Sustainable Computing: Informatics and Systems 36 (2022) 100780

Contents lists available at ScienceDirect

Sustainable Computing: Informatics and Systems

journal homepage: www.elsevier.com/locate/suscom

Machine learning for energy-resource allocation, workflow scheduling and live migration in cloud computing: State-of-the-art survey

Yogesh Kumar [a], Surabhi Kaul [b], Yu-Chen Hu [c,*]

[a] Department of Computer Science and Engineering, School of Technology, Pandit Deendayal Energy University, Gandhinagar, Gujarat, India
[b] Department of Computer Science & Engineering, Chandigarh University, Gharuan, Mohali, India
[c] Department of Computer Science & Information Management, Providence University, Taiwan, ROC

ARTICLE INFO

Keywords:
Machine learning
Cloud computing
Energy optimization
Load allocation
Workflow scheduling
Live migration

ABSTRACT

Machine learning and artificial intelligence techniques have been proven helpful when pragmatic to a wide range of complex problems and areas such as energy optimization, workflow scheduling, video gaming, and cloud computing. When machine learning and cloud computing algorithms are combined, they help achieve better outcomes by providing the improved performance of cloud data centers compared to solutions currently employed by various researchers. It is also helpful for migrating the virtual machines based on the current traffic condition and fluctuation due to network congestion and bandwidth availability. The survey aims to present the improvement in dynamic load allocation, task scheduling, energy optimization, live migration, mobile cloud computing, and security on the cloud using machine learning classification. Machine learning algorithms are prevailing analytical approaches that allow machines to identify patterns and simplify the human learning process. The flow of the paper consists of an introduction part, motivation, and background study, including a framework for cloud-machine learning integration, best practices of introducing machine learning in cloud computing, and the objective of the work. The paper also highlights the machine learning-based cloud services and the role of artificial intelligence in different cloud computing platforms. This comprehensive study provides mindfulness and valuable facilities to the researchers by giving thorough studies about various machine learning algorithms and their applicability in cloud computing.

1. Introduction

Machine learning (ML) [41] is gaining importance through various tactics and technologies which are using the concepts of artificial intelligence (AI) that can directly help in the computational and pattern recognition field. As the research is done on ML, it has been observed that ML becomes smoother and better when used with some cloud platforms. Machine Learning (ML), with its many disciplines, has been at the forefront of automation, embodying intelligence in machines to minimize costs and errors and increase efficiency [67].

Cloud providers [56] prompting machine learning have broad value for that. However, that value won't be appreciated if machine learning is smeared on systems that couldn't profit from making predictions based on patterns found in data. So, what's the equation between the cloud and machine learning [37]. The actual value for these two is for business purposes if applied suitably. Many enterprises are using these technologies where cloud and machine learning are worked together.

The machine learning is helping in providing the availability, performance and security for new applications and services. Using real-time approachability, especially in application areas like traffic, e-health, and industry requires communication networks to make real-time decisions autonomously [68]. Through their research, they have found that the game-changer for their business can be machine learning in many cases.

For providing better results and values, machine learning applications are widely used for building the system. Various machine learning applications that have already gained importance from this technology are predictive marketing, inventory management, machine monitoring, and fraud detection. Different solution patterns are being provided as machine learning models cannot be the same every time. Various cloud providers like Google, Amazon, and AWS help deliver the support for three types of predictions. The price of such systems about their software and hardware is much more costly for most firms.

* Correspondence to: Department of Computer Science and Information Management, Providence University, 200, Sec. 7, Taiwan Boulevard, Shalu Dist., Taichung City 43301, Taiwan, ROC

E-mail addresses: yogesh.arora10744@gmail.com, yogesh.kumar@sot.pdpu.ac.in (Y. Kumar), surabhi93kaul@gmail.com (S. Kaul), ychu@pu.edu.tw (Y.-C. Hu).

https://doi.org/10.1016/j.suscom.2022.100780
Received 19 July 2020; Received in revised form 14 May 2022; Accepted 7 August 2022
Available online 10 August 2022
2210-5379/

