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PAPER

Students Emotion and Distraction Detection While Adopting E-Learning Approach

Wiki Lofandri[1], Anas A. Salameh[2](✉)

[1]Universitas Negeri Padang, Padang, Indonesia

[2]Department of Management Information Systems, College of Business Administration, Prince Sattam bin Abdulaziz University, Al-Kharj, Saudi Arabia

a.salameh@psau.edu.sa

ABSTRACT

Currently, e-learning has changed the way students' study by providing high-quality education that is not restricted by place or time. Mobile phones, tablets, laptops, and desktop computers are some of the products that make online learning easier. These devices were used for mandatory online learning due to the COVID-19 pandemic. However, because the e-learning approach prevents an instructor from actively observing a group of students, they may become distracted for many reasons, significantly reducing their learning potential. This paper proposes an intelligent system called the Intelligent E-Learning Monitoring System (IELMS) that helps faculty members keep track of such students and supports them in improving their performance. Convolutional neural network (CNN) techniques are utilized to detect emotions, and once the optimum algorithm for detecting emotions has been identified, it is fused into the model that detects an online learner's distraction. The fused model produces logs of distraction and emotion. These logs will assist the teaching community in identifying underperforming online learners and facilitating counseling.

KEYWORDS

e-learning, mobile learning, distraction, emotion, convolutional neural network (CNN), fused model, Intelligent E-Learning Monitoring System (IELMS)

1 INTRODUCTION

1.1 E-learning management systems

The development of information technology has created both a demand and a possibility for obtaining a wide variety of content at any time and from any location. Therefore, the demand for web-based educational systems can be facilitated by the astonishingly quick advancement of technology in recent years, which can be used to establish e-learning platforms through computers. Researchers are constantly focusing their attention on online educational programs since they can meet the needs of both expert and novice users. [1] Here, the user's preferences should be

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the primary determinant of customization, guiding the design and operation of the complete adaptive learning system.

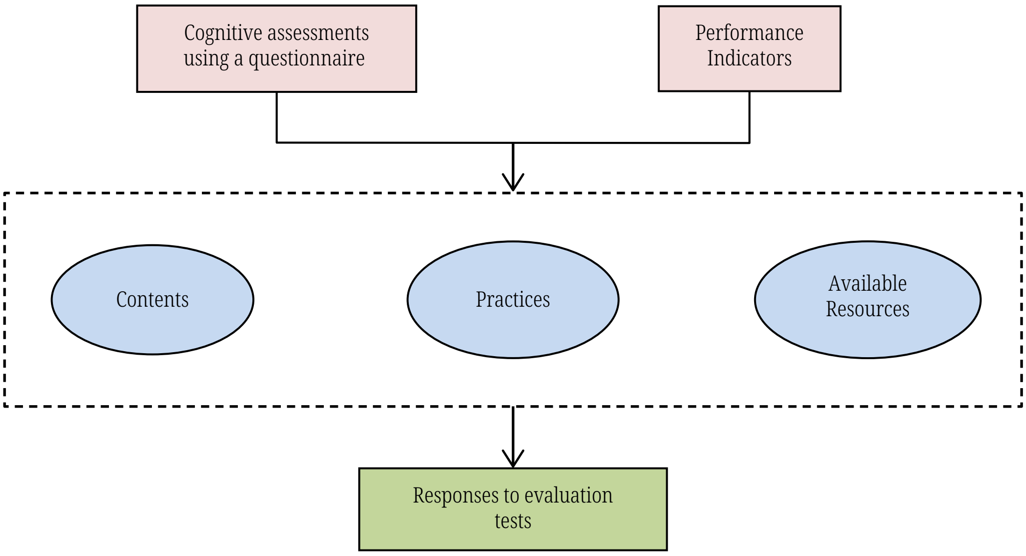

Fig. 1. E-learning architecture

Presently, e-learning relies on intricate virtual spaces for collaboration where students can communicate with teachers, tutors, and other students. A variety of both asynchronous and synchronous services can be provided to the student. In the former category, tutors or teachers can meet with students one-on-one and in virtual classes. The latter category includes always-online simulations or Web-based lectures in addition to traditional didactic resources. Software platforms, such as as training administration systems and learning management systems, are typically used to access these features (see Figure 1).

1.2 Impact of e-learning

A massive amount of learning resources has emerged as a result of advancements in technology for communication and information, particularly in networking, software development, and multimedia. The instructional and learning methods used in organizations have changed as a result of new technology. As an emerging interactive educational setting in the digital age, e-learning has arisen. Massive interest is being shown in online educational programs worldwide. For this investigation, a brand-new framework was created. In the remainder of this part, seventeen levels within four variables are examined. Technology, material, inspiration, and mindset are these elements in education. Seventeen dimensions fell within the four previously chosen variables. These characteristics fall under the category of instructional technology variables and include things such as simplicity, technical assistance, access, knowledge utilization, and quality of the learning system. [2] Under the curriculum factor, the following dimensions were found: organizational encouragement, internal understanding promotion, and financial reasons; under the motivation variable, these dimensions included working groups; content effectiveness; quantity and quality of learning; and spatial and temporal flexibility. With the help of the variables depicted in Figure 2, this study creates such a framework.

