International Journal of e-Collaboration
Volume 19 • Issue 1

An Improved Computational Solution for Cloud-Enabled E-Learning Platforms Using a Deep Learning Technique

Wenyi Xu, Yunnan Open University, China*

ABSTRACT

The sharable e-learning platform can be presented as a useful learning environment for students on the cloud computing infrastructure. Virtual classrooms are momentarily taking the place of conventional ones, which means that e-learning is becoming more popular. There are currently no strategies for estimating how much cloud resources will be used. Because of this, students can access learning objects without deciding to follow a different learning management system (LMS). The proposed deep learning-based e-learning platform (DL-E-LP) can enable separate LMS embedded in multiple e-learning standards to share the learning objects. Using a smart learning system, teachers can keep track of their students' progress more easily. The convolutional neural network has been used to develop face recognition and monitor students' knowledge learning level in deep learning. The use of modern technologies and smart classrooms makes learning easier for all students. The proposed paradigm is both efficient and productive through experimentation.

KEYWORDS

Cloud Computing, Convolutional Neural Network, Deep Learning, E-Learning Platform, Learning Management System

INTRODUCTION OF E-LEARNING PLATFORM

In online learning, teachers and students can connect using a variety of mediums, including email, online chat, and video conferencing (Semerci et al., 2021). Students will only have one means of communicating (Díaz Redondo et al., 2021). Because many students have a visual memory, they find online learning approaches more appealing (Muzaffar et al., 2021). The classroom is the only place where an effective teacher-student relationship can be formed (Al Rawashdeh et al., 2021). Engagement and questions from a student in a class cannot be duplicated online (Ali et al., 2022). E-learning can be an effective substitute for classroom learning (Ray et al., 2021). It is still the most popular option since it is easier to teach discipline and is a better method of passing on information and knowledge (Gurcan et al., 2021). Due to the advent of online learning, even students with busy

DOI: 10.4018/IJeC.316664
*Corresponding Author

schedules and limited wiggle room can now acquire an excellent education (Tokarieva et al., 2021). Web-based education has made it possible to provide courses worldwide using a single Internet connection (Chen et al., 2021). Standard, digital, and cloud-based education have all come and gone in the education system's history, with the arrival of smart education in the cloud. Traditional learning has been replaced with smart learning, which provides a comprehensive awareness of how to use today's technology to prepare students for a quickly changing world in which adaptability is critical. Students are equipped with a wide range of resources and methods for gaining information at any time and from any location.

E-learning technology, such as mobile devices, digital material, and online learning sources and possibilities, is becoming more popular (Ly et al., 2021). These numbers will expand faster than anticipated under global circumstances (Shetu et al., 2021). There is a growing interest in e-learning research in nations that are very important, such as India, concentrating on computer science and engineering, health, and social science themes (Gherheșet al., 2021). End-user technologies and server-based technologies are now employed in e-learning (Giray et al., 2021). Students employ end-user technology, such as mobile and desktop applications and virtual and augmented reality, to access platforms and material they can interact with remotely (Alshahrani et al., 2021). Server-side technology holds the application and data for cloud-based services (Darejeh et al., 2021). Up to Massive Open Online Courses, there are a variety of courses available (Mangaroska et al., 2021). Due to the growing popularity of e-learning and the vast variety of technologies utilized on both sides, a suitable design of server-side resources has become important (El-Ariss et al., 2021). Cloud resource provisioning has been a research focus, emphasizing forecasting virtual machine resource use (Tawafak et al., 2021). Current research focuses on resource allocation and consolidation, elasticity, workload analysis, and prediction (Mahrlamova et al., 2021). Workload prediction is a major focus of current research, and our study likewise focuses on this kind of analysis (Siew et al., 2021).

E-learning is critical in advancing educational fairness by integrating contemporary education with information technology. Behaviour classification-based E-learning performance (BCEP) prediction framework selects the features of e-learning behaviours (Qiu et al.2022). It uses feature fusion with behaviour data according to the classification model to obtain the category feature values of each type of behaviour. Our approach provides a new way to evaluate e-learning categorization algorithms in terms of their ability to accurately anticipate student success on assessments. An E-learning system's capacity to identify a student's preferred learning method has become more important. A Convolutional Neural Network-based Levy Flight Distribution (CNN-LFD) method was suggested in this study to predict learning style (Alshmrany et al., 2022). Adaptive e-learning systems were separated into learning style prediction and categorization depending on the number of learning styles incorporated. Predict a student's learning style less in image classification using the CNN-LFD algorithm.

Due to the current Covid-19 epidemic, several educational institutions have been obliged to change how they offer the teaching and learning, including providing relevant learning material (Suprio et al., 2022). An online learning platform called E-Learning was created. Students' personal information is at risk from various threats, including assignment theft, piracy, password usage by careless users, and more. The researcher planned to use the Fuzzy C Means method (FCMM) to categorize students' understanding of their E-Learning information security. Students' performance clusters on E-Learning information security have been grouped based on the findings received. Most educational institutions have already started holding online classes to minimize the impact of this epidemic on the education sector. Deep learning-based algorithms (DLA) that monitor student emotions, such as anger, contempt, fear, happiness, sorrow, and surprise, have been described in this study (Bhardwaj et al., 2021). Based on these findings, the Mean Engagement Score (MES) is computed by evaluating the results of facial landmark identification, emotional recognition, and the weights from a survey completed on students during an hour-long class. The suggested automated methodology can achieve a better and unique digital learning technique and a lower participation ratio.

E-learning is a good way to assist students in developing digital and data literacy throughout their studies, especially in the age of Industrial Revolution 4.0. This research aims to determine what elements contribute to students' overall happiness with e-learning (Thoo et al., 2021). The respondents were selected using a sampling method that had a clear purpose, and data were analyzed using a statistical package for the social sciences (SPSS). A favourable correlation was found between satisfaction with e-learning and the mode of distribution and the material content. This study's findings offer an effective teaching approach for general education institutions and achieve a high error rate. The DL-E-LP approach has been suggested to overcome the existing methods, and the DL-E-LP approach has been recommended improving performance, error, assessment, participation, and image classification.

DL-E-LP proposes a solution for the following serious issues: In the first place, no prior research has been done to forecast how much cloud computing resources would be used in e-learning programs. Video streaming and online testing are two examples of activities that might use varying resources. Previous research has relied on a dataset that focuses only on virtual machine activities, lacking specificity. However, the traced tasks do not have any special features that would make it simple to link to an e-learning system while being quite complete in terms of time and the number of analyzed machines. Existing cloud resource monitoring and forecasting approaches do not consider the system's unique properties. It is necessary to include this step to design the monitoring phase correctly.

The main contribution of this paper is,

- Deep learning-based E-learning systems are characterized, their resource consumption is predicted, and modifications are made to the already used resources.
- The basic objective of education is to assist students in experimenting with and discovering their intrinsic abilities and capabilities in new and different environments. It can be good for students with social anxiety to participate online with their peers.
- Predict the use of resources in e-learning applications with the help of a CNN-based model. The accuracy of the video matching categorization can be improved by using CNN.

Accordingly, the rest of the DL-E-LP approach can be organized. Section 3 details the simulation results and discussion. Section 4 concludes the report by going into great depth on the observations and developments that have taken place and the future aspects.

