Cognitive Learning Environment and Classroom Analytics (CLECA): A Method Based on Dynamic Data Mining Techniques

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Abstract: With the advent of modern data analytics tools, understanding the bits and pieces of any environment with the abundance of relevant data has become a reality. Traditional post event analyses are evolving toward on-line and real-time processes. Along with versatile algorithms are being proposed to address the data types suitable for dynamic environments. This research would investigate different dynamic data mining methods that can be deployed into a modern classroom to assist both the teaching and learning atmosphere based on the past and present data. Time series data regarding student's attentiveness, academic history, content of the topic, demography of the classroom and human sentiment analysis would be fed into an algorithm suitable for dynamic operations to make the learning ambience smarter, resulting in better information being available to educators to take most appropriate measures while teaching a topic. The research objective is to propose an algorithm that can later be implemented with proper hardware set-up.

Keywords: Dynamic data mining, Time series analysis, Smart environment, Classroom behavior, Intelligent guidance

1. Introduction

Applications of intelligent technology in almost all the sectors of modern society have become particularly evident in the last five to six years. One of the key problematic issues arising out of today's in-class learning style is, in most cases, not being able to recognize student's degree of attention and the degree of mental involvement. The students may be sitting in the class, but it could very well be that their attention is dropping, or they are just not able to creatively engage with the lecturer. This seriously hampers their ability to learn, think, and remember the knowledge altogether. Cognitive learning is considered as a key method that encourages students to use their brains with increased efficiency as the level of engagement process remains high [1]. However, to develop a classroom setting that is conducive to cognitive learning requires high degree of digital involvement and data analytics to fully comprehend students' behavior, which dynamic in nature and varies with time and environment. In this research initiative, a framework has been proposed to collect a range of relevant data from a live classroom and through an innovative and effective data mining algorithm, valuable insights can be obtained that should boost the students' performance; and in fact will encourage them to learn how to learn and internalize concepts with ease. Students should also feel confident in connecting, explaining, and justifying their ideas. It has also been observed from previous research that learning analytics can in general can play a key role in enhancing and understanding of students' learning behaviors [2]. Additionally intelligent analysis of learning data proved useful for all parties alike such as policymakers, instructors, and learners [3].

1.1 Novel Contribution of This Research

This research proposes an effective and novel implementation of one or multiple algorithms suitably prepared to monitor, control, and provide suggestions to the audience as well as the instructor in a classroom. The dynamic platform would be capable of understanding different patterns in real time and make necessary adjustments or provide insights for a better management. The key outcome that our research attempt achieves;

(1) Analyze attentiveness of the audience as a function of time.

(2) Understand the dynamic nature of the student–content interaction.

(3) Understand the lecture delivery approaches based on the history of a student group.

(4) Make intelligent decisions in the forms of non-intrusive controls and suggestions that does not reveal confidential data of a student group.

The outcome of this research initiative would be to use simple classroom utilities such as microphone, close circuit cameras as data collection points and turn those data into valuable knowledge to control volume level, airflow, and timing of a content delivery and approach of a content delivery.

2. Related Works

This work is motivated from some of the previous attempts to introduce intelligence in a learning environment. One of those is embedded computer networking that makes it possible to implement new information paradigm called ambient intelligence (AmI). AmI can facilitate control schemes that takes full advantage of man–machine awareness. In [4], an AmI system is deployed based on speech recognition techniques, RFID technique to identify different role players, and a fuzzy approach for behavioral analysis. The purpose of implementing AmI is to control a test bed intelligent classroom. For understanding the learning approaches of students paper [5] uses the level of comprehension of a content. Based on this comprehension, a system is developed to scrape websites and present relevant data at teacher's disposal for better interaction with the students. In [6], a method has been proposed in a smart class room to detect the gesture of lecturer to strategically capture video and virtually control mouse pointer. The paper prepared a hybrid human model to understand the motion features and an algorithm called primitive-based-coupled hidden Markov model is presented for action recognition. In [7], performance of seven individuals has been analyzed based on different vocal behavior such as fundamental frequency, frequency range, jitter, shimmer, and words per minute. The idea is to search for a relation between teacher's vocal characteristics as well as being effective in the classroom environment to teach. In [8], researchers have deployed association rules mining and fuzzy representations to examine and analyze student learning, behaviors, and experience within a computer-aided classroom activities. Association rule mining [17] sheds light on how learners with various cognitive types interacted with a simulation for problem solving while to fuzzy representation was used to inductively gauge how students handle questionnaire data.