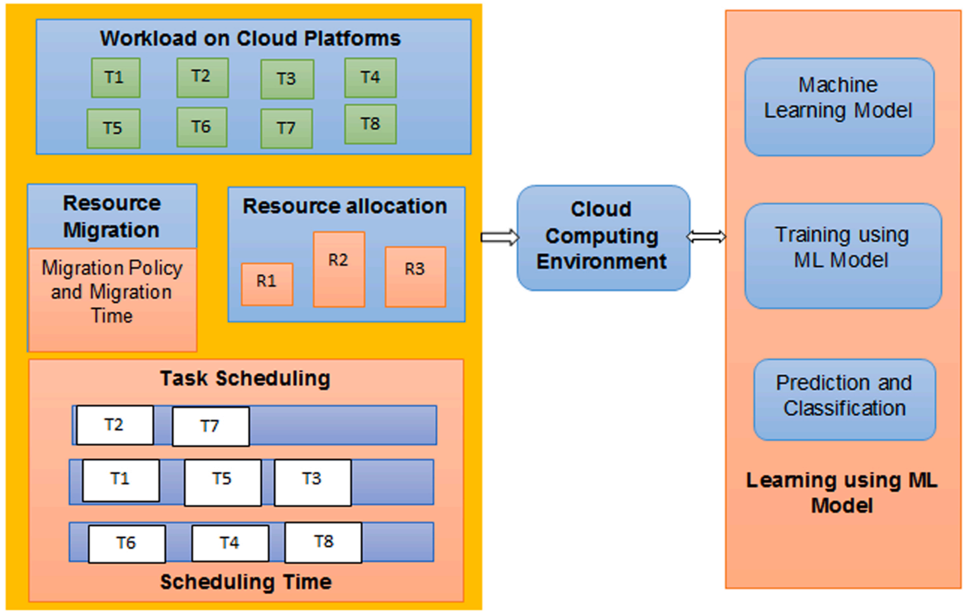

Fig. 1. Framework for Cloud-Machine Learning [43].

Additionally, if firms could pay for these expenses, that does not mean that they are talented enough to handle prediction models' design. Many machine learning techniques are used to plan virtual machines (VM) to provide dynamic scalability, reallocation of resources, energy efficiency, and dynamic load balancing on CC. The purpose of ML in the cloud location is to optimize results for better accuracy, less response and execution time. The technologies related to machine learning train the machines to perform their work independently [61], and minimum human participation is required. ML is a subcategory of AI that contains a huge number of data sets for testing purposes. After using these developed learning methods in machine learning, the idea is to learn about the structures or latent variables that would help achieve the data in a compact form by supporting various functionalities. For such cases, there is a dynamic and emergent role of the AI [69]. The machine built over such technology can work in any environment, and their output varies based on input provided to them and the environment where they belong. Moreover, these machines can learn from their past experiences [47]. Machine learning is gaining importance in every field. Recently, machine learning is associated with emerging sixth-generation (6 G) technology in the market [70].

The main agenda of this paper is to get the capability of machine learning for cloud computing environments. The article's novelty in suggesting the redeemable energy key lies in studying machine learning based on energy-efficient resource allocation mechanisms. The paper also covers the different machine learning-based scheduling strategies, learning-based virtual machine migration policy, choosing the better mobile cloud computing framework and offering the best security to the cloud using machine learning-based classification and prediction. Finally, this paper puts forward a systematic and comprehensive survey on the machine learning-based cloud solution, with the key areas such as energy optimization, resource-aware allocation, live migration, dynamic load balancing [24], and mobile cloud computing and choosing the secure path for cloud infrastructure.

2. Background study

This section expounds on the framework of cloud-machine learning integration, which describes the dynamic task scheduling, resource allocation and migrations, objectives of the work, and various advantages of machine learning (ML) in the cloud computing environment. The section also describes AI and ML in the cloud platform and machine learning-based cloud services.

2.1. Framework for cloud-machine learning

In this section, we emphasize the framework [43] for cloud-machine learning integration for dynamic scheduling, resource allocation, and performing migration tasks. The agenda is to use the different ML techniques for improving cloud computing performance with respect to active resource management, emphasizing the prediction of required virtual machine allocations. The machine learning techniques are more efficient in using resources, workload consolidation, and energy saving.