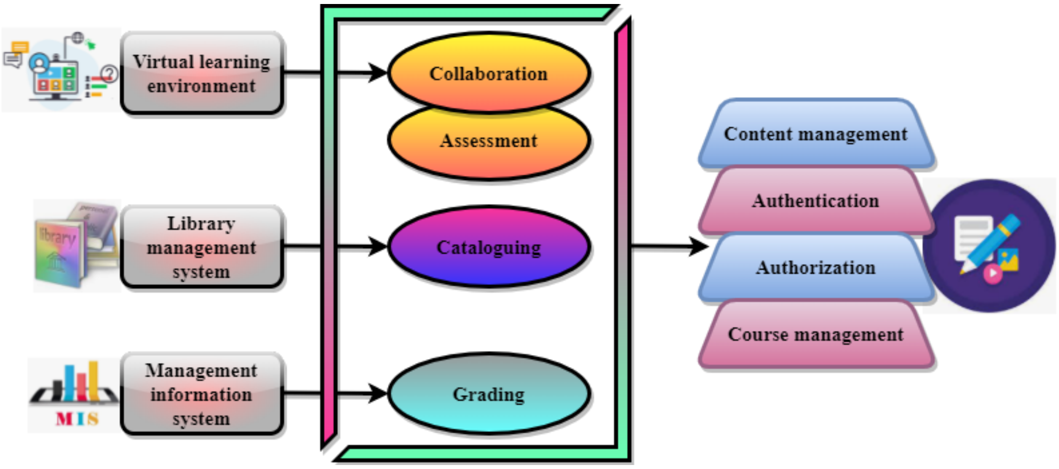
PROPOSED METHOD

Deep Learning-Based E-Learning Platform (DL-E-LP)

E-learning is an effective method of education with DL. Increased demand for educational services, materials, and resources has made it difficult to keep up with the ever-expanding e-learning system's needs. Educational institutions struggle to keep up with the increased demand for information technology assistance for educational research and development operations. DL recovers all the increasing demands in the educational research and development of the Institution. As technology advances, cloud computing presents a great chance to improve e-learning, allowing for resolving many developed issues that can be overcome by DL. For the most part, cloud computing is focused on executing programs as services through the Internet in a scalable environment with DL techniques. Due to CC's technology, students who lack the technical knowledge to maintain their infrastructure can now use cloud computing on demand. The DL-based E-learning platform is more advanced in educational Institutions.

Fig 1 shows the web-based learning system. Internet-based learning is used in traditional e-learning. E-learning through the Internet improves efficiency in educational services since it offers advantages like variety, flexibility, openness, control, and more. A virtual learning environment (VLE)

Figure 1. Web-based learning system



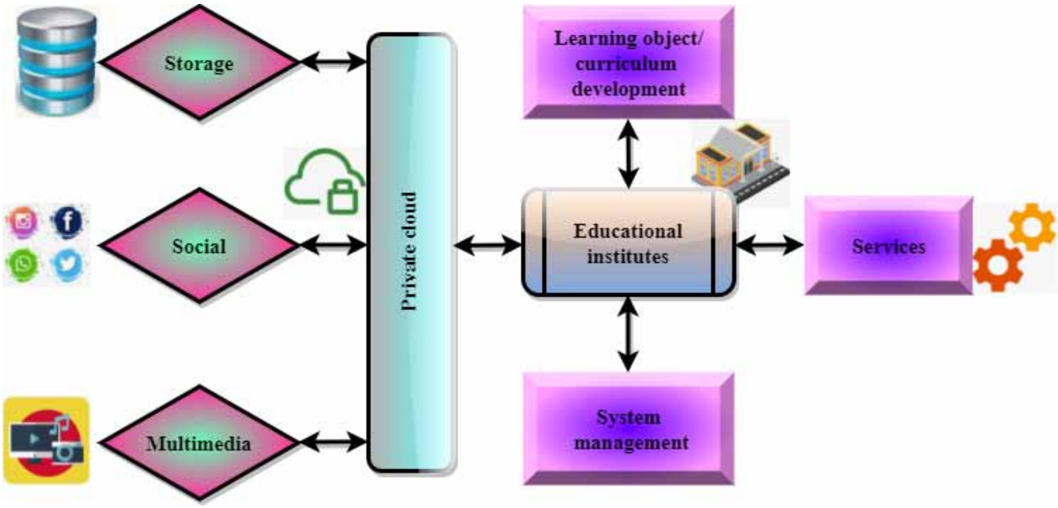
is a web-based platform used to manage the digital parts of educational courses using educational technology. Resources, activities, and interactions are presented in a course structure, and they provide for the various levels of evaluation. A library management system is needed to keep track of everything a library does. Keeping track of new books and those members who have borrowed them and their due dates is made easier with this tool. The library management system is software designed to automate the library's manual processes. The backbone of an organization's operations is a computer system comprised of software known as a management information system (MIS).

Data is gathered, analyzed, and reported on by an MIS to assist management in making decisions. Collaborative learning is an e-learning strategy that allows students to connect socially with their teachers. As part of an e-learning evaluation, an individual's knowledge and abilities can be documented in quantifiable terms using an online technique. In online courses, teachers and managers utilize assessments to determine whether or not students have grasped the material being taught. A catalogue is a collection of classes accessible to students by a school or Institution. They can concentrate on a particular subject or cover a wide range of subjects, such as regulatory compliance. When a teacher grades students, they assess their learning through classroom examinations and assignments, the environment in which that process is set up, and the discussion around grades and how different listeners interpret them. The online course can be implemented for all types of educational institutions like engineering and arts.

The single learning content management system platform handles multi-user creation, delivery, publication, and analysis of content. Authentication is a critical component of an online learning environment. Many E-learning systems enable students to log in to their learning area by authenticating their identities. Assessments, tasks, and discussions fill their personal space. A server assesses whether or not a user has permission to utilize a resource or access a file through authorization. An educational software platform in postsecondary education called a course management system allows teachers and institutions to manage many courses with many students and multimodal learning resources.

Fig 2 shows the architecture of an intelligent E-learning system. The private cloud with smart e-learning to control the cloud services helps to increase the scalability and security in the e-learning environment. The suggested system can provide and exchange educational content using a private cloud and a smart e-learning system. A private cloud environment is provided in this approach, allowing the Institution to have complete control over cloud services. When it comes to reducing IT expenses and increasing scalability, flexibility, availability, and security of the smart e-learning system, cloud computing can be a good alternative. The cloud platform enables educational institutions

Figure 2. Architecture of an Intelligent E-Learning System



to develop and distribute numerous types of learning material that can be accessed through their Learning Management System. For example, virtualization, data sync, multi-sharing, and service provisioning have been integrated into the suggested system to deliver better educational services by integrating with current IT technology. Furthermore, educational institutions can use various cloud service models and the private cloud to deliver better educational services.

Users can store recorded data on a distant network through online data storage using the Internet. As a cloud service component or other solutions that do not need on-site data backup, this data storage approach can be employed using social learning technologies that allow students of all levels to share and learn from one another. Video, audio, visual, and text are included in multimedia eLearning tools, interactive exercises, and quizzes. Students are guided along a predetermined path, where they are required to participate in predetermined activities, exercises, and evaluations. With the help of learning objects, instructional designers can now construct modular instructional pieces that can be reused, scaled up, and adapted to suit a wide range of different learning scenarios. Learning objectives, lessons, and exercises are included in an online training program's e-learning curriculum.

