Scalable Computing: Practice and Experience, ISSN 1895-1767, http://www.scpe.org

Volume 26, Issues 3, pp. 1116–1131, DOI 10.12694/scpe.v26i3.4262

CLOUD COMPUTING-BASED DYNAMIC RESOURCE ALLOCATION, CC-DRAM, FOR ONLINE LEARNING PLATFORM

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Abstract. A cloud classroom is a new type of online education that has recently evolved within the framework of the Internet and education. Learning in a cloud classroom means students access course materials and goals online, collaborate with instructors and peers, and construct their knowledge base via the Internet. There is an insufficient individualized suggestion module and no way to alleviate information overload, which are features of the conventional cloud classroom model of instruction. Hence, this paper proposed a Cloud Computing-based Dynamic Resource Allocation Model (CC-DRAM) to improve content delivery and increase resource allocation in online learning. Consequently, the CC-DRAM operating under the customized recommendation system is used in this research. The system uses a collaborative filtering recommendation algorithm to enhance cloud work scheduling, learn users' preferences, and provide better suggestions. It also allows for the integration and integrated management of different resources through technologies like distributed storage, virtualization, and networking. Based on experimental analysis of the CC-DRAM platform, which provides 24/7 access to digital materials for students and educators, we can now create individualized lesson plans that students and instructors may read, download, print, and share. In this proposed method, the scalability of distributed storage, user satisfaction, performance, the effectiveness of collaborative, and resource allocation metrics are analyzed and compared to the existing method; the values are gradually increased by the ratio of 97.8%, 98.2%, 99.34%, 96.12%, 98.41% respectively.

Key words: Cloud Computing, Resource Allocation, Online Learning

1. Introduction. Cloud computing has revolutionized several sectors, including education, by offering scalable, efficient, and adaptive resources [1]. A cloud classroom is a concept that has emerged in this dynamic setting. Teachers and students in an online classroom collaborate and share educational materials over the web [2]. According to this streamlined access to materials, peer engagement, and instructor support, students are able to build their own knowledge bases. Additionally, it enables students to learn in an interactive and cooperative setting [3]. In evaluation, conventional cloud school rooms have numerous problems, particularly with offering customized gaining knowledge of experiences and dealing with facts overload. Due to its lack of sophisticated methods for offering personalized records, the conventional method often leaves students feeling filled with stuff this is both superfluous or unneeded [4]. Some have proposed the use of the CC-DRAM to address these troubles. By streamlining the allocation of assets and the dissemination of information presented by means of on-line learning systems, this advanced technique pursuits to decorate the educational enjoy as a whole [5].

Advanced cloud computing technology such networking, virtualization, and disbursed garage permit CC-DRAM to efficiently combine and control a various range of educational content material [6]. The core of CC-DRAM is a collaborative filtering recommendation algorithm that powers a custom designed advice device [7]. The system can research user alternatives and offer personalised hints, so the studying enjoy can be customized to suit each person's desires and tastes. Improving cloud work scheduling requires a collaborative filtering advice mechanism [8]. An critical a part of those enhancements is this approach's guarantee of green

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useful resource distribution in keeping with consumer behavior and preferences [9]. In addition to mitigating the difficulty of facts overload, dynamic resource allocation improves the efficacy of content distribution by way of ensuring that students gain enticing and relevant contents [10].

Experiment results exhibit that the CC-DRAM platform efficaciously offers ongoing get entry to to digital pedagogical materials [11]. The ability to view, download, print, and share these resources at any time helps create a more adaptable and responsive learning environment for both students and instructors [12]. Individualized learning paths that address each student's unique needs are made possible with the help of CC-DRAM's facilitation of course plan preparation [13]. Cloud computing (CC) has grown rapidly since students realized its advantages over conventional IT systems. This paradigm enables distributed computing systems, data management, and computing resources via scalable networks, data processing centers, and web services [14]. Thus, this technology is driving the distributed computing revolution and accelerating commercial and public platform development. Users must negotiate and sign a service level agreement (SLA) to access items in utility computing. After signing a contract for computing commodities, users and the CC system (via service maintenance) must cooperate [15]. This marketing approach legally demands CC systems to maintain QoS, hence the internal architecture must dynamically monitor and adjust to demand. The range of innovative underlying technologies, such as web services and micro services, virtualization, dynamic resource allocation, and service farms, has enabled dynamic service delivery regardless of user demand.

Contribution of this paper.

1. Designing the Cloud Computing-based Dynamic Resource Allocation Model (CC-DRAM) to improve content delivery and increase resource allocation in online learning.
2. Introducing the collaborative filtering recommendation system to recognize and recommend each student's choices may meet their needs. This personalized approach aims to improve online classes' inability to customize learning.
3. The paper aims to reduce information overload in online classes, and the proposed CC-DRAM offer educational materials without overloading pupils. This method makes learning more flexible and responsive and improves information delivery.
4. CC-DRAM employs distributed storage, virtualization, and networking to manage instructional resources efficiently. This facilitates the early creation of individualized lesson plans and ensures constant access to digital resources. This method improves online education's overall efficacy by decreasing overwhelming material.

2. Related works. Allocating assets dynamically is critical in cloud computing for optimizing pace, however it faces challenges with power consumption, fault tolerance, and service quality. The cloud computing enterprise faces each and every one of these difficulties directly. In mild of these issues, this paper gives fashions and strategies to decorate cloud computing overall performance. A famous method that complements fault tolerance and strength intake at the same time as lowering makespan and digital system costs is the Spacing Multi-Objective Antlion technique, or S-MOAL. The Adaptive Multi-Objective Teaching-Learning Based Optimization (AMO-TLBO) algorithm can stability masses and store charges by means of adjusting to purchasers' ever-changing expectations. These methods improve virtual machine balance and offer efficient useful resource allocation through tackling scheduling troubles via multi-objective optimization.

The cloud's dynamic resource allocation is considered one of its quality capabilities. However it has considerable problems with power use, fault tolerance, and carrier best. Finding a solution with a purpose to decorate cloud overall performance even as also fixing these vital worries became vital. To higher and extra speedy respond to customer call for for sources, it introduces a model for dynamic resource allocation. To similarly lessen the makespan and rate associated with digital machines, it suggests a multi-objective seek algorithm called the Spacing Multi-Objective Algorithm (S-MOAL) [16]. Its results on electricity utilization and fault tolerance had been additionally investigated. According to the outcomes of the simulation, our method outperformed the PBACO, DCLCA, DSOS, and MOGA algorithms, mainly whilst thinking about makespan.