The structure of the cloud-machine framework allows dynamic scheduling, resource migration, and load allocation using a machine learning model. As shown in Fig. 1, the workload on cloud platforms is distributed in different tasks such as T1 to T8. And the resource allocation block shows how many jobs are allocated to the other resources such as R1, R2, and R3. Further load is also balanced using task migration from resource one to resource two. The time to transfer the tasks is computed using migration time, including pre-migration and post-migration evaluation parameters. The role of the ML model is to train and organize the cloud resources to perform the dynamic scheduling for load allocation and migration.

2.2. Motivation

The motivation is to find and explore the machine learning techniques applied to workflow scheduling, dynamic resource allocation, live migration on the cloud and energy efficiency tasks on cloud computing. The primary concern of machine learning for cloud computing is to benefit from different research activities on a cloud. The primary motivation for the work is:

- To study and analyze different machine learning methods for a cloud computing task.
- To apply the optimal machine learning methods for energy optimization, task scheduling, live migration, cloud computing security, and dynamic resource allocation.
- To perform the comparative analysis based on performance parameters, a lot of research has been done in cloud computing using machine learning methods.

Table 1
Artificial intelligence-based research applications for different cloud platforms.

Applications based on AI	Amazon Cloud	Microsoft Azure Cloud	Google Cloud
Image recognition	Recognition Image	Computer Vision APICustom Vision ServiceFaceAPI, EmotionAPIContent Moderator	Vision APIAutoML Vision
Analysis of video	Recognition Video	Computer Vision APIVideo IndexerContent Moderator	Video Intelligence API
Way to convert speech to text	Transcribe	Bing Speech APICustom Speech ServiceSpeaker Recognition API	Speech API
Way to convert text into speech	Polly	Bing Speech API	Text-to-Speech API
conversions	conversions	Translator Text API	Translation API
Language analysis	Comprehend	Text Analytics APIContent ModeratorLanguage UnderstandingWeb Language Model APILinguistic Analysis API	Natural Language API
Online platform to chat over the system	Lex	Azure Bot Service	Dialogflow

2.3. Investigations

The study carries following investigations.

✓ ***Investigation 1:*** *Impact of supervised and unsupervised machine learning models*
✓ ***Investigation 2:*** *How artificial intelligence techniques are embedded in cloud computing for different services.*
✓ ***Investigation 3:*** *The most thoroughly investigated Machine Learning for Energy-Resource Allocation, Workflow Scheduling, Live Migration and others in Cloud Computing and a year-by-year evaluation prediction studies.*
✓ ***Investigation 4:*** *Influence of ML in CC for different purposes*

2.4. Benefits of ML in the CC environment

ML, the subset of AI, is gradually building ways to enter enterprise applications [36] in business intelligence, fraud detection and customer support. Many reasons are there to have faith that the best results will be achieved by combining cloud with machine learning.

1. The cloud follows a pay-per-use prototype, which is best used for much larger workloads in ML.
2. The business uses various try-out with ML abilities to scale up their projects for better invention and growth in demand with the help of the cloud.
3. There is no need for any enhanced techniques for making intelligent capabilities accessible by the cloud in data science or artificial intelligence.
4. Microsoft Azure, Google Cloud Platform, and AWS suggest various ML options which don't need much knowledge about AI, a team of data scientists, or machine learning theory [20].

2.5. Role of artificial intelligence and machine learning in the cloud platform

To deal with the data over the cloud, machine learning is putting the best it can do. With regular research in AI [2] and in the CC environment, CC has become more intelligent than before. Machine learning has become so crucial that every cloud these days uses machine learning for its better use. Big companies in cloud computing like Google, Microsoft, and Amazon have invested a lot of research in AI and machine learning. They are doing a fusion of these two technologies in the cloud to get the best and the new services in the field of technology.

Researchers have done tremendous work in artificial intelligence and cloud platforms for performing research activities. Table 1 states some of the primary critical points on artificial intelligence for different cloud platforms.

Bringing machine learning abilities [9] to enterprise applications is one of the most significant evolutions in technology. The expertise was required to use their skills to form, train and organize ML models, and its extraordinary hardware supplies lifted its budget for manual labor, infrastructure and development. Such difficulties can be solved using cloud computing [15]. Various platforms supporting cloud work make it easier for enterprises to influence ML skills to crack business evils without any burden. The leading contributions in this group are mainly motivated by some aspects of Natural Language Processing [9].