Mathematical Evaluation of Cloud-Based E-Learning Platforms

Cloud-enabled E-learning platforms $\frac{dN}{dR^H}$ have made it possible for students β with hectic schedules to get a high-quality education N is defined as

$$\frac{dN}{dR^H} = 1 - \frac{\beta N}{\beta R^H} + \frac{\beta N}{\beta T^M}\left(1 - \frac{\beta R^{WT}}{\beta R^H} + \varphi\right) + A_k \tag{1}$$

As presented in equation (1), E-learning has a minor effect R^H on academic accomplishment T^M and it has a direct influence on learning time R^{WT} and an unanticipated effect on time spent studying and class length on students' thinking abilities. The number of students φ with the visual aids A_k is implemented for calculating the engagement rate of the student based on the E-learning concept. Many students φ find that visual aids A_k make studying more engaging, which is one of the major reasons they like E-learning A_k is stated as.

$$A_k = \beta Z_k - \alpha G_k - \varphi R_k^F + \mu T_k^L \tag{2}$$

As presented in equation (2), when it comes to learning in a virtual classroom $Z_k \beta$ is the extension of virtual reality, while αG_k is real-time interactions, R_k^F denotes the learning rate, and μT_k^L is the total time spent in training. E-learning has grown in popularity $G_r^{\ k}$ as a function of the efficiency f and accessibility Z^r it provides, as well as a wide range of options $U^k t^k_{\ \ r+1}$ it offers the time h^{k+1} it saves students are given as,

$$G_r^{\ k} = f\left(Z^r h^{k+1}{}_r - U^k t^k{}_{r+1} - Zbd\right) \tag{3}$$

As presented in equation (3), to examine educational resources U^k offered to students in support of their $t^k{}_{r+1}$ educational growth. This includes examining the pedagogical resources Z available to assist students during their educational growth cycle; examining the bd management of E-learning; r referring to innovative drive in training sequences; k noting teaching quality; noting a different way of thinking, and noting development abilities. Achievements in education $B\left(Z\right)$ can be controlled J, and E-learning can be treated w, H as follows,

$$B\left(Z\right) = \sum w, H \prod_{j=1}^{J} \exp d\left(w_j, H_j, V\right) - \gamma \vartheta f\left(w\right) \tag{4}$$

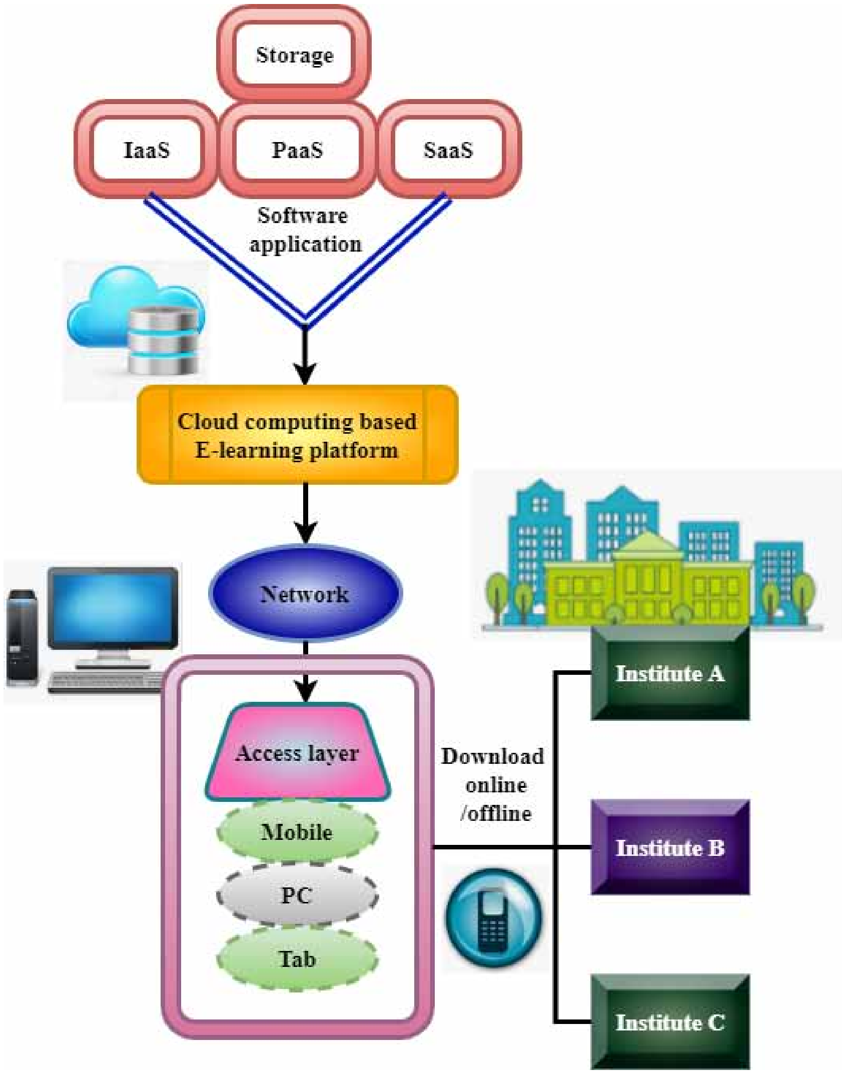
As presented in equation (4), w_j is the administrative component of the training H_j that is used to V provide material, the course $\gamma \vartheta f\left(w\right)$ and to keep track of the teaching process j. Network service innovations $P\left(w\right)$ have created a challenge for the profession, and pleasure in the cloud is defined as,

$$P\left(w\right) = \log\left(R\left(w \mid b\right)\right) - \alpha \ \log\left(M\left(v\right)\right) - \beta \mu f\left(w\right) \tag{5}$$

As presented in equation (5), the interaction process $R\left(w \mid b\right)$ is used to suggest a teaching environment approach α, the logarithm function is adjusted to an auxiliary growth set in a positive proportion to teaching, $M\left(v\right)$ denotes the number of expression boundary prediction environments, μ is the achievement of learning requirements and activities, and refers to a sustainable educational system $f\left(w\right)$ while β indicates content to raise students' interest in teaching. The interaction process in a teaching environment is correlated to an auxiliary growth set in a positive proportion to teaching. The boundary prediction environments lead to the achievement of learning requirements in the educational system that helps to raise the students interest in teaching.

Fig 3 shows the cloud computing-based E-learning platform. Students can benefit from successful multimedia learning through e-learning based on cognitive science concepts. E-learning is a rapid, efficient, and cost-effective method of learning that is convenient for both the user and the Institution.

Figure 3. Cloud computing-based E-Learning platform



Infrastructure-as-a-Service (IaaS) is the fundamental building block of cloud computing, including operating systems, networks, and virtual machines. An established approach for executing applications in cloud computing, Platform-as-a-Service (PaaS), eliminates the burden of maintaining the software systems on the user side. Users can access these application software capabilities whenever they need them using the software (SaaS). The service provider will take care of all of the application's set-up, installation, and operation for users. Data storage is a common feature offered by cloud computing service providers, allowing software applications to store organized and unstructured data.