3. Proposed Methodology

The proposed method is based on classroom behavior of the audience (students) at different times of a session, at different contents of the session, and the past academic history of that student group.

The data input points are as mentioned earlier close circuit camera (if required multiple), strategically placed microphones, content of the lecture, and academic records. Cameras would be used to understand students' attentiveness toward the instructor. Simple image processing techniques such as eye-tracking and lip-tracking will be developed to understand different levels of attentiveness. At the same time, body movements or physical posture would be analyzed to predict whether students are enjoying the lecture or not. The microphones would be used to detect classroom noise. Noise-level detection would be carried out using signal-to-noise ratio. Here, the voice of the instructor is the signal and the humming generated due to the students talking to each other is the noise.

The signals generated from the instructor's voice would also be used to understand his/her psychological condition at real time. Instructors whether feeling happy to deliver a lecture or feeling a bit irritated toward a certain audience may produce signature in the signals. This research would use data mining techniques to investigate those emotion signatures. Application of data mining algorithm for developing intelligent system has been studied for quite sometimes now [18].

Based on the pattern generated in a classroom, finally, a decision-making process would be invoked to take intelligent decisions in form of non-intrusive suggestions or minor controls in classroom ambience such as volume control, airflow control, regulation of illumination, shedding, and the method of delivering the content. The overall project outline can be summarized as shown in Fig. 1.

3.1 Detailed Discussion on the Proposed Methodology

In this section, an overview of the research steps will be discussed. In a real classroom, multiple cameras would be proposed for the tracking purposes. Here, only one camera feed and one student have been chosen for demonstration purpose.

The first target data will be tracking of eyes. A student can either look toward the instructor or away based on his attention level. By tracking the cornea region, a trace of relative attentiveness can be done. The tracking will be carried out using eye detection followed by color thresholding and calculating the area of the bounding boxes. Similarly, by tracking the lips data on whether a student is paying attention, talking, or yawning can be aggregated. Figure 2 shows the method of tracking and some levels of identified patterns. These patterns are prepared to train a set of supervised dynamic data mining algorithms. For thresholds, the elbow method is the recommended one.

The other image processing method will be to track body movements. Based on the body movement or posture data, whether students are feeling interested toward the topic or feeling fatigued may be estimated.

Figure 3 is used as reference where along with image data, a time series data of overall body movement for a small period is shown. In this figure, each attempt represents a second in time domain. In real-life operation, sample frequency would be a bit lower to comprehend the data throughout an entire period (40–60 min) of lecture.

The resource required to conduct the experiment inside a classroom is subjected to the size of a classroom. The ideal case would be to have one camera monitoring one student. However, depending on the aperture of the camera, the number can vary. For detecting the motion of the body, a distance-based analysis needs to be carried out. It is because the body movement from one meter versus the body movement detected from a ten meter distance would vary.