The cloud data center allocates resources for multiple fine computational granularity jobs, a non-polynomial complete issue. The needs of customers and the capabilities of apps are subject to constant change. It provide a dynamic resource allocation technique in Cloud computing using an Adaptive Multi-Objective Teaching-Learning Based Optimization (AMO-TLBO) algorithm to close the gap between the ever-changing customer requirements and the available service infrastructure [17]. Adaptive teaching factors, tutorial training, self-motivated learning, and the number of instructors are all introduced by AMO-TLBO to enhance the capabilities for exploration and exploitation. Minimizing makespan and expense while optimizing utilization by load balancing among virtual machines are the aims of AMO-TLBO. Machine learning and AI have provided practical solutions to complicated issues such as energy efficiency, workflow scheduling, video gaming, and cloud computing. Combining machine learning and cloud computing techniques improves cloud data center performance compared to existing examiner solutions. It also aids virtual machine migration depending on network congestion and bandwidth availability. It uses machine learning categorization to show improvements in dynamic load allocation, work scheduling, energy optimization, live migration, mobile cloud computing and cloud security [18]. Machine learning algorithms are popular analytical methods that help computers find patterns and simplify learning. Introduction, motivation, preliminary analysis, framework for cloud-machine learning integration, best practices for incorporating machine learning in cloud computing, and work target make up the paper. The analysis also discusses machine learning-based cloud services and AI in cloud computing platforms. This complete analysis of machine learning techniques and cloud computing gives researchers with insightful and essential resources.

When compared to cloud computing, edge computing is capable of efficiently resolving the issue of excessive latency that is present in cloud gaming. However, there are still a number of obstacles that need to be overcome to maximize the performance of the system. Unpredictable gaming demands might overburden servers and networks however, player movement makes the system dynamic. A tradeoff between fairness and latency has been generally disregarded, despite the fact that prior work has investigated game fairness and latency independently to enhance the Quality of Experience (QoE). Optimization also faces network and computational load balancing constraints [19]. It present an adaptive resource allocation technique for a dynamic gaming system that makes use of Deep Reinforcement Learning (DRL). This strategy takes into consideration latency, fairness, and load balancing all at the same time. This method solves difficult multimodal reward issues better than standard optimization and classical reinforcement learning algorithms, according to experiments.

Cloud computing is a milestone in commercial distributed computing and offers promising possibilities. It uses virtualization to aggregate large resources from disparate locations for unified administration and consumption. Optimization of virtual machines allocation improves resource usage, reduces expenses, and saves computation time. A multiobjective optimization strategy for dynamic resource allocation for multivirtual machine distribution stability is proposed in this paper. Each application load's present and future anticipated statistics are used to calculate virtual machine relocation costs and stability [20].

The operational model is laid out to illustrate the interdependencies between the variables. This study takes an explanatory approach by surveying 143 college students utilizing cloud-based e-learning. Data quality is ensured using descriptive statistics and validity tests, while hypothesis testing utilizes Mediated Regression Analysis. Social influence has an unclear direct effect on cloud-based e-learning, although relative advantage and user happiness have a beneficial effect. Adopting cloud-based e-learning is complex, as behavioural intention does not mediate the interactions as imagined. This research helps fill gaps in understanding how educational institutions evaluate new technologies by shedding light on the complex dynamics in the decision to use cloud-based e-learning [22].

The Cloud computing-based online and offline hybrid teaching resource-sharing method is constructed with a three-tiered cloud platform for sharing virtual and physical educational materials; this platform will employ the fuzzy neural network model and the Tucker decomposition technique to combine the features derived from the resources. The next step is to develop a paradigm for sharing teaching resources that utilizes layered agent technology. This model will allow for the combination of online and offline teaching resources. This paper presents a design method that consistently achieves a resource request success rate of over 80%, a maximum data sharing of over 98%, and a sharing time of less than 1 s. Experimental results confirm that this method has a high sharing efficiency [23].

Mobile learning technologies (MLTs) allow for discovering correlations and patterns relevant to adaptation via examining extensive datasets that include markers of student behaviour, performance, and engagement within online platforms. By looking back at factors, including teachers' level of technical competence, their level of motivation, and their capacity for self-regulation, the OLAMLT framework may provide tailored suggestions.

The project aims to bridge the gap between the need for flexible learners and the lack of resources to cultivate this important quality by promoting focused educational interventions. The author hopes that by strengthening online learning systems, it can better withstand and recover from future shocks, such as pandemics or other unexpected obstacles. Thanks to this study, education technology and pedagogy have taken a giant leap forward, which adds to the continuing push for a more robust and flexible online learning environment [24].

An online learning management system that can be accessed anytime and anywhere makes managing learning materials, course administration, and digital interaction with students easier. These are some ways a cloud-based learning management system can improve access and quality of education. This is why this research was carried out. Quantitative approaches were used in this study. This approach is a means of gathering testable facts and numerical information. Student questionnaires were distributed to gather data. In addition, you will have access to the data in Excel format, which may be analyzed using SPSS according to the findings of the questionnaire distribution. According to the study's findings, a cloud-based learning management system can potentially increase the quantity and quality of educational opportunities. Beyond that, a cloud-based learning management system may enhance instructors' competitive performance in the classroom [25].

This research used various statistical methods to delve deeply into the complex issues surrounding cloud computing and its consequences. Several statistical methods were used to examine the data in this extensive study. These included t-tests, descriptive statistics, and analysis of variance (ANOVA). This study highlights the significance of skillfully addressing localization, script support, and linguistic differences in disseminating Arabic information. This research highlights the significant possibilities of cloud computing to improve online education's effectiveness and user experience [26].

Agricultural professionals may use a high-efficiency online learning platform in the cloud that employs real-time streaming analysis to track the network string flow as users watch videos and dynamic allocation to get the most out of each server. Users may stay inspired while enrolled in top-notch virtual classes. It wants to build cloud-based course materials tailored to agricultural knowledge to enhance user motivation and learning effectiveness. This study used satisfaction surveys and the UTAUT model to evaluate the research results further. The model determines whether the positive effect of users' performance expectation, effort expectancy, social influence, and enabling factors on perceived satisfaction and usefulness is significant. Based on our verification of this fact, this study deduced that digital learning may greatly benefit the agricultural community [27].

