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Comparison of algorithms for the assessment of student attention in online learning systems

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ABSTRACT
Various algorithms are used in online learning systems to compare students' attention in the classroom. Two algorithms are compared in this work. The first algorithm assesses student attentiveness in the classroom by examining their facial expressions. In order to determine if students are paying attention or not during the electronic learning process and to identify instances of academic dishonesty, this algorithm uses an interactive video-capture facial recognition technology. The Classroom Attentiveness Classification Tool (ClassACT), a system created to track student attention during several instructional stages within the learning environment, including lectures, group projects, evaluations, etc., is the second algorithm. ClassACT can tell the difference between attentive and inattentive behaviour by gathering data about the user, the user's surroundings, and the device itself using the many sensors integrated into the tablet. This essay contrasts these two algorithms in terms of methodology and outcomes.
Keywords: Student attentiveness, online learning assessment

1. INTRODUCTION

Finding out if there are any instances of academic dishonesty occurs depends heavily on the examination of student attentiveness and honest behaviour in both online and offline courses. The facilities are all available to the students during online classes. The student can use the Internet to look up the answer while courses are in session or when a test is being given, or he or she can choose to be inattentive during lectures or group discussions. Keeping an eye on every pupil physically is a tiresome duty for teachers. If there is a means for automatically identifying pupils who are not paying attention in class, teachers could create some unique teaching strategies for those individuals.

n this essay, we compare two significant algorithms that evaluate pupils' levels of attention. These algorithms are applicable to both offline and online learning environments. Based on student facial expressions, the first algorithm evaluates alertness. Eye tracking, facial detection, and expression monitoring have all been utilised to evaluate learner conduct as a result of improved image processing techniques [1]. The eye movement indicators, such as the length of the eye fixation and eye fixation, can be used to measure attentiveness. When reading a challenging section versus an easy passage, eye fixation time must be longer [2]. According to psychological theory, understanding and evaluating attention during learning can be done by recognising facial expressions [3]. Summative evaluation strategies are used in traditional teaching approaches to assess student performance. This will assess the learners' cognitive functions, but it won't reveal anything about their mental reflections. Methods based on eye tracking also fall short in assessing how crucial attention is to the learning process. By observing the learners' facial expressions, this study uses video-capture facial recognition technology to determine their level of attentiveness [4]. Since online learning programmes are becoming more popular, it's critical to keep an eye on students and identify slow learners so that you can help them learn and develop their skills.

Through the sensors incorporated into the PC or Tablet, the Classroom Attentiveness

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Classification Tool (ClassACT) overcomes some of these problems. These measurements are tracked and sent into a classifier to ascertain the level of pupil attention. Inattentive behaviour should be a sign of cheating in the classroom or other malpractice committed while taking the course. This method assesses inattentive conduct during the majority of learning phases, group discussions, online tests, etc. ClassACT is able to discern between attentive and inattentive behaviour by gathering data about the user, the user's surroundings, and the device itself using the many sensors integrated into the tablet [2].

2. COMPARISON OF METHODOLOGY

MONITOR ATTENTIVENESS USING FACIAL EXPRESSION ANALYSIS

First, the user must enter a valid user ID and password to access the e-learning portal. The learner examines the content after that, and the user's system's webcam records the learner's facial expressions. Three different degrees of the learner's attention are evaluated by the interactive e-learning system module. The learner lowers or turns his or her head during the first stage, which is a momentarily distracted stage. In order to get the learner's attention, the system then responds by opening a message window with an audible sound. The system replies by creating an online quiz in the style of a game to make the learning interactive when the student nods off at the second level, which is the moderate lack of focus. The third level is characterised by a complete lack of focus, during which the student either nods off or converses nonstop, to which the system responds by urging the student to participate more actively in class discussions.

The learner visits the e-learning website in the first stage, as depicted in Figure 1, and the webcam identifies facial expressions and takes continuous pictures over the course of a set amount of time. In step 2, the image is analysed by splitting it into two parts: an outline of the facial profile and localised internal features, which are then subjected to a color-space transformation to assign distinct colours to the various facial characteristics. Three characteristics of facial features are used by the system to examine concentration in Step 3: avoidance (frequency of facial movement), concentration (eye movements), and happiness (distance between the lips). Higher scores indicate that the student was paying more attention, and these are scored and totalled. Based on changes in face movement, changes in eye movement, and changes in lip opening, respectively. The learner is engaged and not distracted if there is a modest mean variation in facial movement, such as when there is no chatting to peers or moving around. Similar to this, if the learner is very attentive and not dozing off or shaking his/her head intentionally, the mean variation in eye movement, if the value is minimal, indicates this. Finally, a cheerful learner is more likely to be attentive, whereas yawning may indicate an unfocused learner. The student is therefore focused on learning if there is little variance in the mean size of the opening between the lips. The method uses weighted ratios of attention scores, which the system manager can modify as necessary [3], because different learners have varied learning characteristics.

