \text{...................(5)}$$

$$\sum_{i=1}^{n} \mathrm{SF}\left(x_i\right) = \begin{cases} 0 & \text{if no face} \\ \sum_{j=0}^{m} F_i + \sum_{k=0}^{p} E_j + EOC\left(x_i\right) & \text{otherwise} \end{cases} \qquad \text{...................(6)}$$

SF	*Score computed in a frame*	F_i	*Number of faces detected in a frame*
E_j	*Number of eyes detected in a frame*	*EOC*	*Either eye open or closed*
x_i		*Individual frame or image being processed for score*	

By looking at this information, teachers can identify students who may require additional help or support and distinguish areas in which they are struggling [38]. Learning frameworks usually track the students at their expertise level, e.g., the quadratic mathematical statement as shown in Table 1. This analysis can help students to identify what to focus on and teachers to know the areas where they need to develop further guidelines [39].

Table 1. Variable means for student data

Face	Frontal or profile	Eyes	Number of eyes	FPS	Total score
0.91	0.85	0.91	0.85	0.51	0.88

Pattern analysis in general refers to the act of gathering data and endeavoring to detect the next example, or pattern, in the data. Online organizations, such as Khan Academy, use pattern examination to anticipate what students are intrigued by or how learner investment increases or decreases. In education, pattern analysis answers questions such as what changes happen in student learning over time. At the school level, pattern investigation can be utilized to analyze test scores and other student markers over time and to help to assess the impact of various strategies as shown in Table 2. In IMM, pattern investigation regularly refers to methods for separating a basic sample, which may be somewhat or entirely obscured by information that does not contribute to the model, i.e., noise. Despite the fact that the real information required for pattern investigation changes contingent upon what data is of a premium, usually extensive information from no less than three points in time is required.

Table 2. Cluster centers for the attention assessment variables

No.	Face	Frontal or profile	Eyes	Number of eyes	FPS	Total score
1	1	0.5	1	0.5	0.25	0.71
2	1	1	1	1	0.2	1
3	1	0.5	1	0.5	0.75	0.71
4	0	0	0	0	0.5	0
5	1	1	1	1	1	1
6	0	0	0	0	0	0
7	1	1	1	1	0.75	1
8	1	1	1	1	0.5	1
9	1	0.5	1	0.5	0.5	0.71
10	1	0.5	1	0.5	1	0.71

The data analysis group is, generally, more tolerant of open experimentation attempts as they drive information mining and examination innovations [40]. As learning examination, practices have been connected principally with advanced education up to this point.

Expanding the utilization of eLearning offers chances to coordinate appraisal and realization with the goal that data expected to enhance future guidelines can be accumulated; when students are learning on the web, there are numerous chances to abuse the force of innovation for a developmental evaluation. The same innovation that supports learning exercises also supports data collection and that data can be utilized for assessment. The objective of making an interconnected input framework aims to guarantee that key choices about learning are made in an informed way, the information is accumulated, and made open at all levels of the learning framework to ensure constant adaptation and improvement.

Linear and Generalized Linear Models

A direct relapse model is a routine technique for fitting a quantitative model to information. It is suitable for use when the objective variable is numeric and continuous. The gathering of data focuses with non-Gaussian distributions. Straight relapse models are iteratively fit to the information after changing the objective variable to a certain numeric value. A dataset with a numeric value, thorough target variable, develop the same model, using an alternate count. The calculated estimation is parameterized by the scattering of the objective variable and an associated limit relating the mean of the objective to the inputs as shown in Table 3.

Table 3. Summary of the multinomial regression model

Coefficients							
	Intercept	**Face**	**Frontal or profile**	**Eyes**	**Number of eyes**	**Total score**	**FPS**
1	-100.46	21.93	-26.49	21.93	-26.49	12.82	14.89
2	-83.35	-8.54	14.72	-8.54	14.72	3.82	9.18
Std. Errors							

1	63158.43	15120.88	20279.59	15120.88	20279.59	5714.65	12033.86
2	297.10	297.95	631.39	297.95	631.39	2155.06	6166.24
Value/SE (Wald statistics)							
1	0.00159	0.0014	-0.0013	0.0014	-0.0013	0.0022	0.0012
2	0.2805	-0.0286	0.0233	-0.0286	0.0233	0.0017	0.0014
Residual Deviance: 0.0001 AIC: 16.0001				Log likelihood: -0.000 (8 df) Pseudo R-Square: 1.0000			

Examples of utilizing expectation incorporate tasks like distinguishing certain student practices, such as gaming the framework, taking part in inappropriate conduct, or neglecting to answer an inquiry accurately regardless of having an ability as shown in Table 4. The model has been utilized for students' assessment that what practice as a part of an online learning environment.