2.6. Machine learning based cloud services

The cloud computing business is gaining importance in the field of intelligent cloud [4]. Lots of research has been done in this field to make it more live. The cloud vendors are much concerned about their storage, computing, and storage purpose as these are the main pillars for cloud business. Still, simultaneously machine learning is to gain space in the cloud background. In a cloud environment, AI is working its best. The following reasons that make AI [28] work best in the cloud are scalability, less operational cost, and massive power to investigate vast amounts of data. So the fusion between cloud computing and ML is valuable for both technologies. Various services are listed down, showing how machine learning is becoming an essential aspect of the intelligent cloud [27].

- Chatbot as a Service

These days' interactive bots are gaining support, while mobile app adoption is getting stagnated. Bots are quickly replacing apps because of their conversational practice with users. With WhatsApp, Facebook messenger, we chat all gaining popularity, the plea for implanting bots [55] has also increased. The concept of bots is not developed now, and it was developed long ago in the initial time of yahoo chats. Machine learning is just making its use to its best these days. With the help of machine learning, developers are training bots based on their past patterns. Only queries can be handled using bots. Moreover, they can help in providing meaningful discussions with users too. Various examples for such types of platforms are provided by Microsoft Azure Bots and IBM Watson Botkit.

- Business Intelligence as a Service

Merging machine learning in cloud computing business intellect services are also getting much more intelligent. Both these technologies [6] are helping enterprises to work better. This also helps show the different data in a single place and collectively work on the provided data. The blending of cloud computing with machine learning algorithms serves its best to improve the existing condition and incorporate intellect systems.

- Machine Learning Based Internet of Things

IoT [63] has been used for a few decades in various forms; it is a cloud platform that is getting its trends back in the market with new versions of it. Different data is to be captured with the help of sensors first to query them, then process and examine the significant trends, with the help of machine learning in IoT [62], making it more intelligent and best to use. Numerous machine learning algorithms work to get the perfect system that can be best associated with accepting the outline of datasets produced by devices. Such a system can proactively discover irregularities that ultimately fail machines. This proficiency has taken the business of IoT [66] to the next level. Examples in this area [53] can be IBM Watson IoT and Microsoft Azure IoT Suite.

- Speech-based Personal Assistants

Machine learning [65] enhanced the voice-based personal assistants more capable as compared earlier [7]. Using past choices and usage trends, these assistants can get customized experiences like voice-based personal assistants will make a playlist according to your mood dynamically within the prescribed period. Just like the notifications and the reminder that we are getting these days, it could be more useful in such a manner. These assistants help expose the APIs by giving the power of Machine Learning to the hand of developers. Further, they modify the experiences supplied to users. Some examples of personal assistants powered by machine learning [59] are google assistant, Microsoft Cortana, Apple Siri and Amazon Alexa.

- Cognitive Computing in Cloud

In the large cloud amount of data is to be stored. For the machine learning algorithms, this data is working as a primary source. Cloud [64] is used for data sharing, networking and storage by billions of users. Using this information, machine learning algorithms [8] have become much better. These applications are used to execute the cognitive processes and predict the outcomes. To give better performance in cloud computing research on cognitive computing leading big players in artificial intelligence technology. Examples of Cognitive AI [54] are IBM Watson, AWS and Microsoft. But with time and with improvements and enhancement in machine learning and AI, these organisms will be used in more critical fields such as healthcare, marketing, finance, and many other sectors.

3. Reported work on cloud computing using machine learning classifications

This part represents the reported work done in cloud computing using machine learning classifications. The detailed work is discussed below:

