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Enhancement of Cloud Computing Environment Using Machine Learning Algorithms MLCE

Mohammed E. Seno[1], Ban N. Dhannoon[2], Omer K. Jasim Mohammad[3]
[1]Computer Science Department, Al-Ma'arif University College, Ramadi, Iraq, [2]College of Sciences Al-Nahrain University, Baghdad, Iraq, [3]Head of Quality Assurance and Accridition, University of Fallujah, Fallujah, Iraq
[1]mohammed.e.seno@uoa.edu.iq, [2]ban.n.dhannoon@nahrainuniv.edu.iq, [3]Omerk.jasim@ufallujah.edu.iq

***Abstract*— *Cloud computing is an evolving and high-demand research field at the forefront of technological advancements. It aims to provide software resources and operates based on service-oriented delivery. Within the infrastructure as a service (IaaS) framework, the cloud offers end customers access to crucial infrastructure resources, including CPU, bandwidth, and memory. When a cloud system fails to deliver as expected, it is referred to as an event, signifying a deviation from the anticipated service. To meet their service-level agreement (SLA) obligations, cloud service providers (CSPs) must ensure continuous access to fault-tolerant, on-demand resources for their clients, particularly during outages. Consequently, finding the most efficient ways to accomplish tasks while considering the rapid depletion of resources has become an urgent concern. Researchers are actively working to develop optimal strategies tailored to the cloud environment. Machine learning plays a critical role in these endeavors, serving as a key component in various cloud computing platforms. This study presents a comprehensive literature review of current research papers that employ machine learning algorithms to propose strategies for optimizing cloud computing environments. Additionally, the survey provides authors with invaluable resources by extensively exploring a diverse range of machine learning techniques and their applications in the field of cloud computing. By examining these areas, researchers aim to enhance their understanding of efficient resource allocation and scheduling, addressing the challenges posed by resource scarcity while meeting SLA obligations.*

***Index Terms*— *Cloud computing, Resource allocation Prediction, Energy-efficient resource management, Task Scheduling, Machine Learning.*

I. INTRODUCTION

In the last few years, cloud computing has garnered a lot of interest in a variety of apps owing to its capacity to offer a variety of services accessible through the internet. Consequently, cloud computing is an emerging approach that is rapidly developing [1]. Cloud computing enables apps to deliver infrastructure services to large groups of interested parties with varying continuously changing requirements. Technically, the cloud is made up of data centers and hosts, VMs, and resources. Data Centers include a significant number of resources and a variety of applications. Hosts are made up of many VMs. Hosts store and retrieve user application resources via VMs[2].
The concept of cloud computing is based on the dependability of a service and its timely delivery. There is a common belief that cloud computing would make resources like software more accessible, specifically Software as a Service (SaaS), as well Platform as a Service (PaaS), and the last Infrastructure as a Service (IaaS). As part of their IaaS service, cloud-made infrastructure resources such as CPU, as well as bandwidth, and memory are available to end users[3]. Cloud computing was not a Business-to-Business (B2B) approach, but rather a Business-to-Consumer (B2C) one, which allowed customers to access and utilize software and other services through the Internet[4].

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The challenge of providing services through cloud computing stems from the need to anticipate future demands and reserve enough resources in advance. This issue arises from both the perspective of the client, who seeks to reduce the cost of the service, and the cloud provider, who seeks to maximize the effectiveness of the current infrastructure without making any alterations[5]. Cloud providers must guarantee that their service delivery is adaptable to satisfy the needs of varied consumers[6]. The development of massive cloud data centers to accommodate the needs of end-user applications continues to advance quickly. As a consequence, both academic and industry circles are paying increasingly close attention to cloud computing[7]. Researchers attempt to establish the best practices for cloud resource management, which includes several elements such as virtual machine deployment, job scheduling, and workload consolidation[8].

Researchers are attempting to develop optimum strategies for a cloud environment, which includes numerous factors including virtual machine deployment, as well as task scheduling, else workload consolidation. Machine learning will play a significant part in these endeavors[8]. Predictive analysis of resource utilization is essential for various critical system design and deployment decisions in the cloud, including workload management, and capacity planning[9].