Many primary critical success factors (CSFs) and subfactors affect sustaining success in M-learning. This research evaluates and ranks several primary and secondary components of CBML. In both crisp and fuzzy settings, the primary components and subcomponents of CBML were examined and modelled using approaches based on fuzzy analytic hierarchy processes (FAHP) and analytical hierarchy process-group decision-making (AHP-GDM). Higher education institutions must address these primary and secondary aspects to achieve their goals in the teaching-learning system and implement sustainable M-learning [28].

Based on the survey, there are several issues with existing models in attaining high scalability of distributed storage, user satisfaction, performance, the effectiveness of collaboration, and resource allocation. Hence, this study proposes a Multi-objective Optimization Genetic Algorithm(MOGA) to overcome existing problems. The simulation results suggest that the MOGA Virtual Machine Distribution approach has a longer stability time than the genetic algorithm for energy saving and multi-virtual machine redistribution overhead. To address this problem, the MOGA multi-objective optimization dynamic resource allocation approach is introduced for virtual machine distribution. The findings of the proposed method simulation show that these strategies are more effective in managing cloud resources reliably and efficiently than the current methods.

3. Proposed Method. The dynamic and effective gaining knowledge of environments has been ushered in by the combination of cloud computing within the constantly converting subject of training technology. In this studies, a entire framework for enhancing the distribution of instructional substances and aid optimization the usage of smart cloud-based structures is introduced. With the use of cloud computing, information analytics, and sensible allocation algorithms, the cautioned technique seeks to absolutely transform the way that training is taught and learnt. Cloud computing's feature is to assist instructional establishments store charges and deal with their essential enterprise. While vendors pay for the prices of supplying hardware and software, instructional establishments are best paid for the services and sources they use, consisting of computer and

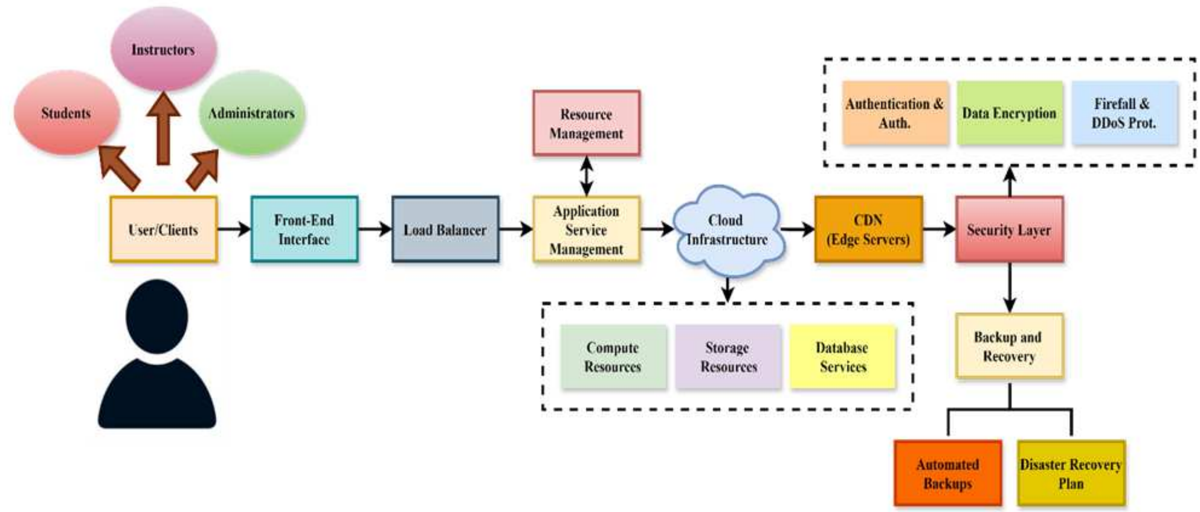

Fig. 3.1: Cloud Infrastructure for Online Learning Platform

storage sources, specialised clinical software program structures, and lecture substances.

A complicated digital atmosphere with many components is interacted with by users/customers. A front-stop interface, typically an internet or cellular app, permits users consisting of students, instructors, and directors to get entry to the machine. Application servers oversee content material transport and scalable instances; a load balancer makes certain that traffic is shipped correctly amongst them. Within a cloud structure, those servers run applications that employ storage, computation, and database services. A Content Delivery Network (CDN) with strategically positioned area servers optimizes content material delivery for advanced overall performance. Authentication, encryption, and defence towards threats like dispensed denial of provider assaults are all a part of a safety layer's activity to maintain person facts and their privateness secure. Data loss and gadget outages may be prevented by backup and restoration procedures, consisting of computerized backups and catastrophe recovery plans. All matters taken into consideration, this complicated layout locations an emphasis on dependability, scalability, protection, and person experience, permitting customers to have interaction with the platform without any hitches whilst yet ensuring the safety and accessibility of their information shown in Fig.3.1.

$$U_j j = J(-N < T_p < -1)U_p j, p + J(T_p < -N)u^J u, n+1 \tag{3.1}$$

Users' satisfaction or utility levels throughout defined time periods T_p are denoted by the equations $U_j j$ and U_p, respectively in Equ.3.1. The notation N denote distinct time intervals that allow for modifications to be made to the allocation of resources. The concept of iterative improvement and updating of consumer needs and satisfaction (u) across subsequent time periods (n+1) is implied by the phrase u^J u,n+1.

$$D_o qw = GP(-Qa < Ws_p < -1)CU_p pk, se + O(WdT_p < -W)fu^J mu, nw + 1 \tag{3.2}$$

In the Equ.3.2, D_o and qw, the demand and quality of service weights are represented. For a certain process CU_p, the range that is appropriate of workload Ws_p is represented which guarantees that it remains within optimum bounds. The term GP $(-Qa < Ws_p < -1)$ is used to describe the efficiency of resource utilization or computational utility for process p, which is affected by parameters pk and se. To make sure the distribution of workloads over time Ws_p stays below a threshold W, the optimization function is shown by the component $WdT_p < -W$.

$$QV_q(u) = \frac{1}{\forall_e d(u)} \sum_{n=1}^{P} Q + e \sum_{f}^{e} r + s * (w + at) - (r_s(u)) \tag{3.3}$$