3.1. Energy-efficient resource allocation on cloud using machine learning

With less energy utilization and without hampering the performance and quality of service delivered on the cloud using machine learning, maintaining a balance between power utilization and system performance is the main challenge. Thandar Thein et al. (2018) [57] defined a framework in which high data center energy is used and also helps in preventing SLA violation. Mohamed Deiab et al. (2019) [16] explained a recent survey about the tool for power efficiency in cloud computing. In cloud computing, data centers are the leading center where business information is stored and managed by the running applications. The main concern of the data centers is high performance. While working on this concern, power consumption and performance cannot be considered. The main concern is to provide the stability among both system and power consumption. A.Stephen McGough et al. (2018) [42] described the High Throughput Computing (HTC) systems which help provide a suitable mechanism for the execution of different works. The main benefit is to provide large amounts of power without any cost. The only drawback is that if the computer requires its primary use, running tasks are to be sacrificed. Mostly, the job terminated task which restarts on another computer causing wastage of time and energy. The author reveals how to decrease energy wastage by giving jobs to computers that are less used for primary use and through ML predicting the idle time. Multilayer Perception and Random Forest integrated both these machine learning approaches, 51.4% of energy we can save without affecting the completion time of the tasks. N.R.Rajalakshmi et al. (2019) [52] represented a virtual machine method using RL to maximize performance and energy efficiency in cloud data centers. In the experimental results, results are better in energy-saving and performance using the virtual machine methods. M. Lawanyashri et al. (2017) [38] suggested an approach that helped decrease energy usage and cost in cloud computing. Thus, through the help of various research done on energy-efficient using machine learning, many problems have been solved with efficient results. Table 2 presents the overall summary of energy-efficient resource allocation using machine learning.

Table 2
Summary of the papers for energy-efficient resource allocation using machine learning.

Authors	Techniques	Benefits of work	Limitations
Thandar Thein et al. (2018) [57]	Reinforcement learning and fuzzy logic	Presented work provides the effective management of physical resources hosted by the infrastructure using dynamic resource demand patterns, Service Level Agreement and resource utilization.	It reflects only energy sources and the energy consumption for CPUs and data centers. Resources could also influence the result of the scheduling technique.
Xiao-Bo CAI et al. (2017) [10]	K-Means and page rank	Machine learning algorithm to save the energy consumption of data center.	The computation performed by the proposed algorithm to eliminate the unnecessary redundancy is very high.
McGough et al. (2018) [42]	Random forest and multi-layer perceptron	Presented the work to observe low overhead and less energy consumption using ML techniques.	The proposed approach uses real trace logs allowing for complex situations in the presented platform.
N.R. Rajalakshmi et al. (2019) [52]	Reinforcement learning	In the presented work, the learning agent improves the quality of the VM consolidation algorithm for energy consumption.	The number of hosts can be increased to simulate the check the behavior of the proposed work.
M. Lawanyashri et al. (2017) [38]	Multi-objective hybrid fruit fly optimization	The proposed work used the sleeping strategy to reduce energy consumption.	The work can be extended for load balancing workflow with quality of service factors.
R.k. Jena (2017) [29]	Task scheduling using clone selection	The proposed work solves the problem of task scheduling under the cloud computing environment where the number of data centers and jobs changes dynamically.	The load balancing, cost and bandwidth can be added to make work more robust.
Nimisha Patel and Hiren Patel (2017) [51]	Host utilization aware algorithm	The presented work provided the study to calculate a lower threshold value which is used for the detection of the underloaded host.	The presented work can be extended in a real-time environment for load allocation on data centers.

R.K Jena (2017) [29] defined a multi-objective CSA-based optimization algorithm that is used in task scheduling problems where data center and user job changes dynamically. In this changing environment, the resources of cloud computing require to be working optimally. A multi-objective CSA-based algorithm that efficiently uses the system resources is appropriate for cloud computing to reduce power consumption. Xiao-Bo CAI et al. (2017) [10] proposed ML for reducing energy consumption using the concepts of CC. The search depicts that the existing algorithm helps to save energy consumption. ML combined with distributed technology has provided an effective way to solve the energy efficiency cloud problems. Nimisha Patel et al. (2017) [51] suggested (HUA) Host Utilization Aware Algorithm, which is used in a dynamic cloud environment for underloaded host discovery and putting its VMs on another host. In the workload consolidation process, under-loaded host detection is one of the significant stages. A survey has been proposed with existing methods to work out the lower threshold value applied to detect the underloaded host in this search. Duggan, M. (2016) [19] presented a comprehensive survey regarding the works done in machine learning to obtain answers related to power efficiency in the cloud computing area. The author described a relative categorization of the suggested procedures. The authors have formulated the formula for finding the energy efficiency, which is listed in Eq. 1.

$$Ews(p)\quad \Delta \quad \Sigma k\varepsilon K \quad wk \quad \Sigma u\varepsilon Uk \quad Rku \quad (p)/ \quad gk(p) \tag{1}$$

Where E_{WS} = energy efficiency metrics.