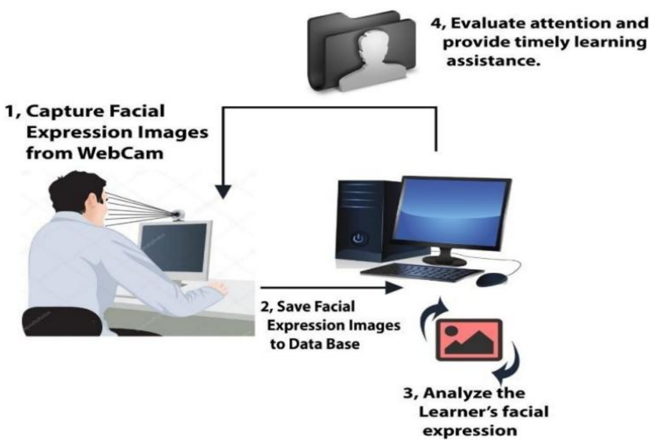

Figure 1. Structure of e-learning system with facial expression capturing

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The outcome is assessed using a purposeful sampling method. A concept-page group, a tutorial simulation group, and a case-study group are each assigned to a section of the group [3]. The 16 students in the concept-pages group had access to pointers on key subjects and were given hyperlinks to the course material. The tutorial simulation group, which consisted of 15 students, received interactive multimedia instruction that was intended to increase student engagement in the learning
process. The third group consists of 15 students and was exposed to real-world applications of the material being studied. The instructional content for our e-learning study was a course on computer networks. This course consisted of three units: wireless transmission, IP addresses, and subnets. The course required 3 weeks of study, three times per week, for a total of 450 min. The objective of this study was to examine the relationship between concentration and learning effects.

CLASS ACT SYSTEM

The ClassACT system is made to keep an eye on the classroom and categorise students' behaviour as either attentive or inattentive while they are working on a task. The "assigned task" for this subject is an examination that must be finished in the allocated time without assistance from peers, teachers, books, notes, or the internet. Any action—or inaction—that runs counter to the specified duty constitutes being off-task and inattentive. Any academic dishonesty is against the task set, as described, and is consequently viewed by the system as an inattentive conduct. The ubiquitous analogy [4] was employed during the system design process. The resulting design process for pervasive systems requires the design of the physical system in parallel with the computing system.

A. Data Collector

A data collector block runs in the background for the entire session, monitoring the physical and system environments. The system collects data from the webcam, microphone, screenshot, and active window at every scheduled time interval.

B. Image Processor

The image processor must determine the difference between two images from either webcam or screenshots. A pixel-by-pixel comparison is done, where the difference between two corresponding pixels is added to a running total. This can be an effective way to determine the level of motion between two images.

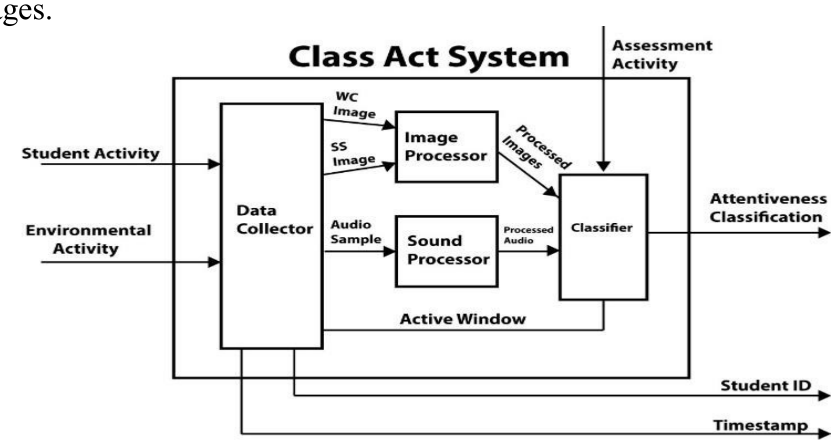

Figure 2. Structure of ClassACT System [2]

C. Sound Processor

The sound processor block takes the sample of sound collected by the built-in microphone and determines the sound intensity level in decibels (dB). In the end, bels (B) were used instead of decibels, in order to get all the data to be around the same scale of magnitude.

D. Data Aggregator

The Data Aggregator fetch data from the files that store the details of the exam and the data from the data collector. It then transforms the data into a matrix form to make this understandable to the data classifier. The data used is the average values from each sensor for each question. The data

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from the data collector and the exam are synchronized by their time stamps.

There are two different modes for data aggregation based on the classifier mode. The modes are training and testing. During training, the aggregator collects the data from all the students, and all the exams after the desired number of exams are completed. This is done to compile a large training set with which to train the classifiers. During the testing mode, the aggregator only collects data from one student, and for only one question at a time. This one sample is passed to the classifier for real-time classification.

E. Classifier

The Multilayer Perceptron (MLP), the Support Vector Machine (SVM), and the Proximal Support Vector Machine (PSVM) are three classifiers that have been trained and tested for comparison. The classifier that consistently performs the best will be the one used in the final application. The classifiers all have two modes: training and testing. In training mode, initial parameters are set, and the training data from the data aggregator block is passed through each classifier. To try to prevent local minima, the MLP needs to be run several times. In the testing mode, the testing data from the data aggregator is passed through the classifier. The classifier takes this single sample, uses the parameters that resulted from training each network, and provides the classification that best fits the learned behaviour.