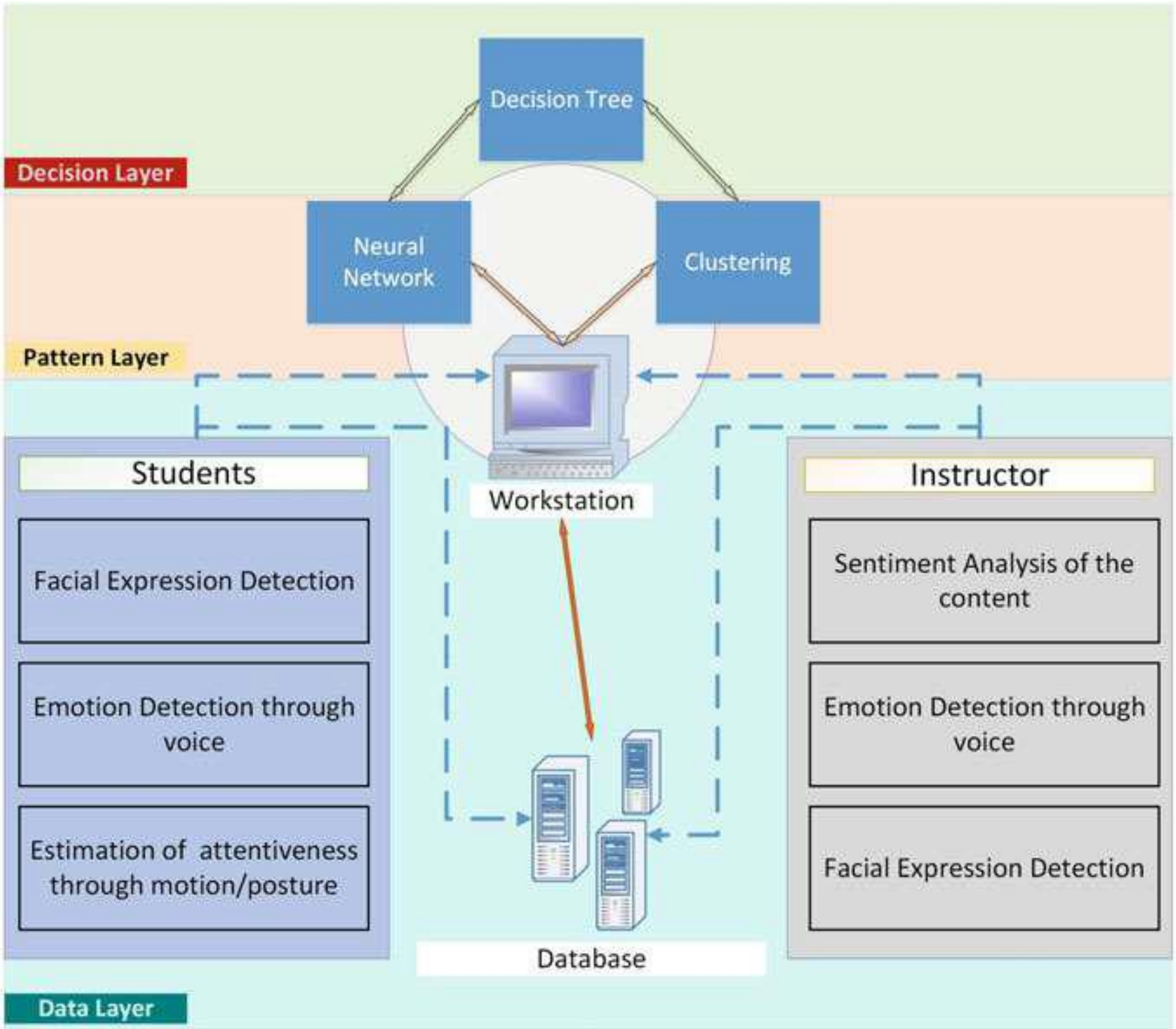

Fig. 1 Research work flow.