Enhancement of E-Learning

Due to the rise in smartphone usage, the quality of E-learning is steadily increasing. Every day, the proportion of students using cell phones grows, and they want to make their lives easier. Smartphone users do not wish to utilize laptops or desktop PCs to access numerous applications. Thus, mobile e-learning has become more popular and gaining popularity since it allows students to upgrade their skills and knowledge at anytime, anywhere. Companies are thus devoting greater attention to this technique of education.

An Overview of YouTube/Video-Based Education

Video-based learning has emerged as a popular and potent tool for education. In video-based learning, academics, researchers, and practitioners share their previously recorded lectures on YouTube. Students and teachers can use the films to enhance their understanding, training, and knowledge of a particular course.

Learning In a Forum

Forum-based learning, in which students share their questions, ideas, and issues on a single platform, is another effective method. The proposed method assisted the student in developing their abilities and confidence.

E-Learning in The Context of Social Networks

In today's world of online education, social e-learning is a contemporary method for enhancing learning and a new trend. The student can participate and express student ideas and experiences and find and investigate the most appropriate forms of education for themselves. Students highly regard this tool to help them learn more quickly and effectively.

The architecture's access layer is responsible for controlling access to cloud e-learning services, such as the kinds of access devices and presentation models offered. The multi-channel access idea is used in this research, allowing a range of available services to be received through several devices (such as mobile phones, smartphones, pcs, etc.) and a variety of presentation models. This approach aims to expand the number of devices that can access the cloud service E-learning through the architecture of unrestricted access devices. The cloud computing user layer includes educational institutions from various institutions.

Fig 4 shows the monitoring attendance and class involvement. As one of its primary goals, the E-learning education system administers high-quality education. Statistical analysis is done on the data based on students, courses, teachers' class attendance, and online class status. Teachers and students can use these modules to check their courses' development and the knowledge state of their students. Class attendance, online learning reports, and class status are among the system's most important functions. Real-time surveillance video from the class can be uploaded to a cloud platform for processing through a real-time streaming protocol. In other words, video-based learning is an E-learning approach that utilizes video to help students learn new skills and expand their knowledge.

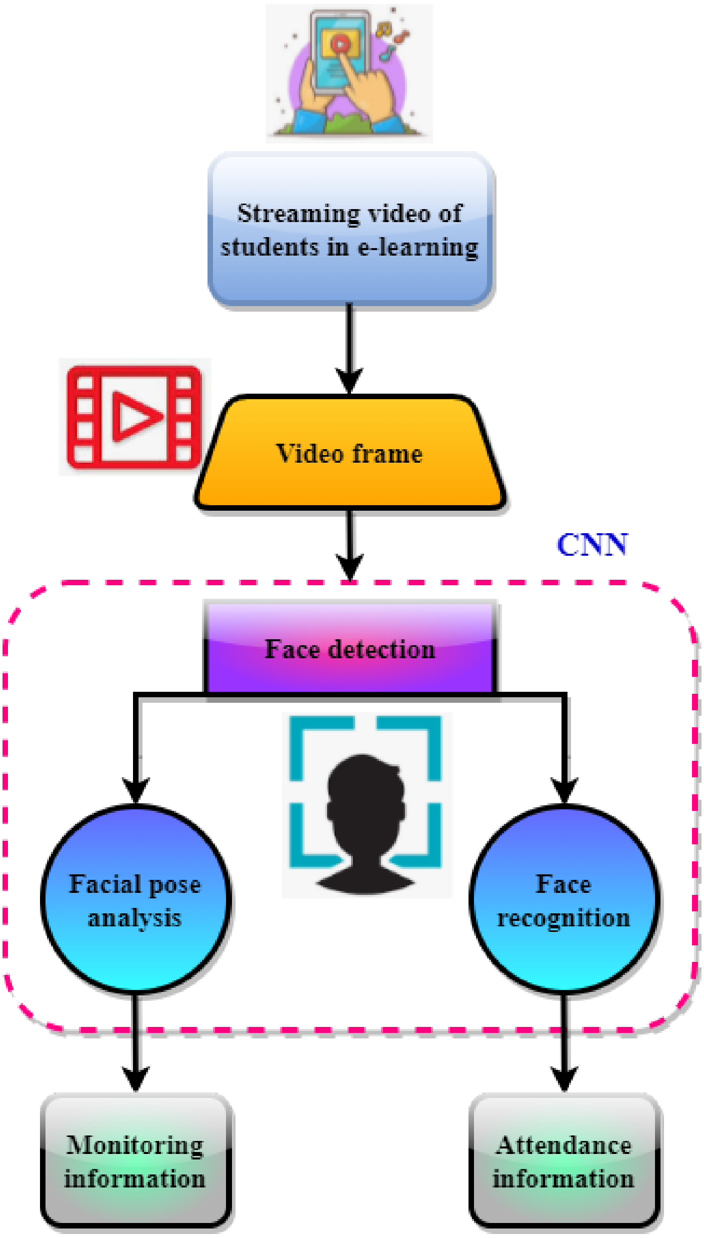
Analysis Of Monitoring Student Activities Using CNN

The framed images on the server are scanned for facial features and body posture, and the findings are then transferred to the database for analysis. Suppose a list of individuals who come missing is added to a database. Teachers' facial expressions, such as rage and a grin, can assist students in interpreting the signals, which can help them adjust their behaviour in the classroom throughout the E-learning and teaching process. A convolutional neural network (CNN) constructed using a classifier can detect students' faces. CNN's P-net, O-net, and R-net flowing networks can be used in the early phases of feature identification to identify face characteristics.

Three training programs L_{uw} are available on CNN, the probability J_{uw} that a CNN identifies a student's phrase can be expressed as equation (6) for binary cross-entropy loss functions $\log\left(\mu_{uw}\right)$ are defined as

$$L_{uw} = \left[J_{uw} \log\left(\mu_{uw}\right) - \left(1 + J_{uw}\right) + (1 + \log\left(\mu_{uw}\right)\right)] \tag{6}$$

Figure 4. Observing attendance and class involvement



As presented in equation (6), the student's image μ_{uw} from the arriving sample photograph. In the CNN feature vector can be written as $bw = d\left(r\right)$.

The Euclidean distance between the vectors can be estimated as follows,

$$Rj^{bw} = \left\|bw_{t1} + bw_{t2}\right\|_2^2 - \left\|du_{t1} - du_{t2}\right\|_2^2 \tag{7}$$