This survey paper sheds light on the Effect of Machine learning Algorithms to get optimal way management resources in cloud computing that reduces energy usage in data centers power and increases the efficiency of service. And help researchers, create innovative strategies that may result in effective solutions.

The rest of the paper is structured as follows: Section II analyzes different current scheduling methods in the cloud computing infrastructure. It provides an overview of certain heuristics, energy consumption, and task scheduling techniques. Section III Role of Machine Learning to Enhancement in the Cloud Computing Environment. Section IV overview of existing studies is presented in this field. The latter sections of the study conclude and provide suggestions for further research.

II. CLOUD COMPUTING ANATOMY

This section offers an overview of the anatomy of cloud computing with details of the significant main part of the environment of the cloud as follows.

A. Cloud infrastructure

As *Fig. 1* the infrastructure of cloud computing encompasses both hardware and software components essential for delivering cloud services to customers. It comprises physical elements such as networking equipment, servers, and data storage. Additionally, cloud infrastructure involves a hardware abstraction layer that facilitates resource virtualization, leading to cost reduction through economies of scale.

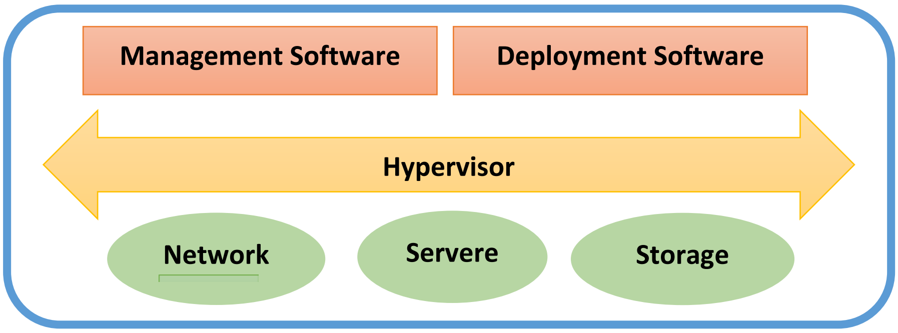

FIG. 1. CLOUD INFRASTRUCTURE.

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Cloud infrastructure comprises several key components, including servers, storage devices, networking equipment, cloud management software, deployment software, and platform virtualization. These elements collectively form the foundation of the cloud environment, enabling the provisioning and management of resources, data storage, network connectivity, and the virtualization of platforms[10].

B. The Resource Management

Resource management is typically an essential topic that is primarily employed in the organization of working duties, which have their own unique applications in problem-solving and decision-making [11]. Due task schedulers have a direct effect on the resource usage and operating expenses of a system[12]. There are two fundamental use scenarios in which allocation is essential: first resource allocation to direct usage, and second resource allocation for the next request[13]. The basic method for optimizing cloud resources concentrates on a specific resource (e.g. CPU) and scalability parameter (e.g. number of VMs)[14]. The cloud computing resources provided to users have access to a resource pool in a cloud environment. Depending on their demands, including performance and cost, users may pick their own configurations, including CPUs, memory, and network bandwidth[3][15].

Computing in the cloud is a concept that relies on a shared pool of remotely accessible resources, which are delivered through the Internet and regulated by an SLA. Because of the massiveness of cloud data centers, resource failure is unavoidable, and it is vital to assure the dependability and availability of such systems. In the event of a problem, cloud service providers must provide a scalable, as well as efficient, and reliable on-demand resource to their clients to meet their service level agreement (SLA)[16].

The challenge with employing cloud computing resources for services is determining the number of resources required and then allocating them. This challenge may be seen on both sides of the client, who is attempting to reduce service costs while still meeting SLAs. From the perspective of the cloud service provider, optimizing resource use helps prevent expensive, unnecessary upgrades[5].
Differing cloud providers may focus several efforts on various areas of resource, like load balancing, maximization of income, minimization of response time, or utilization of server resources, bandwidth, and power[17]. Cloud service providers might have varying degrees of success with resource management depending on their approach[8].
In the next reviewed section various selection procedures to find optimal or suboptimal resource allocation approach is thus difficult, particularly with limited resources.