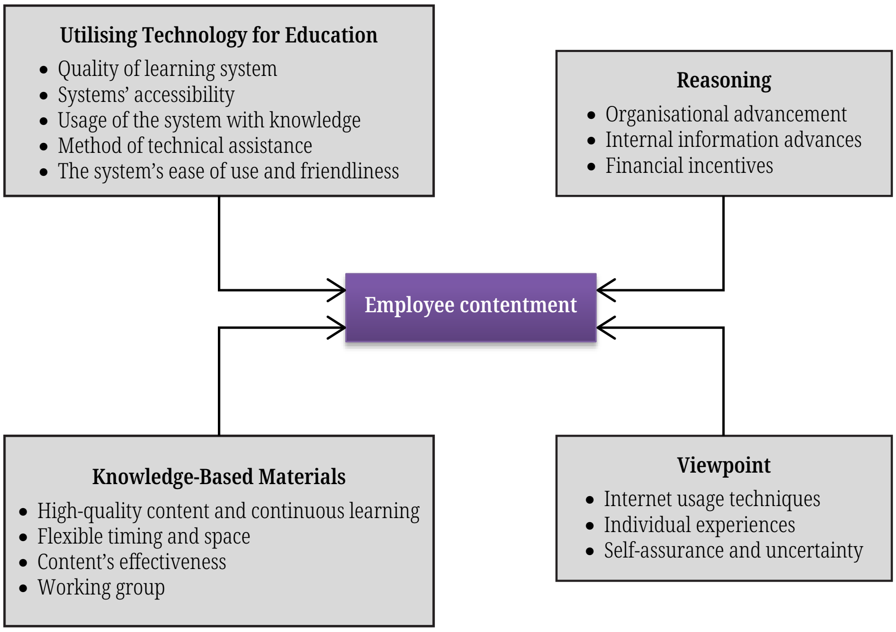

Fig. 2. The effect of e-learning on worker satisfaction

1.3 E-learning challenges

E-learning presents several challenges that are connected to its various facets. [3] Some of these challenges are seen from an educational perspective, while others are seen from a technological one. A summary of these difficulties can be found in Figure 3.

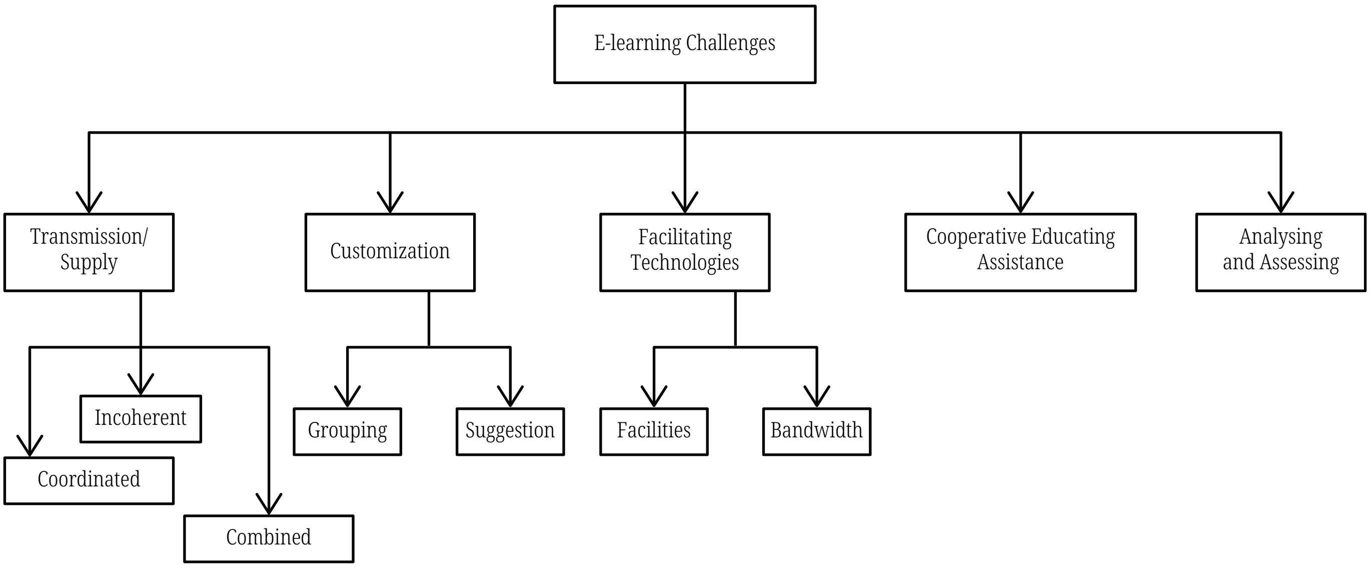

Fig. 3. Flow for e-learning challenges

1.4 E-learning monitoring system

Even though online learning has many advantages for both students and teachers, there are some significant drawbacks as well. Generally speaking, dropout rates from distance education programs are higher than those from more traditional programs for a variety of reasons. One of the main drawbacks of online learning is that students may feel alone and disconnected from the teacher, other students, and even the institution. This is especially true for adult learners who have to juggle work, family, and school obligations [4]. As a result, instructors must offer timely support and guidance to students' assignments as well as typical input on those assignments. Instructors must also encourage and assist student communication by pushing students to participate in the online communities dedicated to that purpose. Regretfully, teachers find it extremely difficult and laborious to keep a close eye on every activity that each student completes in these distance-learning settings. Determining the relationships that occur between people or teams of students is considerably more difficult, meaning that:

- To recognize the leaders and adherents of the groupings as actors
- To identify pupils who are most likely to discontinue the course

To identify possible disputes or breakdowns inside the group before it's too late to effectively handle these challenges. Observing how students and groups interact can assist one in comprehending these relationships and foreseeing these possible issues. This can provide valuable insight into how to arrange learning exercises more efficiently, leading to improved learning results.