As presented in equation (7), the two images bw_{t1} and bw_{t2}, if smaller than Rj^{bw} they are regarded to be the same student. It is difficult to load and operate on the CNN model utilized for face detection du_{t1} since it has a complicated structure du_{t2} many parameters, as well as significant processing overhead. A cloud-based lightweight network unit y' has been created by combining the remaining module y and the predetermined feature map pooling layer r into a traditional CNN Z_d is given as

$$Z_d = y' + y = G_k\left[H_k\left(r\right)\right] - zz^{;} \tag{8}$$

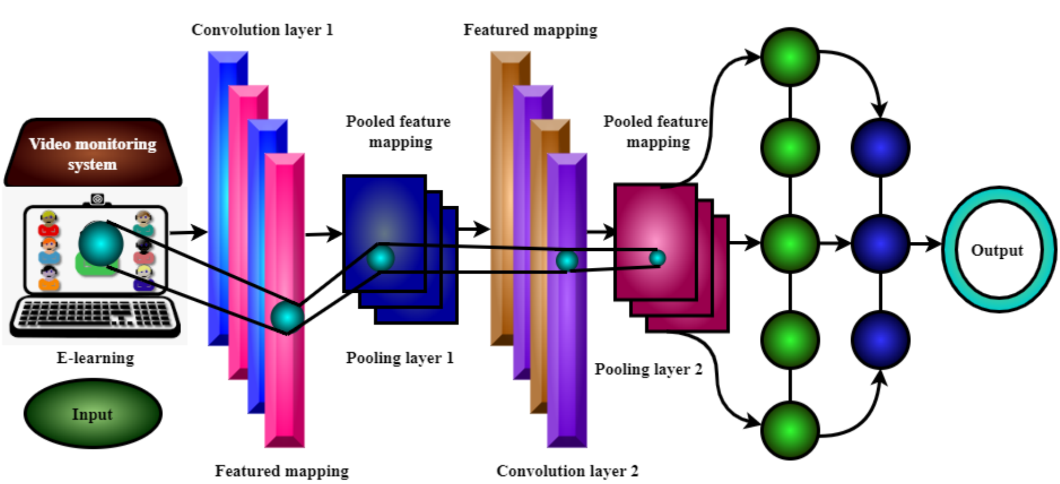
As presented in equation (8), student information G_k and regular daily action $H_k\left(r\right)$ are two distinct images.

Fig 5 shows the convolutional neural network in deep learning. In deep learning, real-time face recognition technology is the objective of CNN. Utilizing frequent E-learning classroom monitoring data, CNN stated that a backward extension of the real-time system architecture had been done using adjustment settings and accurate identifying information. Data sets and real-time inputs must be collected and manipulated to have the best possible recognition accuracy. Due to its ability to recognize a broad variety of full behaviours, CNN's approach has been extensively used in all areas of image recognition. Consequently, it has found new applications in education and training. Many linked neurons make up CNN, and training completes the network's layered structure.

Image Classification Using CNN

Each layer of the network can share the weight of each neuron, allowing that weight to impact the other levels in the network. Some variations between one network include deep short network, backpropagation, and sparse autoencoder. In the deep learning approach, CNN depends primarily on the classification structure of categorized data to train its neural network CNNs are widely used in pattern recognition and classification improvement. These techniques generate small neuronal reception zones in the model's various layers. The sensors are combined with the input to generate n-size maps for local connections. These layers are completely convolutional, and they assess the

Figure 5. Convolutional neural network in deep learning



weights-input split. To develop teaching activities Q^n that help students recognize T the map's distinctive features, and it is necessary to define recognition signals S^n are stated as

$$S^n = T \times \left(Q^n.S - L^n\right) + Z^t \oplus W \tag{9}$$

As presented in equation (9), the number of live-streaming applications on notable websites L^n While the number of frames Z^t And bandwidth deposited W, is referred to as usage in this context.

Feature Extraction

The new CNN model uses feature extraction X_k and fully convolutional layers to identify student activity from exam axial accelerometer data on a mobile device in real-time. It employs a two-layer neural network to evaluate local usability and statistical aspects. It enhances categorization accuracy given as,

$$X_k = L\left(D_k, R_k, T_k^E, R_k^H\right)m + rR_n^{ST}.A_E \tag{10}$$

As presented in equation (10), when students are actively engaged in the learning process, they are referred to as engaged students. The idea of time is approached in various ways by various educational systems. Teachers and teaching assistants benefit from the intellectual class system, classroom issues, and life in general, which aids in their academic interests and performance. Enhancing the academic achievement of students while providing necessary alternatives to significant technological concerns X_k are defined as

$$X_k = L\left(D_k, R_k, T_k^E, \left(R_k^{SU} + T_k^E\right)\right)m - r \tag{11}$$

As presented in equation (11), new students L can be drawn in by the program's ability D_k to be easily learned through the use of modern technology R_k, effective coaching, quizzes, and other fun activities T_k^E. Having an E-learning classroom R_k^{SU} with several teachers r, each with their unique teaching style T_k^E Can cause issues. There is a downside to this, though, since each team regards a distinct perspective m to the table regarding the material at hand and how they teach it.

The net input to the convolution layer E_k is described as

$$E_k = \frac{1}{k}\sum_{c,d}\frac{\left(E_k\left(c,d\right) - E_k\right)}{uD_k} \tag{12}$$

As shown in equation (12), the term convolution kernel k refers to a function mapping, while the term c, d denotes the memory requirements. Teachers u can employ a range of strategies, including E-learning collaboration D_k.

A camera can be used to recognize images W^l in a variety of ways are stated as,

$$W^l = Z^l \circledast T - M^l = \sum_{n=1}^{L} B^{n,k} \circledast H^k - W^l \tag{13}$$

As presented in equation (13), Z^l stands for E-learning performance monitoring, whereas T stands for traditional teaching. M^l a sampled n images of each patch range must be taken into consideration while determining H^k the correlation of any particular patcher $B^{n,k}$.

There is no output mapping before a nonlinear function $G\left(n|n\right)$ is activated as follows,

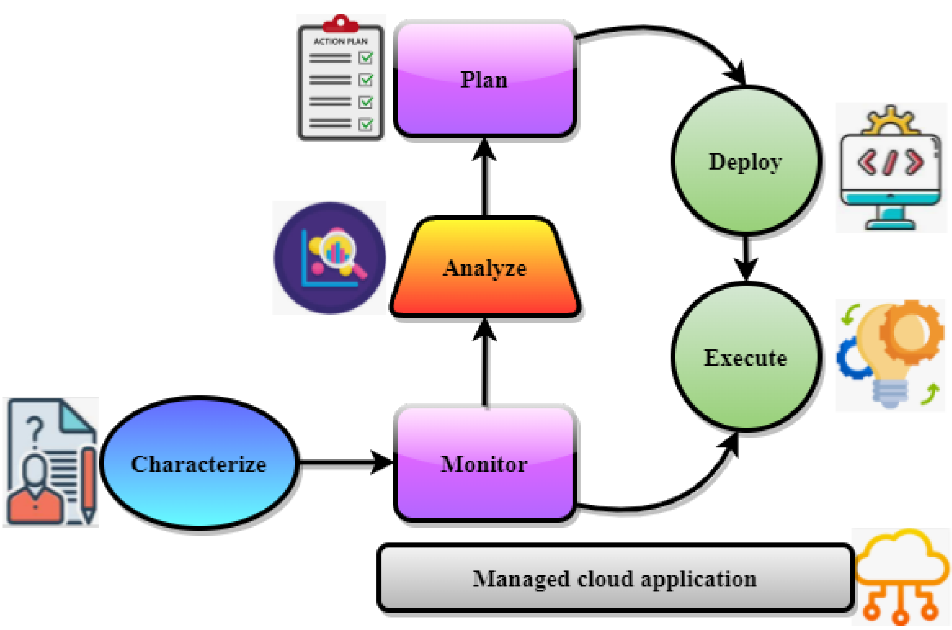
$$G\left(n|n\right) = B\left(n|n+1\right) - Qr\left(n\right).\left(S\left(n\right) + NZ\left(n|n+1\right)\right) \tag{14}$$

As presented in equation (14), websites $B\left(n|n+1\right)$ having video are identified in the overlapping window $Qr\left(n\right)$ by the frame that has been removed. Two categories of data $S\left(n\right)$ are collected, and an average time $NZ\left(n|n+1\right)$ is calculated for each of these variables.