Table 4. Analysis of deviance for response of attentiveness with ANOVA test

Attributes	LR Chisq	Df	Pr (> Chisq)
Face	0.0000398	2	1
Frontal or Profile	0.0000451	2	1
Eyes	0.0000398	2	1
Number of eyes	0.0000451	2	1
Total score	0.0000159	2	1
FPS	-0.000151	2	1

Utilizing these measures, educators can identify students who are not engaging and those who are attempting to but are struggling, and then formulate a guideline for keeping the group at the same level. Ordinarily, the point-by-point learning information the framework gives can be broken into student subgroups, for instance, to assess how students without a course perform, male and female advancement in the course, how the course performs by educator or by year. The learning framework information can support investigation of how well students learn with specific interventions, and how resolutions could be advanced.

Results and Discussion

These results are derived from statistical analysis using various methods. The variables and data utilized in each instance are the same in order to make the outcome more robust and reliable. Working inside of whatever parameters are set by the establishment in which the course is offered, the educator explains the course is learning destinations and recognizes assets and encounters through which those learning objectives can be achieved as shown in Fig 3. The instructed critical thinking allows students to work through complex issues and construct the relevant frameworks, e.g., the way related issues are settled and insights to help them are indicated.

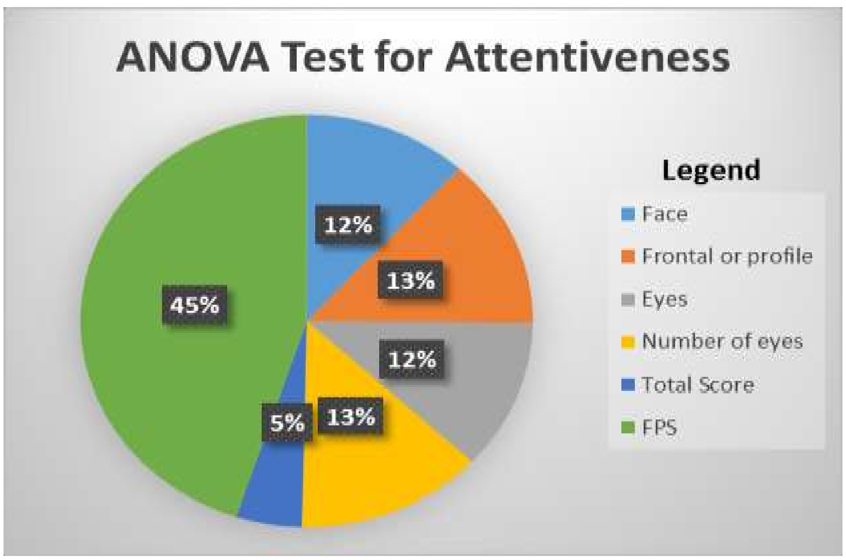

Fig 3. Analysis of response of attentiveness using all variables of ASM using ANOVA test. This chart shows participating variables for classifying the attentiveness of the student.

Kolmogorov-Smirnov Test

The Kolmogorov-Smirnov test is a non-parametric test comparing two means. The paired and the two-sample tests are performed. The statistic calculated is the gathered D estimation. For similar portions, the estimation approaches zero. If the p-value is under 0.05, then we dismiss the assumption and acknowledge the theory at the 95% level of certainty [41] as shown in Table 5. The two samples being looked at originate from the "total_score" variable, accumulated by ‘attentiveness’, with qualities zero and one.