Instructors can use reports for monitoring to simply track a group's participation at specific points and the behavior of their students online, get input from their students, and support fewer active groups. Regulation has temporal dimensions, meaning that as the educational process progresses, teachers must be aware of how well their groups and individual students are performing. Thus, teachers may be able to provide students and groups with immediate support during the regulation process.

2 RELATED WORKS

Assessing the effect of online education on student accomplishments is a challenging task because several additional variables can influence these accomplishments, including how technology is used as a teaching tool, how students learn better when exposed to multimedia material than when it is not, the student's prior experience with the relevant technology, and the subject matter of the course. In every instance, e-learning has become more and more common over time, emerging as the most often used instrument in education these days. [5] International e-learning statistical studies have demonstrated that the widespread use of e-learning will lead to a future in which e-learning services are used on a larger scale.

2.1 System for adaptive e-learning

Considerable research has been done to assist in the creation of adaptive online education systems, including methods for learning observation. To get the most out of our comprehension, the latter entails logging student interactions and evaluating log data to provide an illustration that aids in educators' understanding of what transpires in remote learning sessions. However, it is still unclear if the teachers are prepared to put in the substantial time and effort needed for ongoing observation [6]. Unlike passive tracking, the proposed method enables the system to be informed of any departures from the required learning standards during runtime and provides a list of potential settings for it to modify its tactics.

2.2 Research on face recognition

Utilizing an online picture or clip of the user, facial recognition technology confirms the user's identification. This method was used to give the e-learning application access. A comparison analysis is conducted between various face recognition methods. Different face orientation conditions are used for identifying individuals using the Eigen face algorithm system and principal component analysis (PCA) [7]. The technique was discovered to be quite quick and easy to use at the same time. Nevertheless, because the system is unable to distinguish between different image sizes, it cannot be used for real-time monitoring. Based just on the brilliant magnitude, the system was found to be capable of recognizing faces with varying orientations. Mobile phone authentication by recognition of facial features is possible with the commercial program OpenFace. While many biometric identification methods, including facial recognition and keystroke authentication, are there, face ID has some advantages over the others.

The use of e-learning study techniques is the current area of concentration for the e-learning research community. The application is often a digital content-based remote learning environment that relies on technology to operate and needs to be ready to provide all the services required for the procedure of learning, including monitoring. While creating digital content was the primary goal a few years ago, e-learning organizations are now more concerned with the structure of the information and how students are utilizing it. As a result, a lot of projects and initiatives have emerged with the goal of monitoring and adapting material based on the findings of learners as determined, for instance, by the learning management system [8]. In that sense, adaptive structures have great promise. On the Internet, a project such as a digital book is a common form of educational software.

2.3 Feelings and education

Emotions play a significant role in how individuals learn, according to recent research. Positive emotions may impact students' focus, motivation, and ability to self-regulate their learning, according to the research that is currently available. On the other hand, unfavorable feelings have an impact on pupils' performance and accomplishment, which also influences learning. Anxiety and humiliation, for instance, lower motivation and interest levels. [9] Emotions can elicit distinct associations with non-task-related thoughts, and they can vary in terms of the strength and duration of these connections. For this reason, both happy and sad emotions play a crucial part in the retention and recall of knowledge during learning. Retrieval is facilitated by the activation of associative material in long-term memory, which is facilitated by the activation of emotions [10].

3 METHODS AND MATERIALS

3.1 Architecture of an e-learning system

In terms of functionality, an e-learning platform is a learner-centered system of education with a focus on autonomous learning and heuristics. It must therefore offer a sophisticated, transparent, and integrated interface. The following characteristics of an incorporated e-learning system should be present:

An intelligent environment for learning ought to enable students to choose their methods of instruction, pace, and subject matter based on their needs, interests, and level of expertise.

Individual instruction resources: By assessing students' understanding bases and skill sets, the system should constantly offer relevant learning materials. It should also create an atmosphere for learning that is built around the educational resources. It ought to assess pupils' achievement in real-time as well. Flexible teaching approaches are essential for providing students and teachers with a convenient platform for interaction. Both the teacher and student are free to select the location and time for education based on their specific requirements. Both asynchronous and synchronous interactions should be permitted.

Systemic services that are scalable: An open method's resources, such as assessments, teaching method samples, and data structures, can be revised, shifted, and preserved. Figure 4 depicts the architecture of the intelligent e-learning system.