C. Strategies for Resources Management Scheduling

Inspired by significant literary works presented by [18][19][20][21][22][23]. In general, according to previous studies can be categorize scheduling techniques in cloud environments into three categories: **resource scheduling**, **workflow scheduling**, and **task scheduling**, with this study concentrating only on task scheduling approaches. *Fig. 2* depicts the categorization in its complete. Resource scheduling maps virtual resources to physical computers, while workflow scheduling schedules the processes that comprise a whole project in the proper sequence.
Methods for scheduling tasks might be centralized or dispersed. It may be conducted on reliant or self-reliant tasks in a homogenous or heterogeneous environment.
In centralized scheduling, one scheduler handles entire mappings, while distributed scheduling is divided across many schedulers. When it comes to distributed scheduling, the operational difficulty is significant. However, since the workload is shared across partner nodes in this case, CPU cycles are conserved. Centralized scheduling is simple to set up, but since there is always a single point of

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failure, it lacks flexibility and fault tolerance. There are two sorts of scheduling strategies: The heuristic and also hybrid procedures. The heuristic techniques are divided into static and dynamic scheduling categories. Dynamic scheduling may be done in either online or batch mode and all incoming tasks are scheduled immediately as they are received. In static scheduling, all of the tasks are known ahead of time, and they are fixedly given to virtual resources Furthermore it is easy to set up, but dynamic scheduling is better for real-world situations.

This part develops a hybrid heuristic algorithm by combining two algorithms for example enhanced discrete particle swarm optimization algorithm with the improved ant colony optimization algorithm. Subsequently, a task scheduling strategy for cloud computing is proposed based on this hybrid heuristic algorithm.

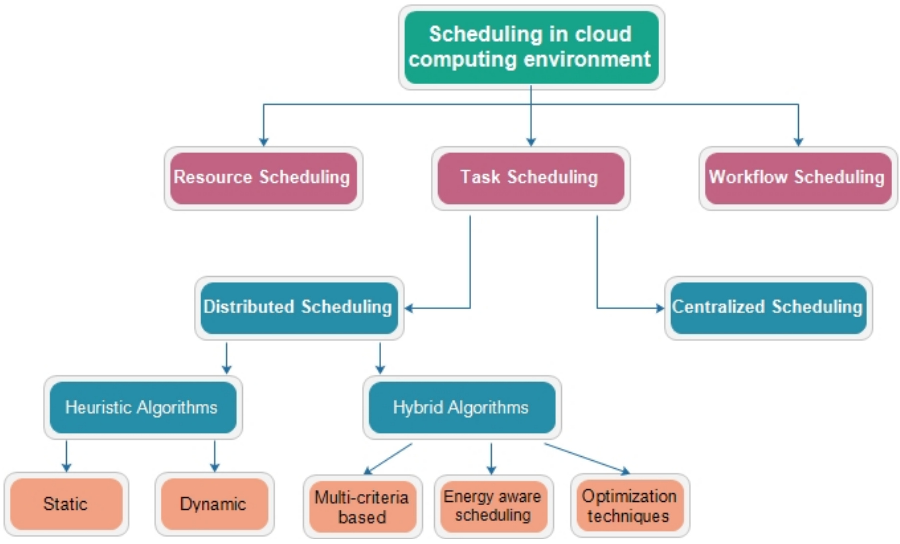

FIG. 2. CATEGORIZE SCHEDULING TECHNIQUES IN CLOUD ENVIRONMENTS.

D. Virtualizations in Cloud Computing

Virtualization is a concept built on top of a distributed system that allows users to move their work from one physical machine to many virtual machines (VMs) located in different physical locations and the host can see the VMs and give them to their users [3].

In cloud computing, a single physical machine (PM) may host several VMs , and each needs it is own unique set of resources[24]. This technology has several major advantages, including better resource usage, lower costs, and simpler server administration[25][26]. Cloud computing primarily depends on virtualization to provide middleware between software and hardware[27].

The numerous users may access data center resources and services, reducing the need to build up their infrastructure to perform tasks that can be done on the cloud[8].

Virtual machine(VM)usage decreases the host's energy consumption[22] and becomes a factor cloud element[28][7]. It has Several distinctive characteristics, one of them is virtual machines (VMs) interoperability with common computer architectures means they can run the same software and applications as hardware platforms. Moreover, the separation of physical resources across VMs considerably improves cloud services' security and availability. Finally, a VM is very accessible and managed because of the setup and packaging of all it is virtualized hardware components within a single image. Since cloud computing has integrated virtualization technology, users have more mobility and expansion, and customers may expand storage space or processing capability[7].