Table 5. Kolmogorov-Smirnov test results

<table>
<tr><th>STATISTIC</th><th></th><th colspan="2">P-VALUE</th></tr>
<tr><td>D | TWO SIDED</td><td>1</td><td>Alternative Two-Sided</td><td>< 2.2e-16</td></tr>
<tr><td>D^- | LESS</td><td>0</td><td>Alternative Exact Two-Sided</td><td>< 2.2e-16</td></tr>
<tr><td rowspan="2">D^+ | GREATER</td><td rowspan="2">1</td><td>Alternative Less</td><td>1</td></tr>
<tr><td>Alternative Greater</td><td>< 2.2e-16</td></tr>
</table>

Wilcoxon Signed Rank and Rank Sum Tests

The two-sample, non-parametric Wilcoxon signed rank test is performed on the two predetermined samples, and these two samples need to be combined. The speculation is that the dispersals are the same. This test does not predict that the two specimens will be equally dispersed. If the p-value is less than 0.05, then we dismiss the theory and acknowledge the assumption, at the 95% level of certainty. The two samples being compared are two variables, ‘total_score’ and ‘frontal_or_profile’ as shown in Table 6. The two-sample, non-parametric Wilcoxon rank sum test, equivalent to the Mann-Whitney test, is performed on the two predefined examples. The theory is that the movements are the same, i.e., there is no shift in the region of the two flows. This test does not predict that the two samples are ordinarily dispersed, however, it does accept they have assignments of the same shape. If the p-value is less than 0.05, then we dismiss the assumption and acknowledge the theory that the two samples have diverse medians, at the 95% level of certainty. The two samples being compared come from the ‘total_score’ variable, grouped by ‘attentiveness’, with values ‘0’ and ‘1’.

Table 6. Wilcoxon test results of the validation of ASM

Wilcoxon signed rank test		Wilcoxon rank sum test	
V	3428	**W**	0
P-value	< 2.2e-16	**P-value**	< 2.2e-16
Alternative hypothesis	true location shift is not equal to 0	**Alternative hypothesis**	true location shift is not equal to 0

Since the value is not equal to zero, this means the total score is dependent on the face, which either is frontal or in profile. It is important that the face location be set to the correct aspect. Frontal face indicates the student is attentive and concentrating on the video lecture [42]. The student's attention gives us the correct score measurement technique, indicating that the ASM is accurate.

Two-Sample F-Test

The two-sample F-test is performed on the two predefined samples. The theory is that the extent of the differences of the values from which they were pulled is equivalent to one. This test accepts that the two samples are normally distributed. If the p-value is less than 0.05, then we dismiss the assumption and acknowledge the theory that the two samples have different variances, at the 95% level of certainty [43]. The two samples being compared come from the 'total_score' variable, grouped by the 'attentiveness' attribute, with values 0 and 1 as shown in Table 7.

Table 7. Two-sample f-test results performed on attention score data

Parameter	Test score
Hypothesized ratio	1
Numerator df	819
Denumerator df	1079

Correlation Test

The two-sample correlation test is performed on the two predefined samples. The two samples are expected to be correspond. The theory is that the two specimens have no relationship as shown in Table 9. If the p-value is less than 0.05, then we dismiss the assumption and acknowledge the theory that the samples are associated, at the 95% level of certainty. The two samples being compared are the variables, ‘total_score’ and ‘frontal_or_profile’ as shown in Table 8.

Table 8. Two-sample correlation test results using “total score” and frontal “face or profile face” variables

Parameters		**P-value**	
Degrees of freedom	9098	Alternative Two-Sampled	< 2.2e-16
Sample Estimates		Alternative Less	1
Correlation	0.9761	Alternative Greater	< 2.2e-16
Statistic		**Confidence Interval**	
T	428.3963	Two-Sampled	0.9751, 0.977
		Less	-1, 0.9769
		Greater	0.9753, 1

Relationship mining includes the location of connections between variables in a dataset. For instance, relationship mining can distinguish the connections between items bought in web shopping. Association mining can be used to discover student mistakes, which happen simultaneously and for rolling out improvements to educating methodologies. These strategies can be used to work with a learning administration framework, with student grades, or to sort out such inquiries. The next example is mining to capture the associations among events, and discovering natural groupings.