K = {0, 1, 2,., K} denote the set of all BSs.

k ∈ K = set of Uk users denoted by Uk{1, 2,., Uk}.

Further research shows non-machine learning methods for energy sustention in data centers and how machine learning used other objectives in CC.

3.2. Machine learning based workflow scheduling in cloud environment

The enlargement of information technologies requires unpredictable progress of both data volume and the complication of the data processing itself. Mikhail Melnik et al. (2019) [43] suggested a scheduling scheme central core of which is ANN and the principles of RL have been used. This pattern aims to allocate the workload fetching according to the needs, and give computation models on computational resources, thereby decreasing the waiting time and reducing execution time to works. Lindong Liu et al. (2018) [39] suggested a task scheduling model based upon I-Apriori Algorithm using fog computing. The model helps obtain better results in case of task execution time and waiting time. Binh Minh Nguyen (2019) [48] suggested that Fog computing architecture is the next generation of cloud computing. The main problem in fog computing is allocating resources to decrease the operational cost and completion time. A new perspective to optimize task scheduling difficulty in the cloud is the fog environment regarding operating expense and execution time. Atul Vikas Lakra et al. (2015) [60] described a multi-objective task scheduling algorithm for mapping to reduce the cost and production capacity of the data centers without breaching the Service Level Agreement. This algorithm gives optimal scheduling procedures. The scheduled task of each algorithm is based on the execution time. But in cloud computing, various other parameters are required to be taken, such as cost, the bandwidth of user and time, etc. TO SOLVE THE PROBLEMS OF RESOURCE SCHEDULING IN THE CLOUD, Hatem M. El-Boghdadi et al. (2019) [21] have used Artificial Intelligence algorithms, Deep Reinforcement Learning.

Most of the cloud provider's main problem is choosing the suitable resource scheduling algorithm for a particular workload, and mainly where the workload might be dynamic. Suvendu Chandan Nayak et al. (2018) [11] explained a scheduling technique used for the deadline-sensitive task. It's tough to distribute resources on-demand within the prescribed time rather than cancel the lease. Different versions are compared with current techniques, which are relatively better.

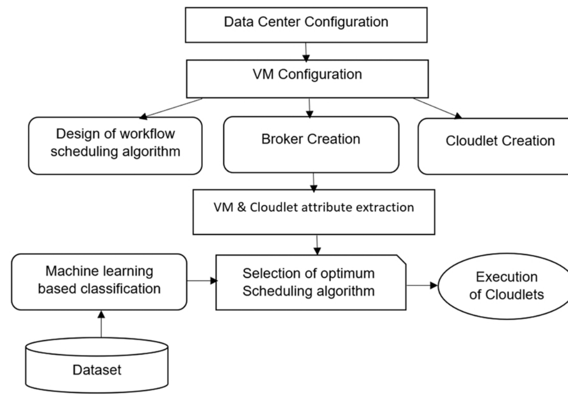

Fig. 2. Machine learning based scheduling in cloud [58].

Table 3
Workflow scheduling using machine learning.

Authors	Technique	Benefits of the Work	Limitations
Binh Minh Nguyen et al. (2019) [48]	Time–Cost aware scheduling algorithm	High-performance processing for scheduling of the tasks.	Time and transmission costs can be reduced.
El-Boghdadi et al. (2019) [21]	Deep reinforcement algorithm	Offline cloud resource scheduling processing is performed efficiently.	The proposed approach can be extended to solve complex scheduling problems.
Mikhail Melnik and Denis Naonov (2019) [43]	Artificial neural network	Optimizing the scheduling process using ANN.	The encoding process of the input phase can be improved to perform the workload in a heterogeneous environment.
Lakra et al. (2015) [60]	Multi-objective task scheduling	Improve the throughput of the data center and reduce the cost without violating the SLA.	Quality of service can be added to make more improvements in the work.
Lindong Liu et al. (2018) [39]	Task scheduling model	TSFC algorithm has better performance for task scheduling.	Bandwidth issues are the major concern between processors, a multilayer task scheduling.
P. Tikar et al. (2015) [58]	Supervised learning	Proposed approach improved resource utilization and response time on the cloud.	It is difficult to classify datasets to minimize the attribution for the scheduling process.
Nayak et al. (2018) [11]	First come, first serve for backfilling	Presented work provided a new mechanism for deadline-based task scheduling using the backfilling concept.	The switching cost of the VMs is a major concern.