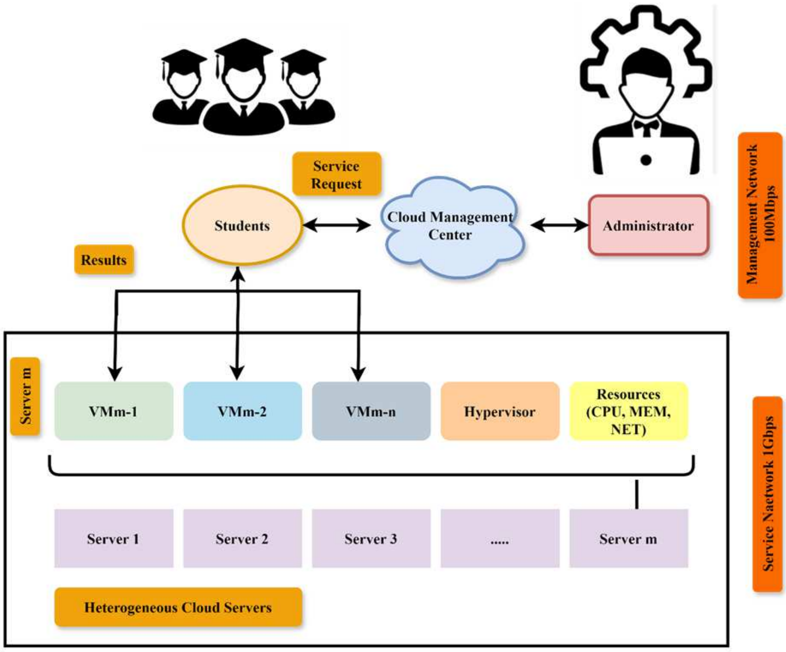

Fig. 3.2: Cloud Computing Approach for Aggregated Data and Information Mining Across Many Platforms

For user u, the quality value is represented by the Equ.3.3, $QV_q(u)$. Every user's overall demand or resource needs are represented by the unit of measurement $\forall_e d(u)$. These measurements are aggregated across P periods or jobs by the summation n=1. In the layered summation inputs from specific resources or tasks are accounted for, and Q represents the basic quality rating inside the summation. e is a scaling factor. With constants r and s, workload w and allocation time at and residual or unsatisfied demand for user, the effective allocation of resources may be represented by $(w + at) - (r_s(u))$.

Cloud computing's statistical Big Data and information mining paradigm, including the Cloud Management Centre and VM servers, is graphically shown in Fig.3.2. Connecting several virtual machines (VMs), the CMC oversees user access for those wishing to utilize the remote statistical analysis services. The CMC also links the various VM servers and handles the VM states. Virtual machine servers are executing user programs. For statistical analysis, please be informed that our cloud computing system provides one virtual machine per user. When processing data offline, administrators have the option of pre-assigning user virtual machines to certain servers; when users are getting statistical analysis findings, these VMs may be maintained in standby mode rather than terminated. Additionally, a management network and a user network are separated to control the networks and provide consistent services. The management network is where user access and VM state management take place. As a result of the ease and effectiveness it provides in managing centralized desktop administration, businesses are increasingly turning to cloud management centres. These centres employ a virtualization approach based on virtual desktop architecture to provide cloud services. This is why we build the cloud-based statistical services into a heterogeneous platform for massive users, capitalizing on the SaaS and DaaS concepts.

$$Q(E) = f^{\frac{-\alpha(g)}{T(U)}} + T(u+1) * \partial T(u) * \partial(F(u)) \tag{3.4}$$

The system's efficiency or quality is represented by the Equ.3.4, Q(E). The influence of a scaling factor $\frac{\alpha(g)}{T(U)}$ across the whole resource time T(u+1) is represented by the expression suggesting an exponential connection in which efficiency declines as load increases. The iterative refinement process is described by the expression

T(u+1), where $\partial(F(u))$ is the time in the following iteration, F(u) is the change in resource time, and $\partial T(u)$ is the change in user feedback or performance metrics.

$$\partial^q(r+1,s,u) = \alpha^q(r,s,e) + T(v) * (1+pqt) \tag{3.5}$$

The modified allocation of resources for the following iteration ∂^q is represented by the equation r+1,s,u, which takes into account the type of resource and the use. The present allocation effectiveness, affected by parameters r, s, and the environment e, is denoted by the expression. The time needed for the process is adjusted by a factor in the formula T(v), where 1+pqt are parameters is an adjustment factor.

$$G(T_B) = \sum_{j=1}^{p}(FG)T_2b^J * (1 + C_F G(H+1)) + (R_f g(k-1)) \tag{3.6}$$

Contribution from every user or jobs up to p are aggregated in the Equ.3.6. The basic gain (FG) T_2b^J a user-specific component is represented by the phrase $1 + C_F G(H+1)$. This gain is adjusted using the equation $R_{fg}(k-1)$ using the factor of correction modified. The next step is to include a residual gain component from the previous cycle's $G(T_B)$.

An interactive getting to know tool, the Cloud Classroom lets in for clean communication among instructors and their students. Digital sources such as readings, downloads, prints, and sharing opportunities are made to be had to students thru an individualized recommendation machine that considers their specific learning necessities. At the identical time, teachers make use of technology for coping with resources to preserve tune of scholar paintings and verify their development. Cloud Classroom Dynamic Resource Allocation Module, or CC-DRAM, is the brains at the back of the Cloud Classroom; it ensures scalability and ultimate resource allocation. Collaborative filtering methods are used in this module to enhance mastering consequences and interactivity. The platform includes assessment measures that measure scalability, consumer happiness, performance, and collaborative effectiveness, in addition to disbursed storage for green records control and retrieval. To take things a step further in phrases of customization, purchaser possibilities are also considered. By offering a flexible, collaborative, and expandable space that promotes efficient instruction, the Cloud Classroom ultimately benefits educators and their students is shown in Fig.3.3.

$$U_j = \sum_{k=j}^{q_r} \forall^{q_1} * \frac{Y^(q1-1) * f^{-\bigcup S}}{\Delta q_j} + PLR\frac{R}{s+q} \tag{3.7}$$

The U_j combines contributions from state k=j in this Equ.3.7. The $Y^(q1-1)$ $f^{-\bigcup S}\Delta q_j$ represents a performance metric where PLR are operates modulated by q_r and the complementary value of s, divided by the gradient $\forall^{q_1}$. The term stands for a universal quantifier function raised to $\frac{R}{s+q}$.

$$PLR([\frac{R}{(s+q)}]) = Q[min(u_j) \ni \frac{O_b}{O}] + (1+sfg) \tag{3.8}$$

The Equ.3.8 in which the variables R stand for resources and the parameters s+q are those that influence the distribution $\frac{R}{(s+q)}$ of those resources. Q is a factor of quality that takes into account the minimal utility for user u_j, conditional on the ratio of observed gain b to optimum benefit $\frac{O_b}{O}$, and the 1+sfg.

$$DS(pe) = \sum_{(j,k)\ni(p,\bigcup,j)}^{r} D_{j,k}(u+1) + (vh+kpr) \tag{3.9}$$

Up to the limit r, the addition of all contribution from pairs $D_{j,k}$ that are components of the combined set $\sum_{(j,k)\ni(p,\bigcup,j)}^{r} D_{(j,k)}$ is represented by the Equ.3.9, DS(pe). The dynamic distribution matrix D for the pairings u+1 updated for the following iteration u+1 is indicated by the phrase $D_{j,k}$.