Table 9. Correlation of the data using Pearson method

	FPS	Frontal or profile	Number of eyes	Face	Eyes	EOC	Total score
FPS	1	0.0791	0.0791	0.0987	0.0987	0.0987	0.0903
Frontal or profile	0.0791	1	1	0.8546	0.8546	0.8546	0.9756
Number of eyes	0.0791	1	1	0.8546	0.8546	0.8546	0.9756
Face	0.0987	0.8546	0.8546	1	1	1	0.9476
Eyes	0.0987	0.8546	0.8546	1	1	1	0.9476
EOC	0.0987	0.8546	0.8546	1	1	1	0.9476
Total score	0.0903	0.9756	0.9756	0.9476	0.9476	0.9476	1

The correlation is drawn for the data collected using the ASM data collection module. The total number of variables is 6, i.e., frames per second, face frontal or in profile, number of eyes, total score, face present or not, and total eyes detected. The key educational uses of relationship mining include revealing the relationship between student activities and discovering which pedagogical methodologies [44] lead to more effective learning. This last field is of increasing significance, and it is suggested that it will offer scientists some assistance in building automated frameworks that model how viable instructors work by mining their use of useful frameworks [45]. The Conditional Tree Model for classification is summarized in Fig 4.

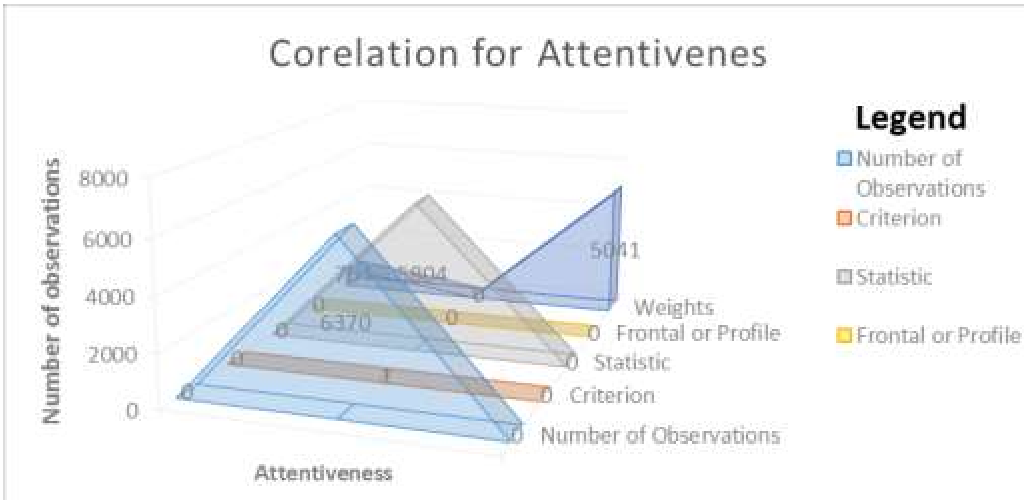

Fig 4. Correlation for attentiveness measure for input variables for the collected data

Each range is investigated in more detail alongside cases from both industry practice and scholarly research. Numerous learning and innovation specialists are excited about the possibility of information driving the student experience as shown in Fig 5. Student data analysis empowers a learning framework that only gives the appropriate measure of direction. Various specialists warn against using an examination alone to identify which topics or abilities students work on next or whether they progress to the next stage.