A CNN classification system can be created from the data of two video surveillance participants, which can then be examined. The purpose of each node's frictional variable is defined as the elbow being isolated from other movements. A pooling layer is an additional CNN construction component. The parameters are lowered, and the network is calculated as the representations reduce. Each of the function mappings has its pooling layer.

Fig 6 shows the structure of resource monitoring. Several components must be considered while characterizing the applications or information systems of interest. Any characterization of the investigated applications or systems within the examined category should be the product of this stage. E-learning systems can be used as a case study for the technique in this study. A list of variables can be selected by researchers when the system's characterization is finished. The computing resources

Figure 6. Structure of resource monitoring in the cloud



accessible to running programs and the communication channels available to those apps are represented by these variables of interest, which reflect two aspects of resource usage. Now, depending on the accessibility of the examined system, monitoring tools can become difficult. System architects should be able to decouple the monitoring process by concurrently monitoring separate components.

Monitoring the system cannot be beneficial if various parts of the information system have different resource consumption expectations—well-documented information about how and where to keep tabs on cloud computing platforms. A dataset is expected to be prepared based on academics regularly monitoring a collection of factors. The data gathered during the monitoring phase can be analyzed using suitable models. These models can predict the platform's behaviour. The data is informative in narrowing down the options for algorithm design. According to a recent analysis, some models are more convenient than others for a given task. Academics must consider the characterization of the researched system and the monitored variables to select an appropriate model. Actions to be taken are determined based on the data studied previously.

The findings of the prior step can influence virtual machine and container placement and consolidation. Many studies have been done on the influence of component location in cloud data centres on overall system performance. Architects and academics can still use optimizing algorithms to design the best possible location. Select the necessary resources and apply the adjustments made in the previous step to the solution developed in the previous phase. Nodes can be deployed in several places, depending on the deployment strategy and the kind of datacenters (cloud). Execute creates a new virtual machine or container configuration based on the current system settings.

The Deploy phase is a new addition to the Monitor Analyze Plan Execute (MAPE) iteration and is distinct from the execute step. The new Deploy phase evaluates which cloud resources should be deployed when required. Depending on the quality of service provided by the providers, the system should intelligently select the resource to be deployed. The system characterization is a new stage in the technique, and it cannot be repeated. Analysts and system architects can now monitor any system using the new technique, regardless of whether they have prior information regarding resource use characteristics. Academics can use characterization to identify the most prevalent categories to build the monitoring architecture. The proposed method improves performance, error, assessment, participation, and image classification.

Numerical Outcome

This suggested Deep learning-based E-learning platform for higher education is predicted to improve smart educational systems. Data gathering started with the consent of 16 students from Brazil, 16 students from the UK, 16 students from Russia, 16 students from France, 16 students from the USA, and 20 students from India on this E-learning platform. Students in higher courses should have their heads down to preserve the system's face-monitoring accuracy across various interference settings. Data for this module's experiment has been collected from security cameras in 45 typical college classrooms for 60 seconds. This study discusses the performance, error, assessment, participation, and image classification are all discussed in this study. An 880-image test set is randomly selected after each video frame to serve as a training set for the algorithm.

Additionally, the dataset includes student demographics such as performance, error, assessment, participation, and image classification using the dataset [26]. The scale factor used by Google Trends for all Google Search data yields the lowest and maximum search interest levels. The technique and procedures used to create this dataset are detailed in the study referred to above.

Table 1 shows the performance ratio. Organizations must pick the highest levels of success feasible to direct and analyze the efficiency of the educational establishment. As derived in equation (13), performance metrics are graphs and statistics that demonstrate how well a student succeeds, what they are capable of, and how well they perform on average. Students' performance ratio is shown in Fig 7. The performance ratio reflects how well students perform based on their responses to the survey questions. The suggested approach has a higher performance ratio of 94.3% than the existing

Table 1. Analysis of performance ratio

Cloud	CNN-LFD	DL-E-LP
Cloud-Brazil	**53.2**	**77**
Cloud-UK	**56**	**92**
Cloud-Russia	**48**	**88**
Cloud-France	**52.2**	**90.2**
Cloud-USA	**58**	**89**
Cloud-India	**51**	**94.3**

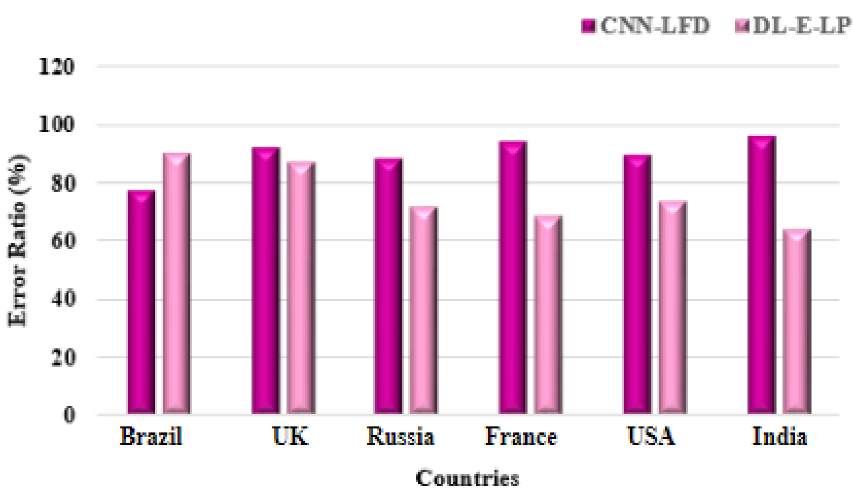
method in Brazil, the UK, Russia, France, the USA, and India. Immediately after data collection, the investigator checks through the findings to ensure no mistakes or contradictions. A CC based on e-learning has been used to evaluate how much the Institution's teaching method has been explored and how it has affected student academic achievement. This boosts the potential of analysis and statistics to improve student performance results.

Fig 7 shows the error rate. Interdependencies between components and well-defined groups of variables should be mapped out in a standard education model. Use E-learning to build diagrams that describe templates. High accuracy, efficiency, and speed levels can be achieved by using them to predict and analyze the interactions between latent structures.

$$r_{gl}^{2}\left(r\right)=\sigma_{fl}^{2}-\left(\int s_{r}\left(u\right)du\right)+p^{2}\sigma^{2}\left(X\right) \tag{15}$$

As presented in equation (15), high error rates $r_{gl}^{2}\left(r\right)$ are blamed on human errors σ_{fl}^{2} or an excessively liberal copy/paste solution $s_{r}\left(u\right)$. Login details p^{2} (username and password) such as the senders have been acquired through email $\sigma^{2}\left(X\right)$ and placed on the platform as passwords. According to this study, mobile learning is influenced by screen size. Compared to CNN-LFD, the

Figure 7. Analysis of error rate



suggested technique lowers the error rate by 63.5% in Brazil, the UK, Russia, France, USA, and India. Despite the smaller screen size of a mobile phone, students had a positive view of E-learning, according to the results, and watching the video decreased their understanding of the subject matter.