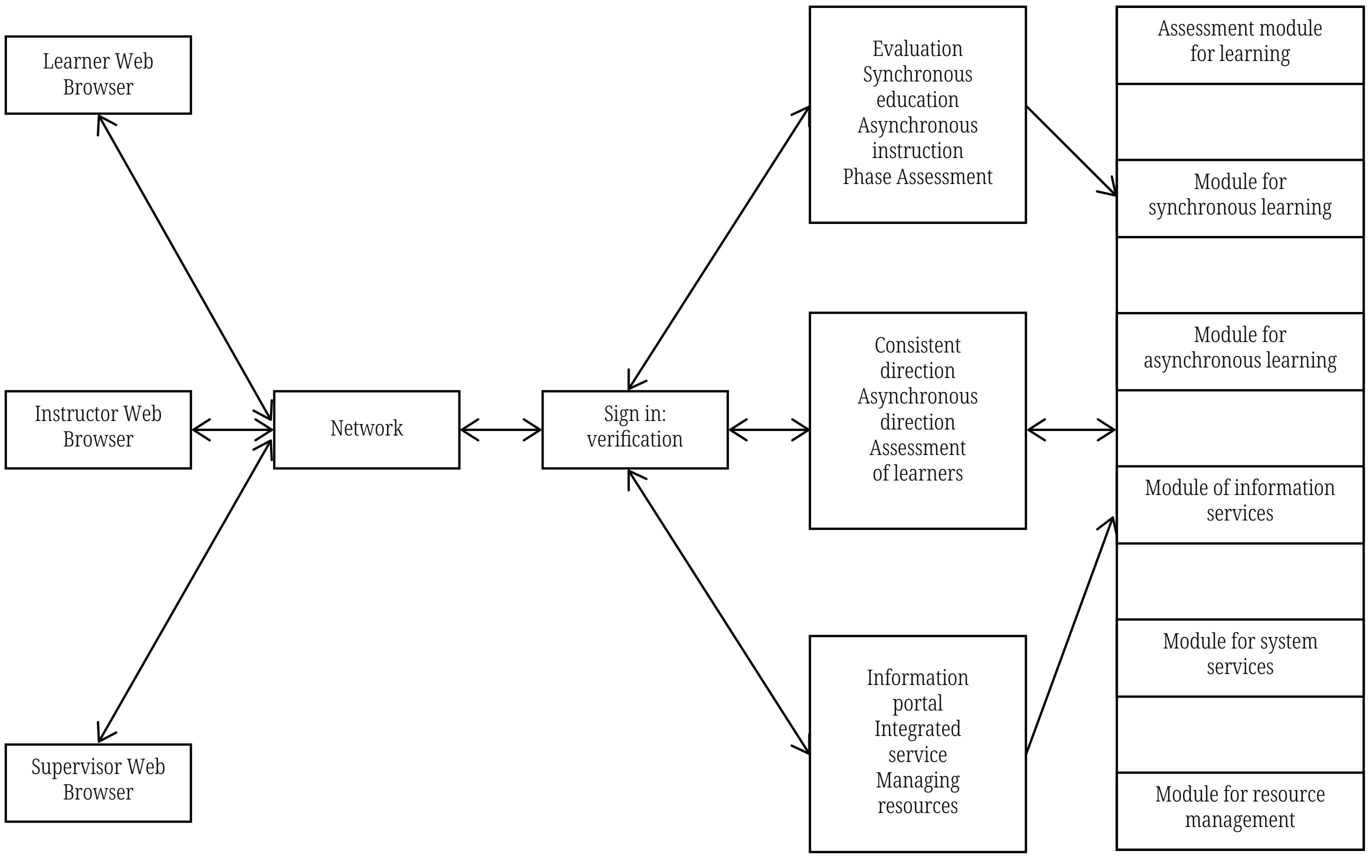

Fig. 4. E-learning system architecture

3.2 Model for e-learning system development

The client or server architecture maintains simple data on the server and places the systemic module on the customer's end. Local area networks can benefit from an e-learning system built on client or server architecture. Nevertheless, it requires a lot of upkeep. Both information and systemic modules are located on the server in the browser or server architecture [11]. On the client, a browser is present. A typical information system built on the browser or server architecture consists of three or four tiers (see Figure 5).

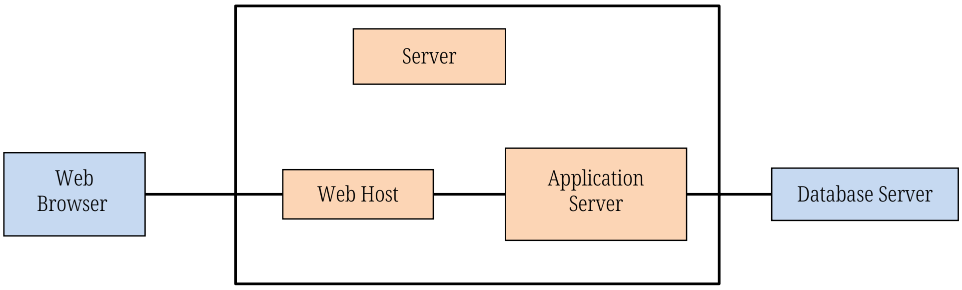

Fig. 5. Bowser server system architecture

The most popular approach for designing systems is the browser or server architecture because it is easy to maintain. Growing interest has been shown in components-based development-based computing on grids. The most promising approach to resolving the software dilemma is thought to use component-based development. Children's building blocks, which may be used to create a variety of application platforms by carefully selecting components, can be compared to CBD. A major corporation that emphasizes sharing amongst e-learning system designs that utilize grid computing uses systems for learning based on CBD to create its systems.