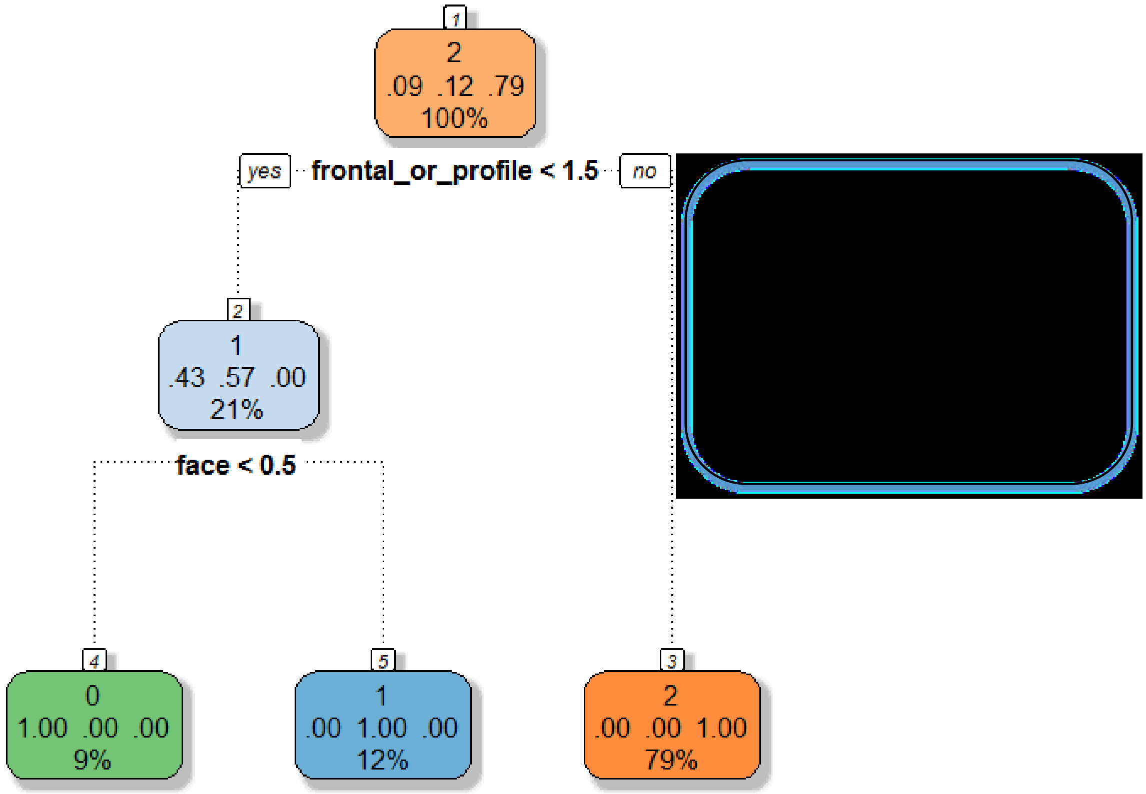

Fig 5. Decision tree for the data. This is created by the decision tree classifier and collected data was used to train the classifier

Consequently, withholding a student on the presumption that difficulty with one topic will prevent them from progressing in another may not be the best strategy. Student information display has been embraced in the manufacture of versatile hypermedia, recommender, and mentoring frameworks. A well-known strategy for evaluating student information is Corbett and Anderson's knowledge tracing model, which is based on the Bayesian system and it, assesses the likelihood considering observations of his or her attempts to perform the task.

Conclusion and Future Work

We have found that comparison is a suitable examination procedure to break down the complex and multi-directional connections in inputs and learning. Working with data and utilizing information mining is quickly becoming fundamental to the education sector. The information mining of student behavior in online courses has uncovered contrasts in successful and unsuccessful students in relation to variables such as the level of interest, and the number of tests finished. To interpret information collected for visual attention assessment requires systematic learning of the predictor, analysts have hitherto been the predominant group to utilize this technique. In the future, advances in visual information, examination, and human-computer interface configuration may well make it possible to make devices that, for example, policymakers, executives, and instructors can utilize. Working from student information can help instructors to both track and advance student progress, and to understand which instructional practices are effective. The student can analyze their evaluation information to distinguish their strengths, shortcomings and to set their own learning objectives by collaborating with each other using IoT based infrastructure and services. The analysis of these activities can also indicate to the instructor that the visual arrangements of the lecture need to be improved.

Further research is required in this field with the specific aim of verifying these results for different types of online courses, as well as for classroom-based courses and for the approaches leading to innovative ideas. A step forward is required in the assessment of the relationship between the progressive structures of teaching and learning in colleges and universities. The scientists working on IMM and learning examination seek to make claims about student learning and consider the student's association with an eLearning framework. Contrasting scores on evaluations and course reviews can verify these cases. Consolidating diverse information sources to make claims about student learning is well established and loaded with challenges in assessment [46], and when applied to high-stakes activities, it must meet proper standards for objective student assessment. Better interaction opportunities can be offered to students if they are aware of their fellows' progress, strengths and weaknesses. IoT based services can help them to learn, collaborate and interact in a better way.

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