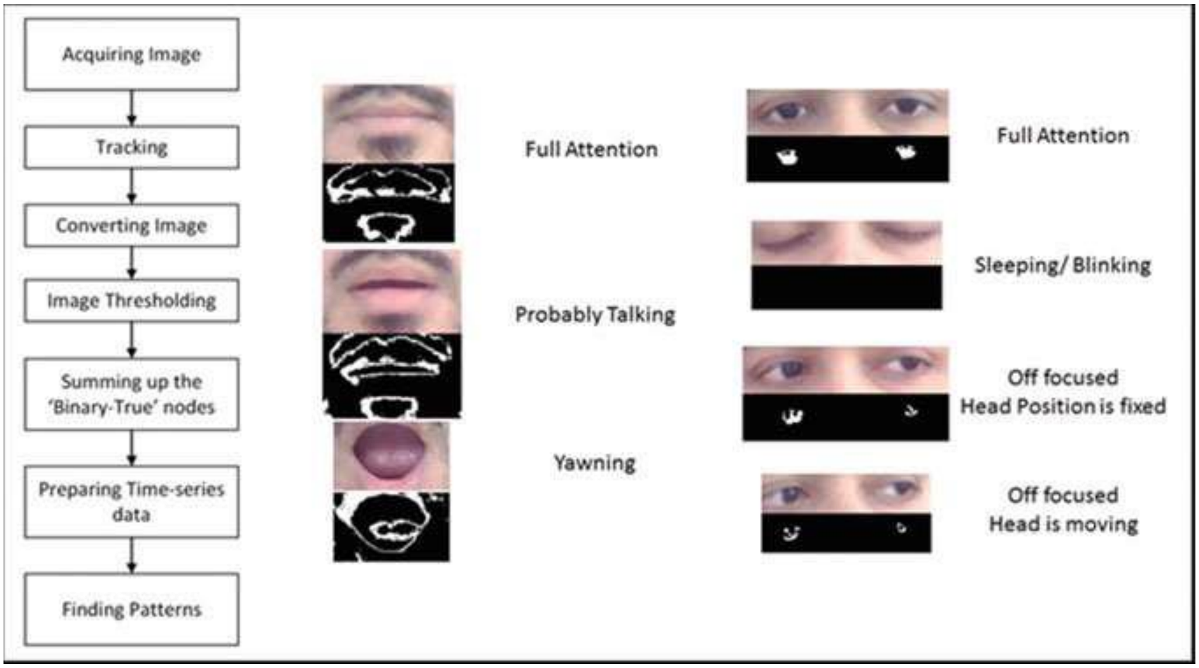

Fig. 2 Processing of eye and lip data

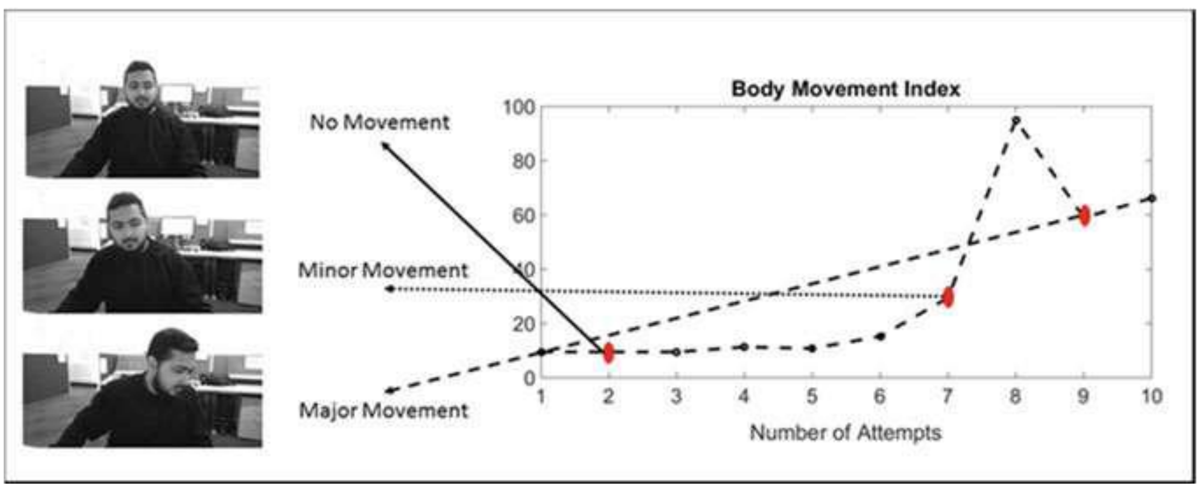

Fig. 3 Processing of movement data

3.2 Data Collection and Mining the Obtained Data

Only using image processing may not provide accurate results all the time. As the data developed here is dynamic in nature, accuracy would be very important for any data mining platform to retrieve meaningful and reusable patterns [14]. That is why strategically placed microphones would also be used. The primary job of the microphones will be to collect voice signals both from the instructor