Table 2 shows the assessment tasks. A student's homework performance can be evaluated by comparing the number of URL visits to the number of assignments uploaded. Students are instructed to look for comprehensive and useful online information when an e-learning system is established. According to several studies, students driven m to do their assignments are more likely to succeed academically h.

$$p\left(F_l^i, V^k, C^*\right) = \prod_{h=1}^{m} DVQ\left(g_h, d_h, B\right) \tag{16}$$

As presented in equation (16), teachers p who are serious about helping their students succeed F_l^i in school V^k provide helpful assessments C^* Remedial teaching DVQ, and a second chance. There is no uncertainty regarding the individual g_h or group findings d_h. With an 87.5% higher success rate B than the existing method in Brazil, the UK, Russia, France, the USA, and India, the suggested DL-E-LP is a step in the right direction. An important part of education is the assessment of students, which affects decisions about grades, placement, curriculum, and funding.

Fig 8 shows the participation ratio. The teacher has seen a decline in using the user logout alternative as a security precaution. Due to utilizing the recommended platform, most students have decided not to sign off. The security precaution in the form of logging details is shown in the form of the participation ratio. Students frequently close the browser window without signing out of their devices.

$$F\left(\vartheta\right) = \frac{1}{M} exp\left[\frac{\left(z\left(n\right) + z_l\left(n\right)\right)^2}{2F_m}\right] * \tau_m\left(L\right) \tag{17}$$

As presented in equation (17), this issue affects students $F\left(\vartheta\right)$ on many sites on, every website M that requires a user $z\left(n\right)$ to log in. The suggested technique has a higher participation $z_l\left(n\right)$ ratio than the existing approach in Brazil, UK, Russia, France, USA, and India. Mobile devices F_m are on track to replace desktop computers $\tau_m\left(L\right)$ as the primary teaching technology of the future, there will be constant improvement and enrichment in the knowledge of each new group of students.

Table 2. Analysis of assessment tasks

Cloud	CNN-LFD	DL-E-LP
Cloud-Brazil	**47**	**78**
Cloud-UK	**52**	**83.3**
Cloud-Russia	**55**	**79**
Cloud-France	**45**	**85**
Cloud-USA	**51**	**75.8**
Cloud-India	**53**	**87.5**

Figure 8. Analysis of participation ratio

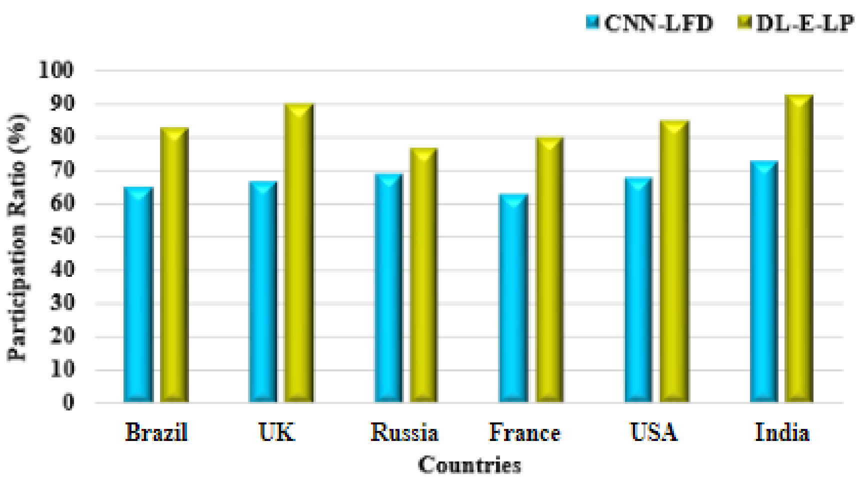
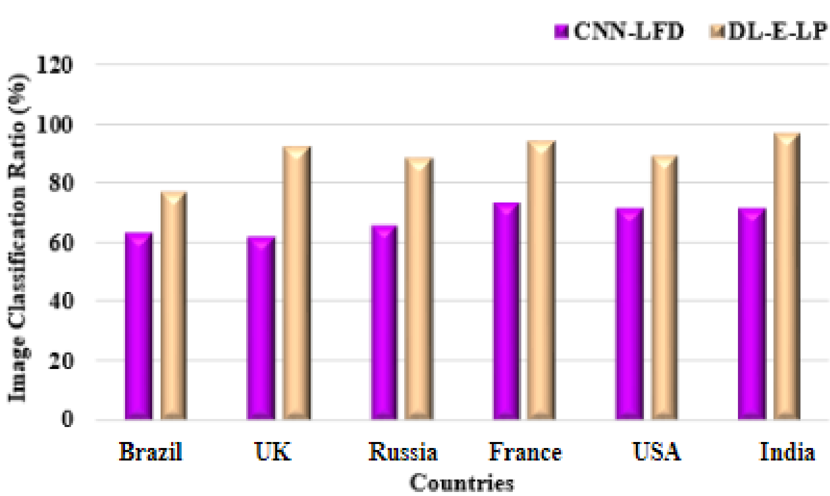


Fig 9 shows the image classification. Data is used to train neural network algorithms to perform several machine learning tasks, such as classifying different types of objects. Convolutional neural networks (CNNs) are sophisticated deep learning algorithms that can analyze images.

$$E_r\left(gt\right) = \frac{1}{dh}\sum_{l=1}^{ch} W_l\left(E_{lt} - ed_{lt}\right) \tag{18}$$

As presented in equation (18), extracting characteristics $E_r\left(gt\right)$ from an image to identify trends dh in the dataset W_l is known as image classification E_{lt}. It would be computationally prohibitive

Figure 9. Analysis of image classification



l to train a CNN model ed_{lt} to classify images because of the massive size ch of the parameters that would be required. Compared to existing methods, the proposed method enhances the image classification by 96.3% in Brazil, the UK, Russia, France, the USA, and India. The proposed method evaluated performance, error, assessment, participation, and image classification.

CONCLUSION AND FUTURE WORK

In the current educational system, students' performance has been recommended to improve by using DL on an e-learning platform. Using the most current teaching techniques and resources, they analyze and reflect on students' expectations and classroom learning conditions. The use and implementation of this new technological innovation should encourage students to pursue higher education beyond the current educational system. Smart classrooms provide new capabilities and techniques of teaching for both teachers and students. It's reasonable to assume that students and teachers are engaged in the digital era. A workplace where students are expected to be skilled with new technologies would help them adapt rapidly. Cameras, remote controllers, and wireless technology are all prevalent these days.

Detail implementations that highlight noteworthy aspects would be an excellent future addition. For example, there are concerns about the disparity in starting and stopping timings between the container and virtual machine deployments. Researchers should be aware of these peculiarities when operating the framework's executor component. Architects can use an optimization technique to determine the best combination of platforms to employ if several nodes are required. DL-E-LP could be improved to detect anomalous activity, which could be useful in spotting emerging cyber-attempts with the help of Machine learning techniques in the future.

Learning objects can be shared across several E-Learning standards using the proposed Deep learning-based E-Learning platform (DL-E-LP). Teachers can keep track of their students' development more readily with the help of a smart learning system. Students' knowledge levels in deep learning have been tracked using a convolutional neural network. For all children, learning is made easier by the use of modern technology and smart classrooms. The suggested approach can help us better understand certain information systems regarding their resource use. The monitoring cycle should assist researchers in better understanding the investigated system and determining which components to implement with more accurate information. Different algorithms can make predictions based on the factors provided and their intended objective. The experimental outcome suggested that DL-E-LP enhances performance (94.3%), error (63.5%), assessment (87.5%), participation (92.8%) and image classification (96.3%).