The User Interface Layer facilitates communication between the educational platform's users (students) and its administrators (teachers) by way of a user-friendly interface. It has features that are customized to

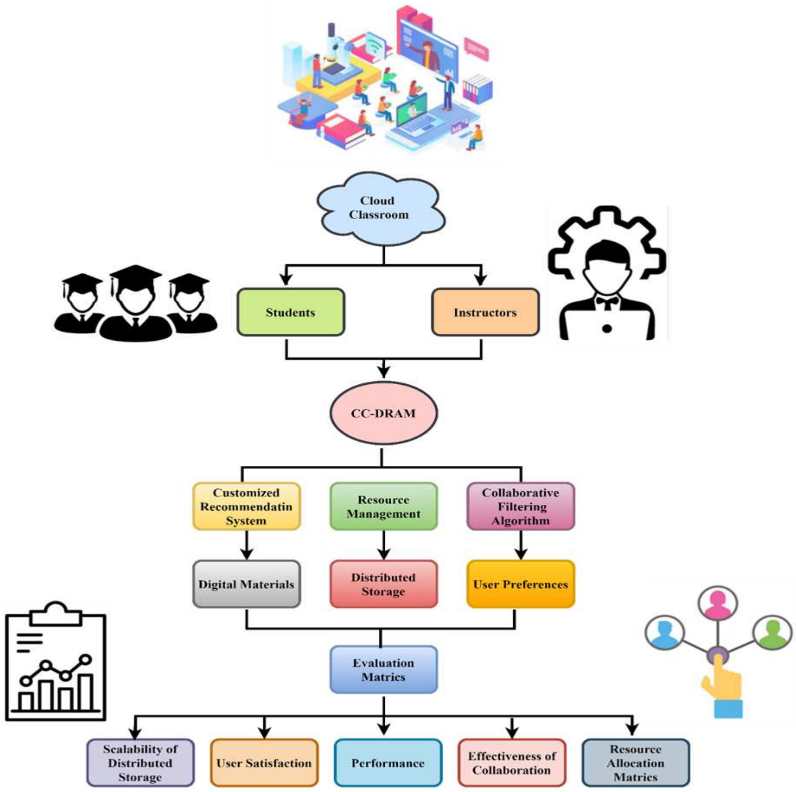

Fig. 3.3: Cloud Computing-based Dynamic Resource Allocation Model

cater to the different requirements of both parties. Under everything is the Application Layer, which is where all the tools for managing content and learning are located. To make sure that instructional materials are easily accessible and organized, here is where the features of content distribution and course administration are coordinated. Incorporating features such as CDN, load balancing, and resource management, the Middleware Layer connects various levels. For steady overall performance and scalability, this sediment optimizes the allocation and use of sources. The platform's functionality and statistics management are supported by way of the VMs, boxes, and database offerings which can be hosted in the Service Layer. Computing, garage, and networking resources make up the Cloud Infrastructure Layer, that's the backbone of the machine and the basis for how the platform functions. Scalability and dependability are guaranteed by CC-DRAM's use of cutting-edge cloud computing technologies, which dynamically manage and allocate computing resources like CPU, memory, and storage according to real-time demand. While improving the user experience and lowering operating expenses, this dynamic allocation ensures constant performance even during high-demand periods. The strong data management approach lies at the heart of CC-DRAM's efficacy. The approach incorporates effective methods for gathering, storing, and analyzing massive amounts of educational data. Data is protected, readily available, and effectively managed using CC-DRAM's scalable storage solutions like data lakes and databases. With this all-encompassing data management strategy, online learning platforms may meet their varied demands, such as keeping track of students' information and course materials and assessing their activities and the results of their lessons. The CC-DRAM system allows online learning platforms to easily adjust to different workloads by combining dynamic resource allocation with smart data management. This connection guarantees the effective and reliable delivery of instructional information while improving resource usage. A vital resource for delivering first-rate instruction, the model can adapt to changing demand and efficiently manage massive amounts of information. Online learning platforms may improve the quality of education

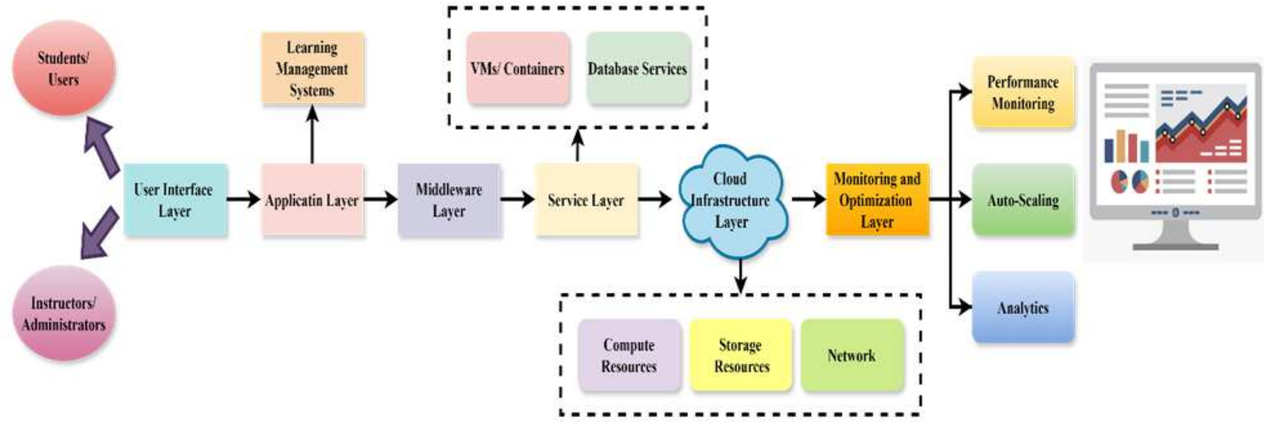

Fig. 3.4: Block Diagram of Cloud Computing-based Dynamic Resource Allocation Model

they provide students by being more scalable, reliable, and cost-efficient using CC-DRAM. Analytics, auto-scaling, and overall performance tracking make up the Monitoring and Optimization Layer, which keeps the device strolling smoothly and effectively at the same time as additionally enhancing the platform's overall performance and consumer experience is shown in Fig.3.4.