Fig. 2 shows the structure of the task scheduling using machine learning methods. Initially, VM configuration and Data Center configuration has been done. Design of data center comprises formation of processing elements & hosts and setting up Data Center features. Virtual Machine configuration includes virtual memory size, processing power (MIPS), image size, and generating several processing elements [14]. Scheduling is a process used to regulate the command of tasks to be achieved by a system. The best scheduler settles its scheduling policy according to the different cloud environments and the type of input task.

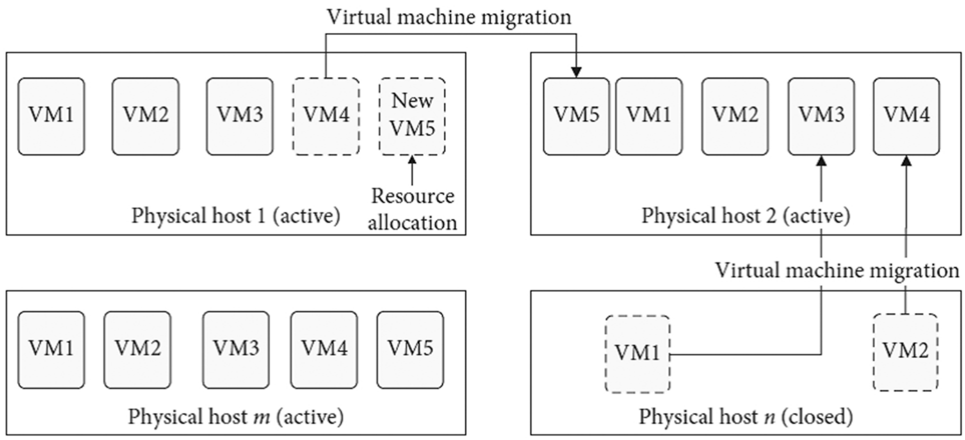

Fig. 3. Resource allocation and virtual machine migrations [13].

Abhijeet P. Tikar et al. (2015) [58] presented a system that works to improve resource utilization and reply time in the cloud with the help of ML categorization. Multiple scheduling is applied instead of single scheduling algorithms.

With the help of ML classification assortment of the effective scheduling algorithm is accomplished. In the beginning, Virtual machine and task attributes are extricated and taken as training data. Machine learning algorithms are used training data as input which further generates classification rules. Practical Scheduling algorithms, which are based upon the classification rules, are selected and accomplish task execution. The given proposal is applied and checked in the Cloudsim Simulation tool kit.

Further, WEKA is used to test datasets and classification algorithm selection. Binh Minh Nguyen et al. (2019) [48] suggested Fog computing architecture. In a cloud environment, Fog Computing is taken as the next generation and used according to the needs generated by the device. The main problem in using Fog Computing is to allocate the computing resources to decrease the operating expenses and execution time. A new technique has been found for optimized task scheduling problems in the Cloud Fog environment in connection with operating cost and completion time. The author has considered the number U of data centers in the cloud infrastructure.

We define the Transfer Time TT(i,j) between two tasks corresponding to a weight of an edge (i, j) ∈ E in the application graph (DAG), which corresponds to the time taken to transfer data from task ti (executed on vmp lodged in data center Ua) to task tj (executed on vmk lodged in data centre Ub), as in the following equation.

$$TT(i,j) \quad = \quad datai,j \quad / \quad Transfer \quad rate \quad (p,k) \tag{2}$$

where data i,j is the size of the output data produced by task ti and transferred to tj.Table 3 represents workflow scheduling on cloud platforms using machine learning classifications for achieving better outcomes.