and inattentive student group creating noises. Figure 4 shows three different types of voice signals. The first type is the composite signal that has both the voice of instructor and students' humming in the background. The second signal is the instructor's voice (authenticated voice signal can uniquely identify an individual with high degree of certainty [13]), and the third one is the filtered signal that has gone through a butterworth high-pass filter [16] in order to cut out the low humming sounds as much as possible.

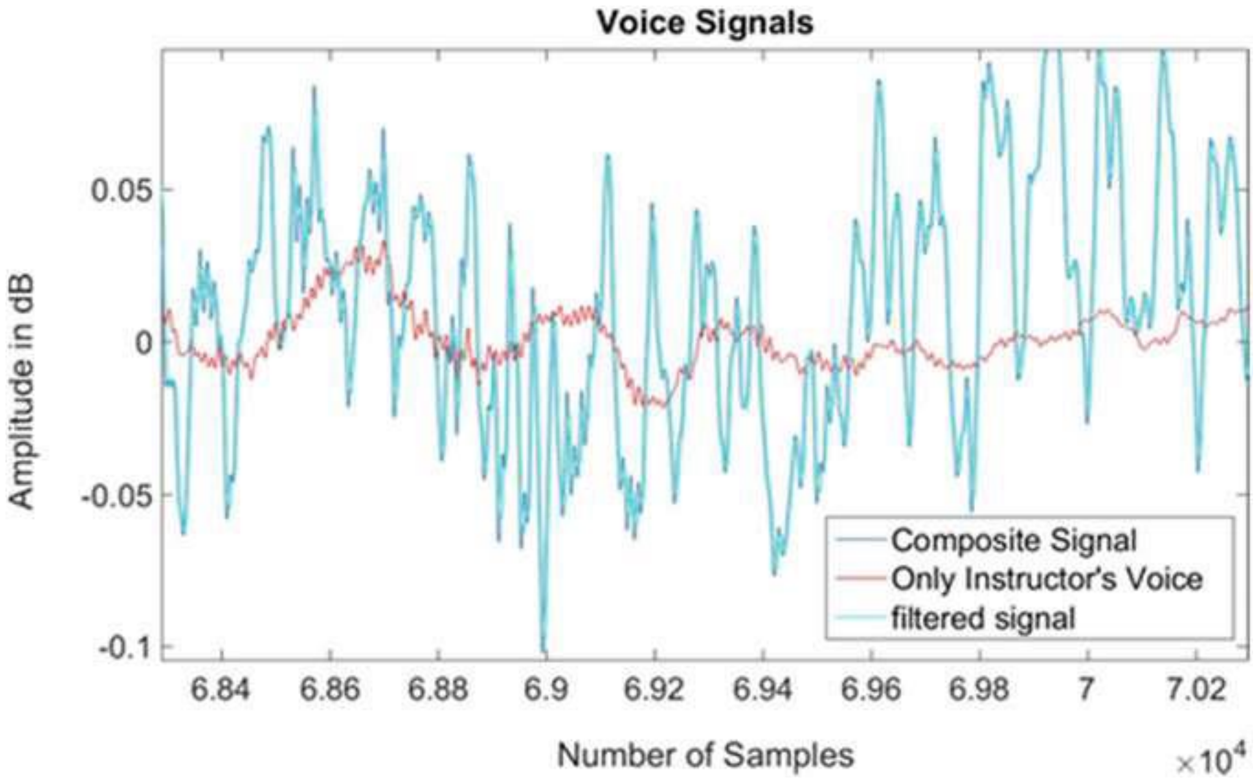

Fig. 4 Voice signals.