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III. PROBLEM DESCRIPTION OF CLOUD ENVIRONMENT

This section presents a general overview of the problem related to provisioning and allocating cloud resources. The key issues identified are as follows:
A. Portability: The cloud architecture should allow for the seamless movement of virtual machines (VMs) between different cloud computing environments.
B. Pricing and Execution Time: Consumers place importance on the cost incurred and the time required to fulfill their requests. The amount paid should be proportional to the time consumed.
C. Architecture: When designing a provisioning scheme and creating a deployment plan in the cloud environment, it is crucial to consider the architecture of the application or service being deployed.
Efficient task scheduling plays a critical role in maximizing resource utilization and meeting performance objectives in cloud computing environments. To achieve this, selecting an appropriate machine learning algorithm that can effectively handle task scheduling is crucial. This section focuses on the process of finding the optimal or sub-optimal machine learning algorithm for task scheduling in a cloud computing environment.

IV. APPLICABILITY OF MACHINE LEARNING IN THE CLOUD

Machine learning (ML) define is a kind of artificial intelligence (AI) that enables software applications to generate results with greater precision without being expressly programmed for this purpose[29]. Machine learning is used to stimulate and restructure the research and forecasting procedure[30]. Therefore, when data features are utilized to train machine learning, they have a significant impact on model performance[31]. The input for machine learning algorithms is information gathered and used to predict future output values. Along with Big data and data science in general, machine learning is experiencing rapid expansion[32]. Another of the fundamental assumptions is that it is feasible to create algorithms capable of estimating futures. In *Fig. 3* there are two primary categories of machine learning algorithms: supervised as well as unsupervised, in supervised learning, models are constructed based on a set of training predictors X1, X2... Xn and the associated response variable Y, wherefore can represent the relation between the host and the request of the user as the relation between (X and Y). But in unsupervised learning, only predictors exist; hence, algorithms must learn the structure of the training data (clustering)[33].

Machine learning methods are extensively utilized in domains such as computer vision, pattern recognition, and bioinformatics[34][35]. Machine learning approaches are beneficial when applied to a broad variety of difficult issues and sectors such as energy management, workflow scheduling, and so on[36]. It is commonly employed in VM task scheduling[24]. Optimized resource management is a significant challenge in cloud services studies because resource often raises expenses for cloud providers and cloud users [22]. The scheduler is critical to enhancing the scalability and dependability of cloud computing[37].

In research on resource management, the most common categories of machine learning models are supervised, unsupervised, and reinforcement learning (RL)[38]. The adoption of machine learning algorithms on the cloud also opens up new possibilities for using ML to optimize resource management tasks, such as workload estimation as well as task scheduling, also VM consolidation, the as well important part is resource optimization, and energy optimization[35]