3.3 Convolutional neural network-based emotion detection of e-learners

Many researchers have used convolutional neural network (CNN)-based methods to enhance involvement detection. They proposed an engagement detection approach for online educational settings that utilized a CNN. They suggested three distinct models, which include the entire network network-in-network CNN and extremely deep CNN, for categorizing the engagement of learners throughout their instruction in an online setting. The three-level choices were reached, and the results showed that the levels of precision were 92.75% for not engaged, 85.66% for normally engaged, and 93.97% for highly engaged. In additional research, the experimental findings of five distinct CNN models were compared to engage student identification, and CNN generated the most accurate outcomes. The "FER-2013" picture dataset, which was utilized for training the CNN model, was employed for this study. Below is a thorough overview of these datasets:

Dataset: A publicly accessible facial picture dataset from the Mathematica data repository called "FER-2013" was utilized for training the networks. This dataset has 30,835 pictures in it. Each image in this case has 46 by 46 grayscale pixels. In all images, faces take up the majority of the information. The goal is to identify involvement in each image before grouping the images into seven different groups: "Neutral," "Angry," "Disgust," "Fear," "Happy," "Sad," and "Surprise." There are 29,719 face images in the initial training set and 3589 photos in the test and verification sets. [12] Additionally, there are two columns in the experimental data: "emotion" and "pixels." Every feeling in a picture is represented by a number in this instance, with values 2 anger, 1 disgust, 1 anxiety, 3 joy, 0 sorrow, 5 shock, and 3 neutralities. On the other hand, each image's pixel values are listed in multiple quotation marks in the “pixels” column. The training data is used to predict emotions in the test set, which only includes the “pixels” column.

Methodology. The suggested system comprises two components: engagement recognition and sentiment recognition. Real-time prediction is possible by using the learned values for both systems. A Haar Cascade Classifier has been employed in this instance to identify eye locations within features for the interaction detection model. For interaction detection, we have employed the CNN classifier after the Haar-Cascade classifier in this work. A Haar-Cascade classifier facilitates the examination of only the eye region on a visage to detect involvement. As demonstrated in Figure 6, Haar-features are determined individually and are useful for identifying edges and arcs. Furthermore, when compared to CNN classification algorithms, a Haar-Cascade classifier executes faster.

The CNN model for recognizing emotions uses facial images sourced from the FER-2013 dataset, training them to categorize emotions including ‘Anger,’ ‘Disgust,’ ‘Anxiety,’ ‘Joy,’ ‘Sorrow,’ ‘Shock,’ and ‘Neutral.’

Haar cascade classifier. A cascade function is trained using a fundamental machine learning classification using a large number of favorable (i.e., face-containing photos) and negative (i.e., face-free) images. It recognizes items from various pictures supplied based on the training. Several feature sets, including the entire body, lower limbs, eye, front-facing face, etc., are used to train this algorithm and stored as.xml files. Only cascading frontal faces and cascading eye recognition are employed in the present study. The four primary steps of this classifier are as follows:

Selection of Haar features: The input image’s sections are where features are calculated. The image’s sections are distinguished by calculating the disparity between the total pixel brightness of neighboring rectangular portions.

Developing a central image: By doing operations on each pixel, a significant amount of calculation is required; hence, this is utilized to limit the calculation to just four images. The algorithm runs faster as a result.

AdaBoost: The precise Haar-like characteristics for classification are chosen using the AdaBoost learning technique. Utilizing a combination of all weak categorization operations, AdaBoost creates an overall strong classifier.

Recursive classifiers: Now, a face can be classified based on significant traits. Since not every area of the picture is a facial location, it is not required to apply every characteristic to every area of the image, as illustrated in Figure 6.

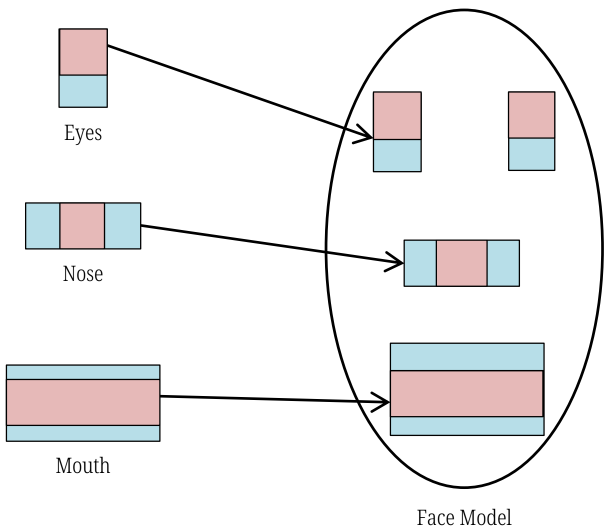

Fig. 6. Haar cascade classifier facial features

Convolutional neural network. A well-known deep learning classifier, CNN is used to analyze pictures and retrieve characteristics faster than with other methods. Using photos as input, it classifies them into multiple groups, biases them towards specific items, and assigns useful weights to them [13]. Using manually labeled eye pictures acquired after using the Haar Cascade network on human faces taken from the FER13 dataset, we trained our CNN for this work. Binary categorization was then utilized to determine whether the subjects were “engaged” or “concentrated.” Data from FER13 is also used to train this network. The output layer makes predictions about the emotion and groups it into seven groups: disgust, anxiety, joyous, sorrowful, shock, and neutral. The CNN architecture that is outlined in our suggested model is as follows:

- The sequential model stores the individual pixel values of the images entered in the 32×32 input layer;
- Low-level characteristics of the source photos are computed using convolutional layers and a set of 3×3 filters;
- Maxi convolutional features’ spatial dimension is decreased by a pooling layer with a 2×2 pool size;
- Relu serves as the function of activation in the classification process through a fully linked layer, which determines each of the class scores.