Once the voice signals are captured and recorded, the signal-to-noise ratio would be used as a time series data to understand whether the students are attentive or talking to each other. Figure 5 shows the signal-to-noise ratio in terms of the voice signal of the instructor and the level of humming noises created by the inattentive students. The noise is calculated by simply finding out the differences between the composite signals and the filtered signals.

Along with these classroom data, other types of data such as student's academic background, previous reactions toward similar lectures, instructor's methods of delivering the lecture, and the characteristics of the content would also be considered. If found relevant classrooms geometry can also be taken account of, as at different season of the year, window side seats may have different comfort levels that may in turn put impact toward learning. Figure 6 shows the temperature distribution in a classroom at summer time. The data is randomly prepared to test the algorithm. The right side of the picture represents window side seats at a sunny summer day. The idea here is to find out the correlation between temperature distribution and irritation developed among the students.

Finally, difficulty level of the content and student's academic background can also be correlated to understand the student–topic interaction. In Fig. 7, a fictitious relation is shown between student's CGPA and mean attentiveness throughout a sixty minute session that has a correlation of '0.8387'. Based on different complexity level of the content, several of such analysis would be carried out. These later types of data would be used to train and prepare the unsupervised data mining algorithms.

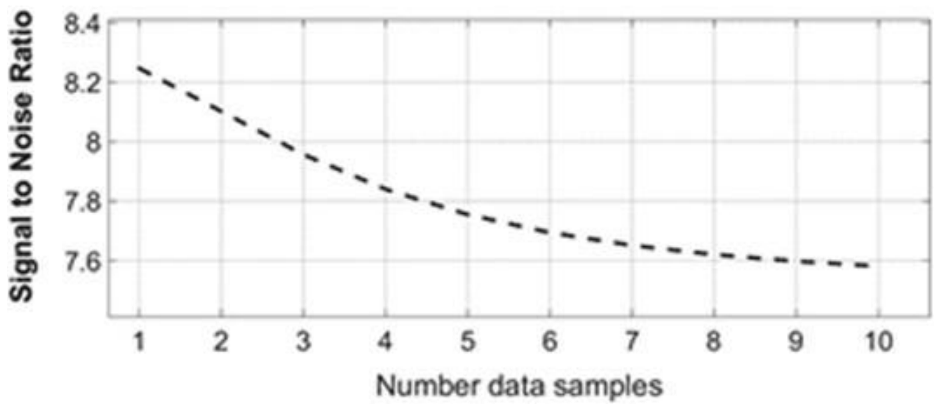

Fig. 5 Signal-to-noise ratio.