$$G_j^e(u) = \sum_{h\forall lhest,k\neq 1}^{p} spef_k * H(u) + \frac{N_k(u) * R_f(N)}{k_j k + e} + (uk + 2) \tag{3.10}$$

The terms up to p in the Equ.3.10 represent the total contributions from $h\forall lhest, k \neq 1$ omitting the values. A particular effectiveness factor $spef_k$ increased by a function of utility H(u) is represented by the expression $G_j^e(u)$. The normalized sum function of the resource is represented as the fraction $\frac{N_k(u)*R_f(N)}{k_{jk}+e)}$, where composite parameter is a setting factor.

$$U_s(u+1) = sf_g(k+1) * H_j^e(k+1) + f * e_k(g+h) \tag{3.11}$$

At iteration Analysis of the scalability of distributed storage, the efficiency of storage allocation for user $U_s(u+1)$ is denoted by Equ.3.11. The interplay of components f and H_j^e regarding g and h parameters, affecting the usefulness of storage, is denoted by the expression $f * e_k(g+h)$.

$$Z_e^q d + e) = (^E_w)sd + (e^f)(u + 2k) + (^f_g e)c(q + w) \tag{3.12}$$

Analysis of user satisfaction Z_e^q and the system's efficiency d+e affected by factors e^f are taken into consideration by Equ.3.12. The last term, $(^f_g e)c(q+w)$, represents the consequences of collaboration between users and resources, which are affected by the parameters sd.

A resource allocation assistance for education is the essential component of the architecture. Information is sent to the resource allocation system via this component, which then releases and allocates resources based on the demand from the school. components of the course materials, class schedules, and more. More "confidence" in the process of changing resource allocation may be assumed, resulting in finer granularity. For instance, aware that there is a class that requires a lot of resources. We pre-allocate resources based on peak-hour demand plus a certain buffer to ensure service quality. So, the resources sit mostly unused outside of the peak period, which is dependent on the school's schedule, but the cloud provider will still take payment. With the system being able to pre-allocate the expected resources before the event, schools would not have to worry about wasting money on idle resources and release resources throughout the schedule's blank spots. Fig.3.5 shows that CC-DRAM approach works just well for both in-person and online class times. When thinking about students using resources and services outside of certain times, the approach would have to change.

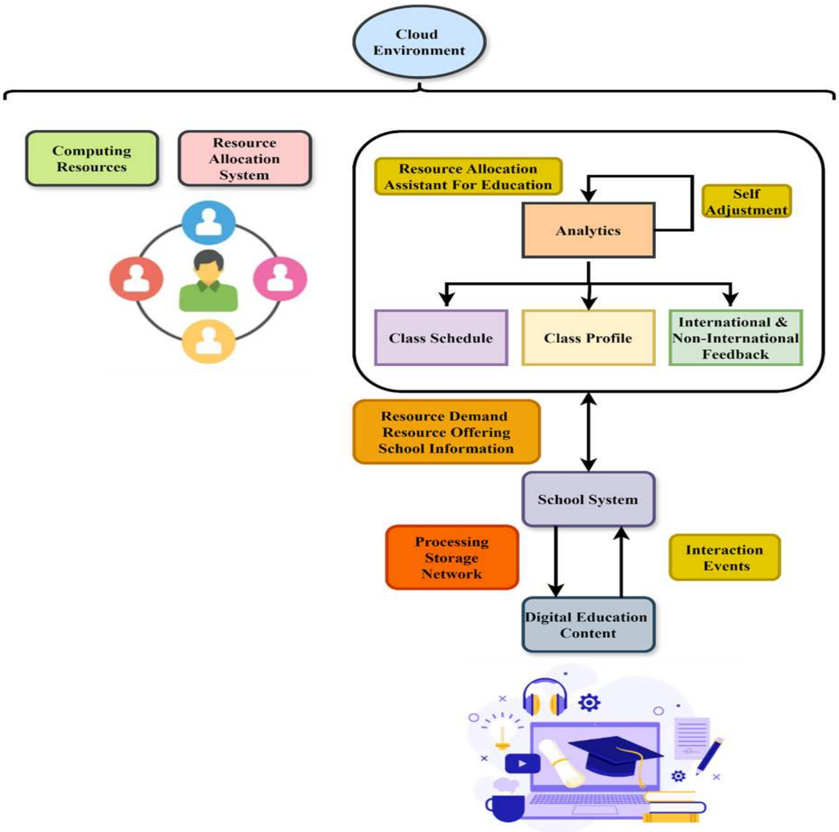

Fig. 3.5: Framework for the Intelligent Distribution of Educational Resources

$$V(u) = V(E_{initiate}, V) + (r + stu_{end}) + e^{-iwt}) \tag{3.13}$$

At the time of initialization in Equ.3.13, the initial level analysis of performance is represented by V(u). The total effect of allocating resources $V(E_initiate, V)$, using the system $(r+stu_{end}$, and a variable representing system stability is accounted for by the expression e^{-iwt}.

$$Z_0.1 + Z_0.2 = U_0 + Xl_e + (U_1 + JR_s) \tag{3.14}$$

Analysis of effectiveness of collaborative separate sources are represented by the Equ.3.14. The basic level of cooperation, denoted as U_0, is affected by the influence Xl_e that is brought about by forces outside of the system $(U_1 + JR_s)$. Furthermore, the adjusted degree of cooperation, denoted by $Z_0.1 + Z_0.2$ component that reflects the combined efforts of collaborators, is also included.

$$A_{01} + B_{03} = E_f(u + 1) + (rsf + (q * w)) \tag{3.15}$$

Analysis of resource allocation within the CC-DRAM system is characterized by Equ.3.15. In this context, the allocation of assets from various sources is represented by $A_{01}+B_{03}$, which adds to the total pool of resources. At the next iteration u+1, the development of the resource environment is represented by $rsf + (q * w)$.