3.4 Distraction in Intelligent E-Learning Monitoring Systems

Problem-based learning can benefit from digital learning since it offers a wealth of materials. However, learners’ ability to retain knowledge will be negatively impacted by the diverse applications and functions of these assets, which will unavoidably lead to increased demands on mental capacity and diverted attention. There were many distractions around students’ learning activities, impeding their ability to solve problems and work with others, even if utilizing technology has become a common activity for the younger generation to learn and acquire knowledge. It was shown that a majority of students (68%) were unable to refrain from using digital gadgets to send text messages during regular class times.

Due to human mental limitations, these off-task behaviors hurt student progress. Learners’ capacity to solve problems, communicate, gather information, and create material in virtual environments may be hindered by a lack of teaching on how to use digital technologies. Meta-attention research on internet use in online courses revealed that students with higher perceived attention discontinuities will visit social networks more frequently and have lower final course marks. On the other hand, students who felt that there were fewer attention discontinuities in their learning generally used more behavioral and mental methods to reduce distractions and had higher final course grades as a result. [14] Furthermore, researchers found that 70% of college students encountered digital distraction due to unrelated occurrences while doing an online search assignment for integrated learning, utilizing a screen recording technique.

Technology diversion: The perceived digital distraction experienced by students during online learning was the main topic of this study. We used the online-learning motivated concentration and control scale to measure student knowledge about learning-irrelevant behaviors, and we selected the eighth item, Reported Concentration Discontinuity subscale. To assess the variable architecture of the PAD subscale, a preliminary factor analysis using a generalized minimum squares extractor was carried out. The variance attributed to a single concept on this scale is 53.43%, according to the EFA results. Using loadings of factors spanning 0.65 to 0.36 and an internal variance of 0.45 for the present sample, the eight elements were put onto the PAD. "*I am conscious because I typically have concentration difficulties while utilizing the laptop to do the projects and reports*," is an example of a sample question. And "*Even though I intend to use the laptop to complete the reports and tasks, computer activities, YouTube, and news often distract me*." The responses of the participants were averaged to generate a digital attention rating with one signifying disagreement to five completely agree on a Likert scale with five points, the same as the technique employed in the initial analysis. Higher index scorers experienced more severe problems with digital distraction.

4 RESULTS AND DISCUSSION

4.1 Performance of an IELMS

This study examined the association between independent learning and performance by analyzing the independent educational competency and learning accomplishment indicators of the intervention group as recorded in the Intelligent E-Learning Monitoring System (IELMS) database. The self-regulated learning processes of learners were examined and evaluated in this study using average learning performance indicators and mean independent learning competence indicators.

Table 1. The autonomous learning metrics

Independent Learning Indicator	Independent Learning Sub Indicators	Description
Index of independent learning competency	The index of success throughout the learning period	The reading time for all course materials that have been learned is added up on the PELS platform to determine each learner's success score for educational time.
	A measure of the degree of effort put forward in studying the course materials.	By dividing the actual reading period by the amount of reading time required to master the course material, one can calculate the accomplishment index of the effort required for studying it.
	The focused study's success index	The legitimate learning time split by the real learning time is the definition of a successful index for intense study.
An independent measure of learning performance	Learner capability index	The theory of item response is utilized to measure an individual's ability score by analyzing each learner's test responses.
	Recognizing the studied courseware's degree index	The accuracy rate of questions chosen at random forms the comprehension degree indicator.

Based on the data collected from participants in the IELMS, Figure 7 shows the average of the autonomous learning competency index variation plot in time order. These findings show that during the four weeks of teaching, the individuals' capacities for self-regulated learning progressively improved. This discovery is corroborated by the average autonomous acquiring competency index, which is determined by combining the four self-learning sub-indicators given in Table 1. This result implies that each learner's ability for autonomous learning is successfully increased by the self-regulated learning strategies that are recommended and supported by the intelligent e-learning monitoring system.

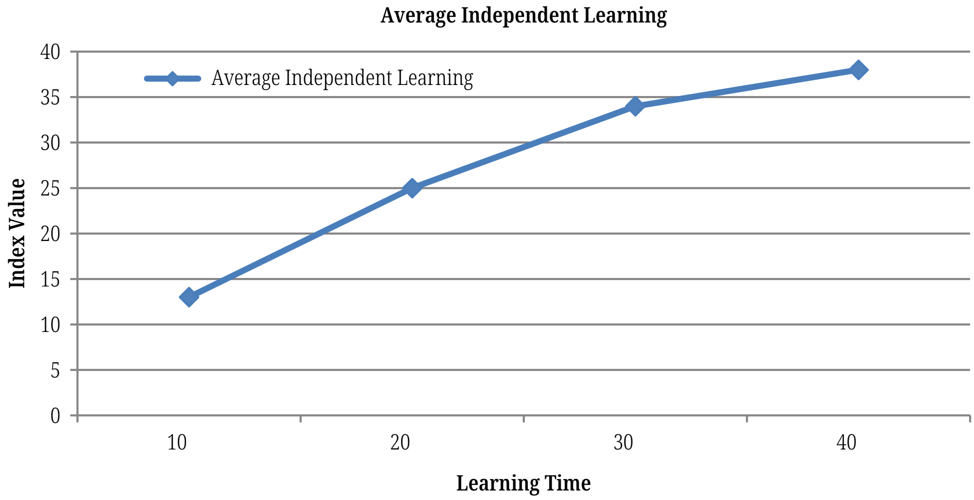

Fig. 7. The sequential structure of the average independent learning skill rating

The experiment's participants were able to handle their self-education period more efficiently and effectively throughout the preceding period, as seen in Figure 8.