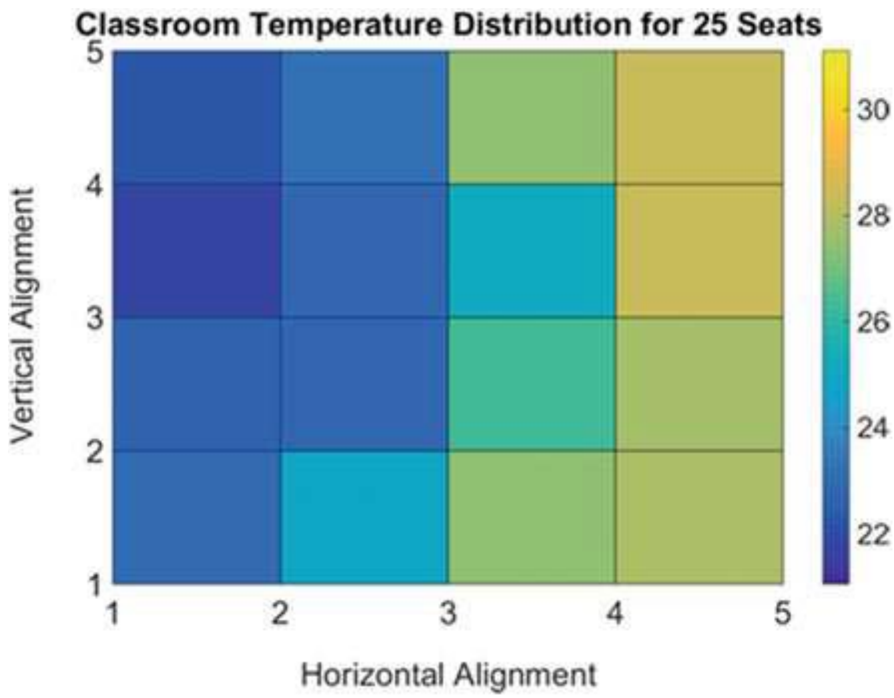

Fig. 6 Classroom temperature distribution

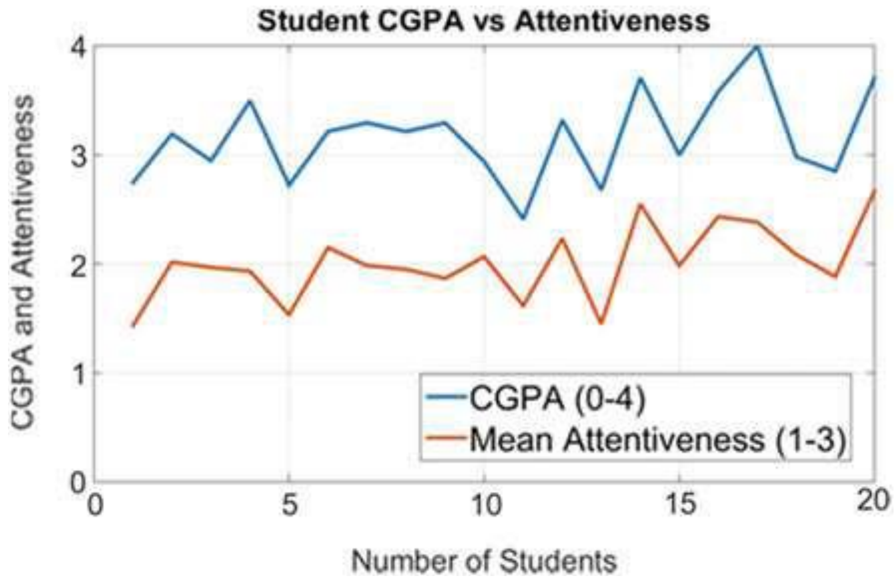

Fig. 7 CGPA versus attentiveness

4. Proposed Algorithm and Expected Outcome

To understand different patterns in the data at first, a test set of different data types would be prepared. Below in Fig. 8, an example of the visualization of a set of data is given. The data is prepared considering that students are attending contents of same difficulty level on two different days. The circles in the plot show the cluster prepared from an algorithm called 'k-means' [9]. The other types of clusters would be based on the content levels of the topic and attentiveness of the students, etc. The recurrent neural network (RNN) would then be used to understand and predict the student's attentiveness based on the previous data. The RNN would be modified in real time based on per minute-based attentiveness of the students.