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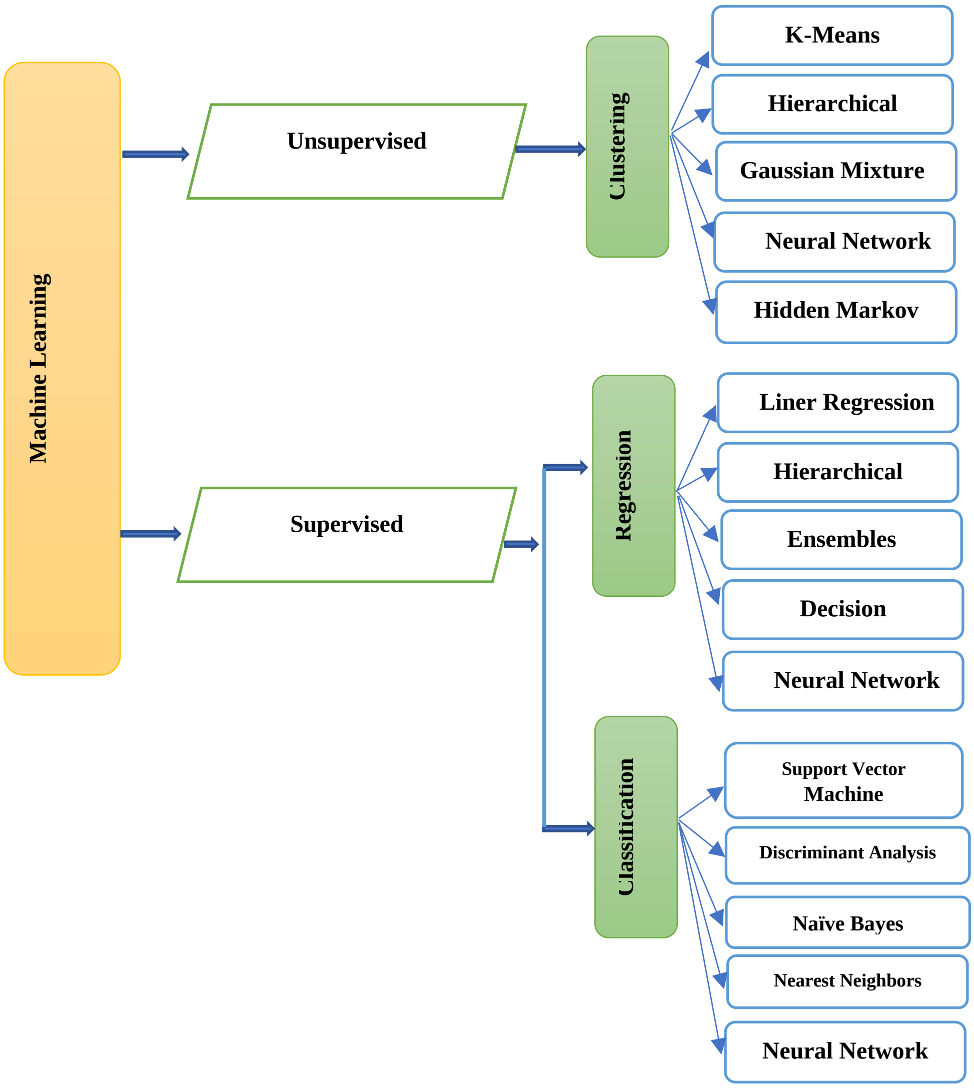

FIG. 3. CLASSIFICATION ALGORITHM MACHINE LEARNING.

V. OVERVIEW OF STUDIES AND ANALYSIS

The aim of this research is seeking to investigate and evaluate to find the optimal or sub-optimal machine learning algorithm applied in a cloud computing environment. So, there are currently no particular solutions to this problem. Researchers introduced studies that have been conducted on different environments and used various optimization methods to find the best result as follows:

Josep Ll. Berral et al [39] present a scheme for an astute integration method that employs various techniques, including turning power-aware consolidation algorithms, and machine learning algorithms to enhance CPU Usage and timing SLAs.

Sadeka Islam et al[9] suggested a model that meets foreseeable resource needs, design provisioning, and monitoring techniques based on predictions using linear regression and neural networks. The findings show that the suggested method provides improved adaptable resource management for the cloud.

Chenn-Jung Huang et al [4] Using support vector regressions (SVRs) to determine the cost of resource usage according to the SLA of each task, a prediction mechanism is implemented, and the

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resources are reallocated based on the present state of all virtual machines running on physical machines. The suggested technique is capable of improving hardware utilization and ensuring the desired quality of service.

Akindele A. Bankole and Samuel A. Ajila[40] built and evaluated cloud customer prediction methods for the TPCW (Transaction Processing Performance Council) web application benchmark as machine learning techniques: using support vector regressions SVM, as well as Neural Networks NN, and linear regression (LR). the objective of Latency and Utilization measuring models.

Ali Yadavar Nikravesh et al[41] presented a model Support Vector Machine (SVM) and Neural Networks (NN) used as time-series prediction approaches, and workloads were used as the performance measurement. According to the performance, this platform may choose the most appropriate prediction approach, leading to more effective predictive outcomes.

Samuel A. Ajila and Akindele A. Bankole[42] In this study, three machine learning approaches are used to create and assess a Cloud client forecast model: Support Vector Regression (SVR), Neural Networks (NN), and Linear Regression (LR). The forecasting model typically includes the level of Latency and System performance to provide service customers with a more effective scaling decision option.