COMPETING INTEREST

The authors of this publication declare there are no competing interests.

FUNDING

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors. Funding for this research was covered by the author of the article.

REFERENCES

Al Rawashdeh, A. Z., Mohammed, E. Y., Al Arab, A. R., Alara, M., & Al-Rawashdeh, B. (2021). Advantages and disadvantages of using e-learning in university education: Analyzing students' perspectives. *Electronic Journal of e-Learning, 19*(3), 107-117.

Ali, S., Hafeez, Y., Humayun, M., Jamail, N. S. M., Aqib, M., & Nawaz, A. (2022). Enabling recommendation system architecture in virtualized environment for e-learning. *Egyptian Informatics Journal*, *23*(1), 33–45. doi:10.1016/j.eij.2021.05.003

Alshahrani, M. Y. (2021). Implementation of a blockchain system using improved elliptic curve cryptography algorithm for the performance assessment of the students in the e-learning platform. *Applied Sciences (Basel, Switzerland)*, *12*(1), 74. doi:10.3390/app12010074

Alshmrany, S. (2022). Adaptive learning style prediction in e-learning environment using levy flight distribution based CNN model. *Cluster Computing*, *25*(1), 523–536. doi:10.1007/s10586-021-03403-3

Bhardwaj, P., Gupta, P. K., Panwar, H., Siddiqui, M. K., Morales-Menendez, R., & Bhaik, A. (2021). Application of Deep Learning on Student Engagement in e-learning environments. *Computers & Electrical Engineering*, *93*, 107277. doi:10.1016/j.compeleceng.2021.107277 PMID:36567679

Chen, F. H. (2021). Sustainable Education through E-Learning: The Case Study of iLearn2. 0. *Sustainability*, *13*(18), 10186. doi:10.3390/su131810186

Darejeh, A., Marcus, N., & Sweller, J. (2021). The effect of narrative-based E-learning systems on novice users' cognitive load while learning software applications. *Educational Technology Research and Development*, *69*(5), 2451–2473. doi:10.1007/s11423-021-10024-5

Díaz Redondo, R. P., Caeiro Rodríguez, M., López Escobar, J. J., & Fernández Vilas, A. (2021). Integrating micro-learning content in traditional e-learning platforms. *Multimedia Tools and Applications*, *80*(2), 3121–3151. doi:10.1007/s11042-020-09523-z

El-Ariss, B., Zaneldin, E., & Ahmed, W. (2021). Using videos in blended e-learning for a structural steel design course. *Education Sciences*, *11*(6), 290. doi:10.3390/educsci11060290

Gherheș V., Stoian, C. E., Fărcașiu, M. A., & Stanici, M. (2021). E-learning vs. face-to-face learning: Analyzing students' preferences and behaviors. *Sustainability*, *13*(8), 4381. doi:10.3390/su13084381

Giray, G. (2021). An assessment of student satisfaction with e-learning: An empirical study with computer and software engineering undergraduate students in Turkey under pandemic conditions. *Education and Information Technologies*, *26*(6), 6651–6673. doi:10.1007/s10639-021-10454-x PMID:33686329

Gurcan, F., Ozyurt, O., & Cagitay, N. E. (2021). Investigation of emerging trends in the e-learning field using latent dirichlet allocation. *International Review of Research in Open and Distributed Learning*, *22*(2), 1–18. doi:10.19173/irrodl.v22i2.5358

Ly, T. N. L., Nguyen, T. L., & Nguyen, H. N. (2021). Using E-Learning Platforms in Online Classes: A Survey on Tertiary English Teachers' Perceptions. *AsiaCALL Online Journal*, *12*(5), 34–53.

Mahrlamova, K., & Chabanovych, N. (2021). Implementation of interactive methodology in medical education: Blended learning approach, e-learning vs conventional learning. *Linguistics and Culture Review*, *5*(S4), 1154–1160. doi:10.21744/lingcure.v5nS4.1752

Mangaroska, K., Vesin, B., Kostakos, V., Brusilovsky, P., & Giannakos, M. N. (2021). Architecting Analytics Across Multiple E-Learning Systems to Enhance Learning Design. *IEEE Transactions on Learning Technologies*, *14*(2), 173–188. doi:10.1109/TLT.2021.3072159

Muzaffar, A. W., Tahir, M., Anwar, M. W., Chaudry, Q., Mir, S. R., & Rasheed, Y. (2021). A systematic review of online exams solutions in e-learning: Techniques, tools, and global adoption. *IEEE Access: Practical Innovations, Open Solutions*, *9*, 32689–32712. doi:10.1109/ACCESS.2021.3060192

Qiu, F., Zhang, G., Sheng, X., Jiang, L., Zhu, L., Xiang, Q., Jiang, B., & Chen, P. K. (2022). Predicting students' performance in e-learning using learning process and behaviour data. *Scientific Reports*, *12*(1), 1–15. doi:10.1038/s41598-021-03867-8 PMID:35013396

Ray, A., Bala, P. K., Chakraborty, S., & Dasgupta, S. A. (2021). Exploring the impact of different factors on brand equity and intention to take up online courses from e-Learning platforms. *Journal of Retailing and Consumer Services*, *59*, 102351. doi:10.1016/j.jretconser.2020.102351

Semerci, Y. C., & Goularas, D. (2021). Evaluation of students' flow state in an e-learning environment through activity and performance using deep learning techniques. *Journal of Educational Computing Research*, *59*(5), 960–987. doi:10.1177/0735633120979836

Shetu, S. F., Rahman, M. M., Ahmed, A., Mahin, M. F., Akib, M. A. U., & Saifuzzaman, M. (2021). Impactful e-learning framework: A new hybrid form of education. *Current Research in Behavioral Sciences*, *2*, 100038. doi:10.1016/j.crbeha.2021.100038

Siew, L. W., Hoe, L. W., Fai, L. K., Bakar, M. A., & Xian, S. J. (2021). Analysis on the e-learning method in malaysia with AHP-VIKOR model. *International Journal of Information and Education Technology (IJIET)*, *11*(2), 52–58. doi:10.18178/ijiet.2021.11.2.1489

Suprio, Y. A. B., & Maulana, M. R. (2022). Grouping Student Awareness on Security Of E-Learning Information Using Fuzzy C-Means Method. *Inform: JurnalIlmiahBidangTeknologiInformasi dan Komunikasi, 7*(1), 33-39.

Tawafak, R. M., Romli, A., Malik, S. I., & Alfarsi, G. (2021, May). Integration of TAM and MOOC for e-learning purpose. In AIP Conference Proceedings (Vol. 2339, No. 1, p. 020056). AIP Publishing LLC. doi:10.1063/5.0044368

Thoo, A., Lee, Y., & Tan, L. (2021). Students' Satisfaction Using E-Learning as a Supplementary Tool. *International Journal of Emerging Technologies in Learning*, *16*(15), 16–30. doi:10.3991/ijet.v16i15.23925

Tokarieva, A. V., Volkova, N. P., Degtyariova, Y. V., & Bobyr, O. I. (2021, March). E-learning in the present-day context: From the experience of foreign languages department, PSACEA. *Journal of Physics: Conference Series*, *1840*(1), 012049. doi:10.1088/1742-6596/1840/1/012049