In summary, when applied to educational contexts, the suggested strategy offers a novel way to distribute and allocate resources. Utilizing the capabilities of cloud computing, managers may dynamically distribute resources according to current demand, guaranteeing efficient and effective use. To maximize performance and

Algorithm 1 Code Snippet for an Educational Data-Driven Dynamic Resource Allocation Scheme

1. **Input:** Class Timetable, Class Outline, Device Connections
2. **Output:** Updated Class Outline
3. 1 class – choose Class (Class Timetable)
4. 2 load – get Desired Load (Class Outline)
5. 3 service Delay- get DesiredServiceDelay (Class Outline)
6. 4 service Resources (class.start Time, ServiceDelay, ClassOutline)
7. While request for resources do
   Observe user interaction and resource utilization
   If request changed then
   Alter resources
   Update (Class Outline)
   Free resources

8. Return classOutline

decrease waste, the framework uses advanced analytics to forecast useful resource wishes with pinpoint accuracy. Additionally, students have clean get right of entry to to educational materials through smart distribution, which encourages active participation and teamwork in the school room. Using technology to enhance instructional consequences and alter to the converting requirements of each college students and teachers is an ongoing undertaking, however this new technique takes a massive soar ahead.CC-DRAM's operation is guided by a personalized recommendation system that customizes the distribution of resources according to the preferences and actions of the user. The program determines the best resource allocation using machine learning techniques to forecast user demands and adapt to unique courses. With its adaptive performance and personalized content distribution, this smart system improves the learning experience despite fluctuating workloads. The combination of CC-DRAM's dynamic resource allocation, powerful data management, and personalized recommendation system makes it a critical tool for creating a better educational experience. Online learning systems may become more reliable, scalable, and cost-efficient using CC-DRAM, which means better education for students.

4. Result and Discussion. Several aspects of the CC-DRAM will be analyzed in this paper to ascertain its potential usefulness in enhancing online education. To determine whether CC-DRAM's distributed storage technology can handle the increasing demands of users and the massive volumes of instructional materials, analysts are examining its scalability. The level of satisfaction of users is measured by the feedback they give on personalized suggestions and their overall experience with the site. Analysis of performance primarily aims to determine the system's responsiveness, resource utilization, and availability. The amount of user engagement and the material's relevance are factors in determining the collaborative filtering recommendation system's efficacy. To ensure the best use of storage and processing power, the last step is to assess how well resources have been allocated.

4.1. Dataset description. Cloud computing is popular because it allows users to pay-per-use for on-demand computing. Energy-aware work scheduling improves resource usage and is cost-effective. Traditional task, resource, and energy scheduling strategies fail with cloud computing. The main objective of the analysis is to compare hybrid and conventional cloud computing scheduling strategies. It compares Shortest work First (SJF), Round Robin (RR), Max-Min, and Min-Min work scheduling algorithms [21]. The best resource scheduling algorithms are STAR, Dynamic Resource Allocation Scheme, Autonomous Agent-Based Load Balancing, Credit-Based Scheduling Algorithm, Greedy-Based Job Scheduling Algorithm, Optimal Algorithm, Resource-Aware Hybrid Scheduling Algorithm, and Honeybee Algorithm. Energy-based scheduling approaches for carbon-reducing scheduling are investigated last. The analysis found that Min-Min surpasses the competition in turnaround and waiting time.

4.2. Analysis of scalability of distributed storage:. The work aims to assess the scalability of CC-DRAM's distributed storage technology is described in Fig.4.1. Performance under varying loads and content

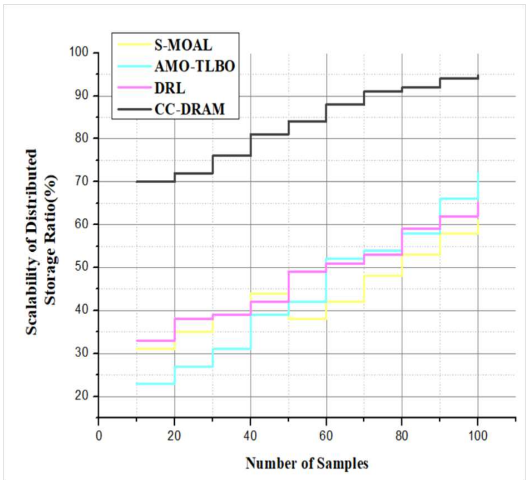

Fig. 4.1: The Graph of Scalability of Distributed Storage

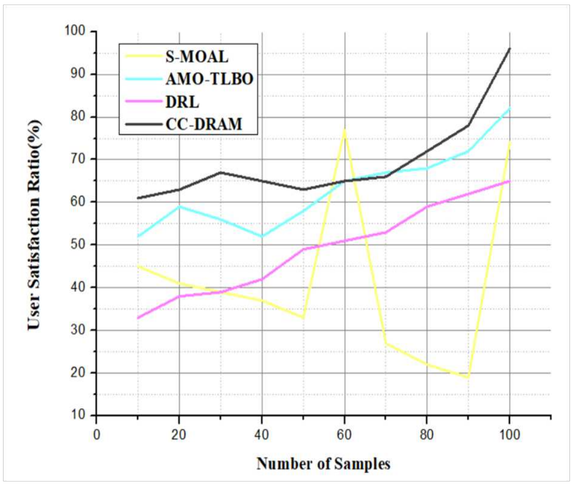

Fig. 4.2: The Graphical Representation of User satisfaction

sizes evaluates the system's capacity to handle increasing user demand and large volumes of instructional materials. According to the results, the distributed storage system can scale well, meaning that it can handle more users and more data without sacrificing speed or availability. Because of its adaptability, CC-DRAM can suit a wide range of educational needs without compromising on economy or speed. The distributed storage scalability is analysed in this proposed method and the values are obtained by the ratio of 97.8% is shown in Fig.4.1.

4.3. Analysis of user satisfaction. The purpose of the analysis is to determine how happy CC-DRAM platform users are with the service generally and with the personalized recommendations in particular which is shown in Fig.4.2. Teacher and student questionnaires and feedback forms show widespread approval of the proposed course of analysis, particularly with regard to its practicality and applicability. The importance of customized suggestions in improving educational outcomes is underscored by user reports of higher engagement and a more tailored learning experience. Positive comments about CC-DRAM indicate that it meets the needs of its target audience. In Fig.4.2, analysis of user satisfaction is improved in the proposed method by the ratio

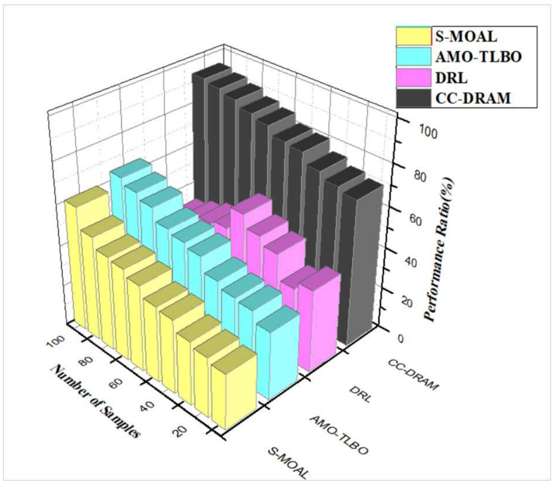

Fig. 4.3: The Graphical Illustration of Performance Ratio

of 98.2% compared to the existing method.