Hussaini Adamu et al[16] suggest a model forecasting hardware model that predicts hardware breakdowns in the actual world in a real-time cloud environment to increase service availability. applied the Linear Regression (LR) Model and Support Vector Machine (SVM) with a Linear Gaussian kernel, offering improved device management, consequently boosting system uptime and avoiding unexpected idle time.

Rafael Moreno-Vozmediano et al[43] develop and assess a new predictive auto-scaling method for time series prediction and queuing theory based on machine learning approaches. The new technique tries to properly forecast a distributed server's processing load and evaluate the optimal amount of resources that must be supplied in order to maximize service turnaround time and meet the user's SLA. The suggested approach enhances prediction efficiency and brings resource allocation closer to the ideal situation.

Zhou Zhou et al[6] introduced a new model by applying four techniques. This study presents a good energy consumption model and assesses it is efficacy in data center energy use, it is important to minimize energy usage while maintaining service quality (QoS). The developed energy consumption model may be used for additional servers in data centers to assist the energy-saving algorithm in reducing energy consumption.

Leila Ismail and Eyad H. Abed[44]presented a new model known as a Locally Corrected Multiple Linear Regression (LCMLR) the primary purpose of achieving an objective comparison, a consistent categorization, and assessment for these linear power models is offered, under a unified setup, benchmarking applications, and error formula to improve prediction accuracy.

Gopa Mandal et al[3] develop a model for VM migration policy from one host to another based on linear regression-based prediction policy for future resource use to enhance prior work on simulated annealing-based optimum load balancing.

Jiechao Gao et al[24] provide a technique for doing the forecast a specific amount of time before the projected time point to enable enough time for task scheduling based on the forecasted workload by offering a clustering-based workload prediction strategy. This strategy performs better than traditional forecasting algorithms in terms of prediction accuracy.

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Piotr Nawrocki et al[5] suggested models use a multilayer perceptron to address the exaggeration of resource use for cloud computing services. Solving this challenge will result in considerable savings for both the client and the cloud infrastructure provider. It highlights the significant value of machine learning approaches for arranging cloud resource reserves for network services.

Nirmal Kr. Biswas et al[17] presented the forecasting model New Linear Regression, The basic goal of the NLR model is for the model to pass through a straight line and a mean point. The suggested NLR model is used to forecast future CPU consumption. The Virtual Machine (VM) consolidation strategy may decrease energy consumption, and SLA violation (SLAV), and boost resource usage.

Ranesh Naha et al[45] Developed a resource allocation system based on multiple linear regression for deploying energy-aware apps in the computing environment. This method reduces device failures caused by power restrictions. The suggested method reduces latency and time consumption by 20% and 17%, respectively, versus the current method.
Jixian Zhang et al[46] Used machine learning classification to construct and evaluate the multi-dimensional cloud resource allocation issue and offered two prediction techniques for resource allocation based on linear and logistic regressions. The findings indicate that the suggested approach has a significant impact on cloud computing resource allocation.

Mohammed E. Seno et al[47] offer a new novel that illustrates the relationship between cloud resource allocation management and machine learning approaches and the importance by deploy of linear regression on task management. Based on the study, the Cloud Liner Regression CLR offers to give an efficient resource solution.

TABLE I. SUMMARY OF PREVIOUS STUDIES

NO.	Authors	Years	Cloud Environment	Algorithm Contribution	Factor consideration	Features
1	Josep Ll. Berral et al [39]	2010	simulator	Machine learning models (not specific)	CPU Usage, Timing SLAs	improve scheduling
2	Sadeka Islam et al[9]	2012	Amazon EC2 cloud	Neural Network and Linear Regression	CPU utilization	resource allocation
3	Chenn-Jung Huang et al [4]	2013	CloudSim	Support vector regressions (SVRs)	CP, Memory	resource allocation optimization
4	Akindele A. Bankole and Samuel A. Ajila[40]	2013	Employed the Wake	Support Vector Machine (SVM), Neural Networks (NN) and Linear Regression (LR)	CPU, response time, and throughput	Response Time and Throughput
5	Ali Yadavar Nikravesh et al[41]	2015	Amazon EC2	Support Vector (SVM), Neural Networks (NN)	CPU utilization, throughput, and response time	improve scheduling
6	Samuel A. Ajila and Akindele A. Bankole[42]	2016	Amazon EC2)	Support Vector Regression (SVR), Neural Networks (NN), and Linear Regression (LR)	CPU utilization,	response time throughput
7	Hussaini Adamu et al[16]	2017	computing system	Linear Regression (LR) Support Vector Machine (SVM)	CPU and memory	enhance system availability