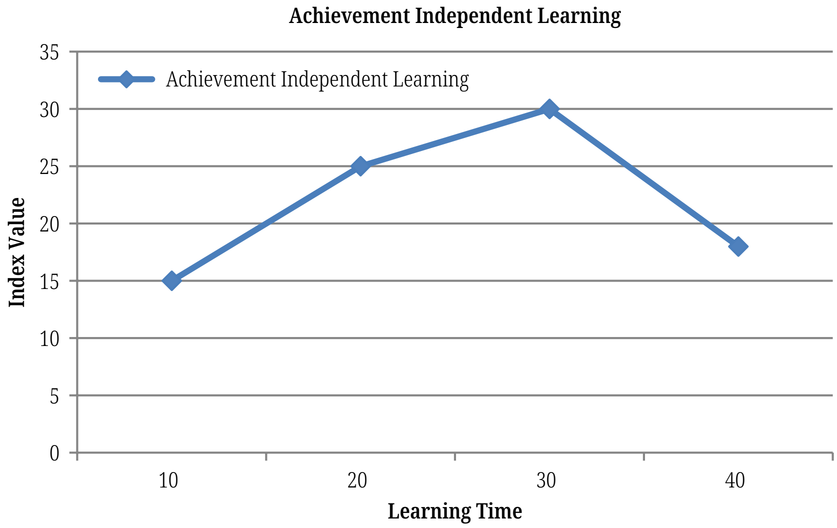

Fig. 8. The educational period index's median achievement in chronological sequence

4.2 Impact of the student's monitoring system

A total of 550 students took the test of competence in 2011–12; of those, 210 took part in the competence course after passing the test in 2012–10. From 2544 hits in 2012–10 to 25, 577 visits in 2011–12, there were more students enrolled in the course. [15] The conduct of pupils who were reached by the observer in 2011 or 12 or who might have received contact in the prior year will be our main focus since we want to increase the levels of involvement.

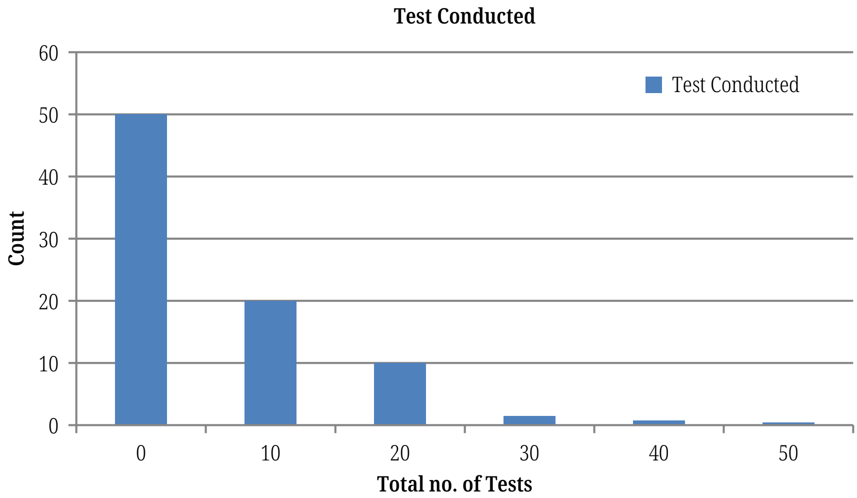

Fig. 9. Analyzing test results for learners who need interaction in November

For students who received notification in November 2011 or could have been approached in November 2012, the breakdowns of the overall number of quizzes finished are displayed in Figure 9. Using a Mann-Whit not parametric test, the disparity between the distributions of data for 2012–11 and 2011–12 was examined because it is evident that these ranges are not normal. They differed significantly ($p < 0.002$) from one another.

5 CONCLUSION

The use of e-learning has completely changed education by providing accessibility and flexibility that are unmatched by traditional teaching techniques. This change does, however, come with some difficulties, namely student engagement and emotional states, which are critical for productive learning outcomes. To assist educators in comprehending and enhancing student performance, this study proposes the IELMS, which makes use of CNN algorithms for emotion and distraction detection. In the asynchronous and frequently isolated world of e-learning, real-time feedback and intervention are critical. IELMS offers a framework for this through the integration of CNN-based emotion detection and distraction monitoring.

The creation of these systems also emphasizes how pedagogy and technology interact, emphasizing the value of flexible learning environments that can be tailored to the needs of each student. To handle the particular difficulties and optimize the advantages of online education, it will be essential to conduct continuing research and put sophisticated monitoring systems such as IELMS into place as e-learning develops. By continuing to innovate and refine monitoring technologies, educators can build more inclusive and supportive e-learning ecosystems, ultimately empowering students to achieve their full potential regardless of geographical or temporal constraints. Educators may create more welcoming and encouraging e-learning environments and eventually enable students to reach their full potential regardless of time or place by keeping up with technological advancements in monitoring.

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7 REFERENCES

[1] H. Fazlollahtabar and A. Abbasi, "A computer integrated framework for e-Learning control systems based on data flow diagrams," *System*, vol. 5, no. 6, 2012.