In a recurrent neural network (RNN), which is a type of artificial neural network (ANN) [12], connections between nodes usually generate a directed graph along a temporal sequence, giving it the edge in exhibiting temporal dynamic behavior [10]. In simplest of terms, (1) and (2) define how an RNN evolves over time:

$$O^t = f_1(h^t;\ \emptyset) \tag{1}$$

$$h^t = f_2(h^{t-1}, k^t;\ \emptyset) \tag{2}$$

where $\boldsymbol{O^t}$ is the output of the RNN at time $\boldsymbol{t}$, $\boldsymbol{k^t}$ is the input to the RNN at time $\boldsymbol{t}$, and $\boldsymbol{h^t}$ is the state of hidden layers at time $\boldsymbol{t}$. As RNNs work with a feedforward approach, RNNs can utilize their internal state, often simply called 'memory' to process variable length sequences of inputs. This makes them suitable for data processing where data features are seemingly unsegmented but connected in some way [10]. RNNs are well equipped to process arbitrary length sequence data.

Finally, based on these two, supervised and unsupervised learning methods [15], physical non-intrusive decision process would be carried out using decision tree algorithm (DT). DT based 'Learning', in majority of the instances makes use of an upside-down tree-based progression method [11].

As the study requires significant effort in pattern mining, the three proposed machine learning algorithms have to work together. For example, to train the supervised algorithm NN and DT, a previously observed and agreed pattern has to be used. Once the system starts collecting data and predicting, based on the accuracy of the algorithm, a bidirectional relation has to be established. For the unsupervised machine learning activities, along with the traditional elbow method, an exploratory data analysis can be used to predefine the number of clusters.

The cluster index has been calculated based on the elbow method and the threshold is set at 5.

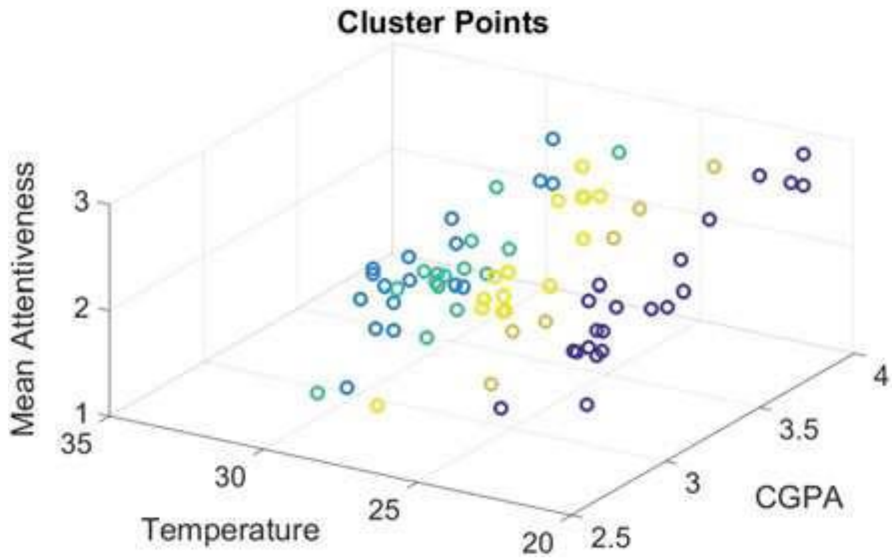

Fig. 8 Unsupervised clusters

5. Conclusion

This research proposes a novel algorithms which can effectively be deployed to monitor, control a classroom and raise recommendations that can highly improve students' attentiveness and knowledge internalization ability as well as insights for a better management. The proposed platform works in real time and is able to adapt to the changes in a range of atmospheric and situational variables. Additionally, the system aids greatly in comprehending the lecture delivery approaches based on the history of a student group and producing intelligent decisions in the forms of nonintrusive controls and suggestions without revealing confidential data of a student group.

The proposed system will bring in the edges of digital technologies into the classroom and will boost the cognitive learning ability within the student cohort; thereby, benefitting not only the students' themselves but also the instructors and the academia in general. It is also believed that the advancement of technologies such as artificial intelligence and image recognition will dramatically increase the effectiveness of the system.

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