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8	Jixian Zhang et al[46]	2018	Xen Server	Linear regression and logistic regressions	CPU, memory, and storage	resource allocation
9	Rafael Moreno-Vozmediano et al[43]	2019	Xen Server	Support Vector Machine (SVM)	fulfill the SLA	optimize The service response time
10	Zhou et al[6]	2019	DELL PowerEdge	Correlation Matrix (CM) and linear regression model	CPU, memory, disk, and NIC	Energy consumption
12	Leila Ismail and Eyad H. Abed[44]	2019	Xen Server	Linear Regression	CPU, memory, disk, and network	Task Scheduling
13	Gopa Mandal et al[3]	2020	CloudSim	simulated annealing and Linear Regression	CPU, memory	improve scheduling
14	Jiechao Gao et al[24]	2020	Google cluster trace	Support Vector Regression (SVR) Long Short Term Memory (LSTM)	CPU and memory	Workload Prediction
15	Piotr Nawrocki et al[5]	2021	Java Environment	short- and long-term	CPU and memory	resource allocation optimization
16	Nirmal Kr. Biswas et al[17]	2021	CloudSim	New Linear Regression (NLR)	CPU utilization	Energy consumption (EC)
17	Ranesh Naha et al[45]	2022	CloudSim	multiple linear regression	CPU utilization	Energy consumption (EC)
18	Mohammed E. Seno et al[47]	2022	Xen Server	Cloud linear regression (CLR)	resource allocation	Task Scheduling

VI. ANALYSIS OF PREVIOUS STUDIES

Table I This section provides a comprehensive summary of the studies discussed in this article. The majority of these studies focused on supervised learning techniques for resource allocation optimization. Specifically, they leveraged previous resource allocation data to improve task scheduling. The primary objectives were to conserve energy and reduce costs by minimizing the number of hosts or virtual machines, ensuring that the assigned workloads have adequate resources. It is crucial to avoid any interference between newly added tasks and existing tasks running on the same host or virtual machine.

On the other hand, unsupervised learning methods were found to be unsuitable for resource management. This is because unsupervised learning tends to group tasks into clusters, often leading to multiple tasks being assigned the same set of resources. Consequently, when task variations occur, unsupervised learning may not be advantageous as the system would allocate identical resources to each member of the cluster.

Overall, the studies highlighted the effectiveness of supervised learning in optimizing resource management and task scheduling, while cautioning against the limitations of unsupervised learning approaches in this context.

Reinforcement learning is the second most used approach after supervised learning[48].In most RL efforts, the feature field consists of tasks, while the activity field consists of task scheduling and determining the amount of task parallelism. Their primary goal is to reduce task completion time.

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The issue with these approaches is that their real-world approaches are not available online. As a result, anytime the task changes, it will result in latency in re-training the system and reacting to that change. In certain cases, they should employ an approach other than RL[38].

VII. CONCLUSIONS AND FUTURE PLANE

The main objective of this study was to enhance our comprehension of the role of machine learning in achieving optimal resource allocation within the cloud computing environment. Furthermore, the study conducted a comparative analysis of machine learning methods across various research domains within cloud computing. Additionally, a brief analysis of the methods was provided, with a focus on scheduling based on multiple parameters. Machine learning is expected to enhance resource allocation optimization and scheduling capabilities. It is anticipated that the findings of this research evaluation will contribute to significant advancements in this field.

In future work, the suggested algorithms will be evaluated using actual cloud architecture, specifically in a Windows server-based cloud environment. Additionally, specific machine learning algorithms such as linear regression CLR(Cloud linear regression) will be applied. As for research trends, the potential of deep learning to enhance solutions and provide optimal outcomes for cloud computing workloads is worth exploring.

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