The entire performance of CC-DRAM is examined in this analysis, with a focus on system responsiveness, resource utilization, and uptime (figure 8). Cloud task scheduling and resource allocation efficacy is measured by metrics including error rates, throughput, and latency. When compared with alternative memory technologies, the findings show that CC-DRAM continually provides superior performance, including short latency and efficient use of resources. In addition, the robust performance measurements show that CC-DRAM can handle the demands of online learning environments, guaranteeing that instructional contents can be accessed quick and reliably. The analysis of performance ratio is 99.34% which is increased in the proposed method is shown in Fig.4.3.

Examining how well CC-DRAM's collaborative filtering recommendation system works is the main goal of the present analysis is shown in Fig.4.4. Analyzing data from user interactions and comments, the analysis determines how well the algorithm can understand user preferences and provide accurate and relevant content suggestions. The results show that the collaborative filtering approach effectively makes the learning experience more personalized, with users being more engaged and the content being more relevant. Keeping students' attention and enhancing educational outcomes both depend on its effectiveness. In this proposed method the analysis of effectiveness of collaborative is achieved by the ratio of 96.12% is shown in Fig.4.4.

4.4. Analysis of resource allocation. The analysis aims to assess how well and efficiently CC-DRAM allocates its resources which is explained in the Fig.4.5. The efficiency with which the system allocates storage and processing power in response to user needs and activity patterns is examined. It was found that dynamic resource allocation ensures efficient use of resources, which leads to less waste and ensures that instructional materials are delivered effectively. By distributing information strategically, one can save students from being overwhelmed with data, guarantee that they will only get engaging and relevant materials, and improve their education as a whole. Compared to existing method the analysis of resource allocation is increased by the ratio of 98.41% in this proposed method.

This paper assesses the CC-DRAM platform on many metrics, including its capacity to scale, user happiness, performance, collaborative filtering effectiveness and resource allocation efficiency. The analysis shows that the distributed storage system can readily scale to handle more users and data without lowering performance or availability standards. People are very happy with it, especially when it comes to personalized recommendations. Better utilization is shown by using overall performance metrics while considering aid use and responsiveness. Collaborative filtering permits for a greater tailor-made mastering enjoy, which boosts hobby and retention way to greater applicable content material. Allocating sources well prevents loss and makes sure that teaching gear are used successfully, which in the end results in a higher studying experience normal. When as compared to

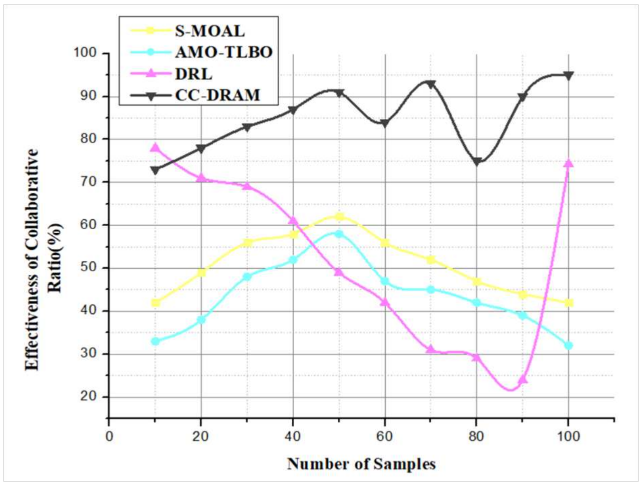

Fig. 4.4: The Graph of Effectiveness of Collaborative

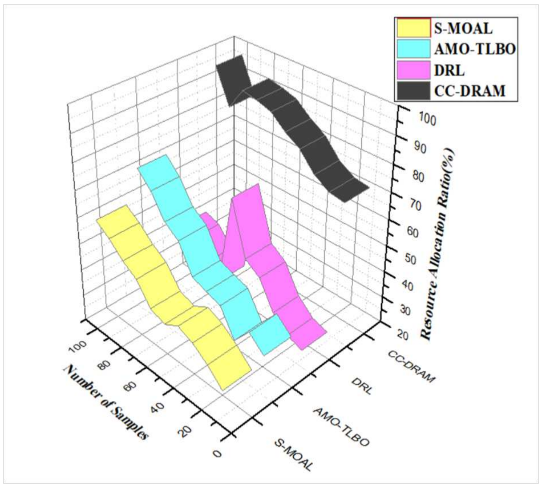

Fig. 4.5: The Graphical Representation of Resource Allocation

the modern-day procedures, every unmarried analysis indicates good sized improvements.

5. Conclusion. The CC-DRAM, which is founded on Cloud Computing, is accountable for a good sized enhancement that complements the skills of on-line studying platforms. This progress is carried out thru the availability of powerful resource management and educational stories that are individualized to the scholar. It is possible for CC-DRAM to personalize the dissemination of material to every person pupil via the usage of a collaborative filtering notion method. This ensures that scholars get assets that are tailor-made to their specific regions of interest. Enhancing mastering results while fending off the downsides of conventional online school rooms, which includes information overload, is one of the advantages of this technique.

5.1. Future work. Future studies will focus on improving the accuracy and adaptableness of advice algorithms as its key number one goal. With the assistance of modern-day device studying techniques, it could additionally be feasible to attain improved customization and predictive analytics. Our primary objective is to enhance the model with extra capabilities that can be interesting to apply and academic assets that can be beneficial. As a result, we believe that CC-DRAM can adjust to the ever-evolving requirements of educators in the modern-day virtual environment.

5.2. Funding.

1. Teaching Reform Project of Colleges and Universities in Hunan Province ”Construction and Practice of Online and Offline First-class Course of International Settlement Based on OBE Concept”, Project No.: HNJG-20231111
2. Project of social science achievement evaluation committee of Hunan Province in 2024:”Research on the promotion of ideological and political education in the era of artificial intelligence” Project No. XSP24YBC033

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Edited by: Dhilip Kumar V
Special issue on: Unleashing the power of Edge AI for Scalable Image and Video Processing
Received: Jul 7, 2024
Accepted: Sep 14, 2024