F. Training and Testing

Training takes place on the sample set obtained by running the assessment and data collection programs six times. The relatively small sample size (96 samples) was used only to see whether everything was programmed and running correctly, and to test the initial performance of the classifiers. The samples were separated into training and validation data sets and were then used to train the separate networks. The SVM and PSVM networks both use cross-validation to find the two user-defined parameters for a Radial Basis Function (RBF) kernel [6], [7], specifically the Gaussian kernel. The MLP algorithm was run with one hidden layer of two neurons and backpropagation. Initial value ranges for the weights of the MLP were taken from suggestions in [9].

3. COMPARISON OF RESULTS

MONITOR ATTENTIVENESS USING FACIAL EXPRESSION ANALYSIS

This part investigates the relationship between learner improvement in the online learning course and concentration scores. The data analysis in Table 1 demonstrates that students improved considerably in their academic performance when the e-learning system instinctively detected their level of attention. This is backed up by the statistically significant positive relationship between the attention score measured by the system and the rise in the students' scores.

Learning Strategy	**Attention Score**
Concept-pages strategy	0.865
Tutorial-simulation strategy	0.710
Case-study strategy	0.629

Table 1. Summary of Pearson Correlation for Improved Score and Attention Score [3]

Improvements in test results were strongly connected with attention scores in the concept-pages and

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tutorial-simulation techniques (.865 and.710, respectively). A modest association (.629) was obtained using the case-study approach [3]. Concept-pages group > tutorial-simulation group > case-study group were the three groups with the strongest positive connections between the improvement in learning scores and the attention scores, according to Pearson correlation coefficients. The learning group using concept pages exhibited the highest positive correlation. The concept-page learning technique featured little interaction with the students, which may have made it simpler for them to get sidetracked throughout the learning session. Therefore, a system that refocuses kids' attention would benefit this group the most. The group that learned through case studies showed the lowest positive correlation. The case-study learning strategy used interactive discussion as the focus of learning and, as a result, students in this group were more likely to maintain attention. Thus, they would be less likely to benefit greatly from a system that redirects their attention.

CLASSACT SYSTEM

A. Training Outcomes

Each classifier's training and validation results were acquired, and they are presented in this section. An RBF kernel was used to operate the SVM and PSVM. With 25 support vectors and 95.82% accuracy throughout training, the SVM, however, fared the best. The accuracy of the PSVM lagged behind that performance at 68.76%. The accuracy of the MLP with one hidden layer of two neurons and logistic functions for each neuron's activation function was about 70.84% [8]. The PSVM trained the most quickly, followed by the SVM. The MLP was many minutes behind the other two.

		Predicted	
		Attentive	Inattentive
Actual	Attentive	40	2
	Inattentive	2	52

TABLE I
CONFUSION MATRIX FOR THE SVM

A. Testing Results

The classifier with the best overall performance after training and validating the classifiers was chosen to test the system, and that classifier was the SVM. The evaluation and data gathering programmes were once more run, and the collected data was then compiled and given to the trained SVM. The system had an accuracy rate of 87.5%. With data from the same test taker, the SVM was still fairly reliable with the 25 support vectors. The test data was also run through PSVM for comparison's purposes. On the test data, the PSVM performed with 75% accuracy.

4. CONCLUSION

In this study, the effectiveness of two algorithms used to gauge students' levels of attentiveness on online learning platforms was compared. Facial expressions cannot be used to infer whether a student is paying attention or not. We must take into account a variety of elements, including the user, his environment, and the system he utilises. These facts lead us to the conclusion that the ClassACT algorithm outperforms the algorithm that merely takes facial expressions into account. Other than this, Class ACT employs SVM and PSVM as classifiers, increasing efficiency once again.

A very promising method for identifying inattention and academic dishonesty during computer-based examinations is the ClassACT system. This programme can assist instructors in proctoring exams in classrooms where each workstation has a computer or tablet. In keeping with that idea, teachers in distance learning courses can use the ClassACT system to help deter students from

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engaging in academic dishonesty.

Much larger sample sizes made up of numerous test takers will be used in future research. The setting and evaluation questions will be created to promote more honest behaviour while engaging in academic dishonesty. You might take into account other neural networks. It is possible to perform feature extraction to determine which features are most important for categorization. This will allow for the elimination of features that don't add much to the system's performance overall and will lower the demand for processing power. Another change is that the instructor's computer will have real-time access to a database that will be set up to keep the information for many students in many classes. The functionality for webcam-based gaze detection may be the most important addition. With the addition of gaze detection, the system will be able to identify various forms of exam inattention in addition to whether the test-taker is looking off-screen for unapproved help. The addition of gaze detection will also make it possible to use ClassACT to examine some of the other stages of the Gradual Release paradigm. Especially noteworthy is the "Focused Instruction" phase, where students are more likely to pay attention to a focal point (the board, screen, or instructor).

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