[2] N. J. Navimipour and B. Zareie, "A model for assessing the impact of e-learning systems on employees' satisfaction," *Computers in Human Behavior*, vol. 53, pp. 475–485, 2015. https://doi.org/10.1016/j.chb.2015.07.026

[3] A. Moubayed, M. Injadat, A. B. Nassif, H. Lutfiyya, and A. Shami, "E-learning: Challenges and research opportunities using machine learning & data analytics," *IEEE Access*, vol. 6, pp. 39117–39138, 2018. https://doi.org/10.1109/ACCESS.2018.2851790

[4] T. Daradoumis, I. Rodríguez-Ardura, J. Faulin, and F. J. Martínez-López, "CRM applied to higher education: Developing an e-monitoring system to improve relationships in e-learning environments," *International Journal of Services Technology and Management*, vol. 14, no. 1, pp. 103–125, 2010. https://doi.org/10.1504/IJSTM.2010.032887

[5] K. S. Maabreh, "The impact of e-learning usage on students' achievements: A case study," *International Journal of Knowledge and Learning*, vol. 12, no. 3, pp. 193–203, 2018. https://doi.org/10.1504/IJKL.2018.092312

[6] L. Dounas, R. Mazo, C. Salinesi, and O. El Beqqali, "Continuous monitoring of adaptive e-learning systems requirements," in *2015 IEEE/ACS 12th International Conference of Computer Systems and Applications (AICCSA)*, 2015, pp. 1–8. https://doi.org/10.1109/AICCSA.2015.7507210

[7] G. Jagadamba, R. Sheeba, K. N. Brinda, K. C. Rohini, and S. K. Pratik, "Adaptive e-learning authentication and monitoring," in *2020 2nd International Conference on Innovative Mechanisms for Industry Applications (ICIMIA)*, 2020, pp. 277–283. https://doi.org/10.1109/ICIMIA48430.2020.9074955

[8] C. M. Baptista, R. M. Silveira, and W. V. Ruggiero, "MSys: A monitoring system for e-learning feedback and content fitting," in *2006 7th International Conference on Information Technology Based Higher Education and Training*, IEEE, 2006, pp. 639–646. https://doi.org/10.1109/ITHET.2006.339679

[9] O. El Hammoumi, F. Benmarrakchi, N. Ouherrou, J. El Kafi, and A. El Hore, "Emotion recognition in e-learning systems," in *2018 6th International Conference on Multimedia Computing and Systems (ICMCS)*, 2018, pp. 1–6. https://doi.org/10.1109/ICMCS.2018.8525872

[10] A. H. Victoria, P. Supraja, V. M. Gayathri, M. S. Khalid, and N. H. B. Sulaiman, "Visualization for emotion detection in mobile-based land monitoring using user-centred design," *International Journal of Interactive Mobile Technologies (iJIM)*, vol. 17, no. 4, pp. 21–36, 2023. https://doi.org/10.3991/ijim.v17i04.37805

[11] G. Chen, "The research on architecture of intelligent E-learning system," in *2009 4th International Conference on Computer Science & Education*, 2009, pp. 1079–1081. https://doi.org/10.1109/ICCSE.2009.5228547

[12] P. Bhardwaj, P. K. Gupta, H. Panwar, M. K. Siddiqui, R. Morales-Menendez, and A. Bhaik, "Application of deep learning on student engagement in e-learning environments," *Computers & Electrical Engineering*, vol. 93, p. 107277, 2021. https://doi.org/10.1016/j.compeleceng.2021.107277

[13] C. H. Liao and J. Y. Wu, "Deploying multimodal learning analytics models to explore the impact of digital distraction and peer learning on student performance," *Computers & Education*, vol. 190, p. 104599, 2022. https://doi.org/10.1016/j.compedu.2022.104599
[14] C. M. Chen, "Personalized E-learning system with self-regulated learning assisted mechanisms for promoting learning performance," *Expert systems with applications*, vol. 36, no. 5, pp. 8816–8829, 2009. https://doi.org/10.1016/j.eswa.2008.11.026
[15] G. Burke, C. Mac an Bhaird, and A. O'Shea, "The impact of a monitoring scheme on engagement in an online course," *Teaching Mathematics and its Applications: An International Journal of the IMA*, vol. 31, no. 4, pp. 191–198, 2012. https://doi.org/10.1093/teamat/hrs010

8 AUTHORS

Wiki Lofandri received a bachelor's degree in the field of informatics and vocational education from Padang State University (UNP), in 2015, and master's degree in informatics engineering from Putra Indonesia University "YPTK," Padang, Indonesia, in 2022. He is currently in office as a lecturer at UNP. His research interests include artificial intelligence, information technology, telecommunications, network security, computer science, 3D modeling, extended reality and adaptive information visualization (E-mail: wiloleaks@unp.ac.id).

Anas A. Salameh is currently working as Associate Professor, Department of Management Information Systems, College of Business Administration, Prince Sattam bin Abdulaziz University, Al-Kharj, Saudi Arabia. He has completed PhD. in Management Information Systems. From 2016 to 2021 he worked as Assistant Professor, Management Information Systems Department, College of Business Administration, Prince Sattam Bin Abdulaziz University. His research interests include MIS, E-Business, E-Commerce, E-Government, Social Integration, SERVQUAL, and Technology Adoption (E-mail: a.salameh@psau.edu.sa).