3.3. Cloud based load balancing using machine learning techniques

In a Cloud, Load balancing help in providing each node with an equal amount of data. Load balancing distributes an equal amount of data from one node to another to get better resource utilization and response time and solve the underloading nodes. At the same time, some are overloaded. This approach is applied for completing consumer requirements and resource utilization ratio. It works for the complete betterment of the system. Proper load balancing is very beneficial in optimal utilization of the existing resources and helps to minimize resource utilization. Samir Chauhan et al. (2019) [12] suggested a load balancing algorithm in cloud computing through the Cloudsim toolkit, created in java language. The author has formulated the formula for achieving the load, represented in Eqs. 3 and 4.

The total loads (L) for all virtual machines can be defined as.

$$L = \Sigma_{i=1}{}^{k}\, l_i \tag{3}$$

i = number of VMs in a data center.

Load per unit capacity, which is also called LPC can be defined as:

$$LPC \quad = \quad L/ \quad \Sigma i = 1 \quad ci \tag{4}$$

C_i = capacity of the node.

In order to get better results and high performance through ML linear regression method is applied. Bakul Panchal et al. (2018) [49] applied a machine learning approach to obtain effective load-balancing results in cloud computing. In terms of maintaining balance where data should be shifted from an overloaded machine to under loaded machine, load balancing is a huge challenge. Abhijith Nair et al. (2019) [44] originate a technique and make a comparison between “Equally Spread current execution load” and “Round Robin” techniques. Different techniques, including the suggested technique, are used as a platform in various windows operating systems. The load balancing technique is more competent as compared with another two in terms of response time. Load balancing algorithms are fundamental to getting practical and better results in the global throughput of Grid resources.

3.4. Live migration on cloud computing using machine learning

Ensuring quality in services to be delivered to users live migration is one of the best-suited approaches. Live migration help in sharing a host with multiple VMs, and each VM further runs one or more application simultaneously. When the host is over-utilized or underutilized, both time live migration is very advantageous. With the various benefits of live migration, like maintaining SLA levels and reducing the energy, the drawback of it can be that these benefits can sometimes harm VM applications, especially during migration. So it is required to use the live migration approach so that the movement between VM and host machine should be fast.

The expression relating the duration of the migration Ti to the relative number of elementary operations for the migration time X and the number of migrations N for the observation period T can be written in Eqs. 5,6.

$$X \quad = \quad k \quad \Sigma \quad Ti \quad / \quad tmin \tag{5}$$

where t_{min} is the minimum duration of an elementary operation;

$$ko \quad = \quad tmin \quad / \quad k \quad . \quad To \tag{6}$$

where T_0 is the length of the monitoring window;.

k is the number monitoring windows.

Table 4
Summary of the papers for live migration on the cloud using machine learning.

Authors	Technique	Benefits of the Work	Limitations
Elsaid et al. (2019) [22]	Supervised learning	Presented work provided the best environment for planning the VMware live migrations.	Live migration costs are high and also service availability degradation.
Duggan et al. (2017) [18]	Recurrent neural networks	Recurrent neural networks perform improved prediction for host CPU and network bandwidth utilization.	Migrations decision needs improvement for cost parameter.
Changyeon Jo et al. (2017) [31]	Machine learning model	High prediction accuracy for live migration in a heterogeneous environment.	Need to perform complex migration scenarios in a heterogeneous environment.
Jing Chen et al. (2019) [13]	Autoregressive integrated moving average	Presented the cost-effective method for host utilization.	It is difficult to manage the random resources and resources on demands.
Patel et al. (2016) [50]	ARIMA and SVR model	Performed effective workload and live migration tasks.	Difficult to move in the different prediction models for performing the migrations.

M. Duggan et al. (2018) [18] explained the linear and non-linear predicting methods with arrangements of various prediction algorithms called an RNN for predicting network bandwidth and CPU utilization in live migration. Recurrent neural networks help create the best prediction for network bandwidth utilization and host CPU when associated with old models.

When a request for a new virtual machine is announced, the suitable physical host for assigning the resources for the virtual machine according to a definite resource distribution policy is to be nominated by cloud data centers, as shown in Fig. 3.

Jing Chen et al. (2019) [13] presented the live migration on CC using ML approaches. In the beginning, the ensemble empirical mode decomposition method decomposes the no stationary host utilization structure into comparatively stable intrinsic mode function components and a residual component to develop estimation correctly. Minal Patel et al. (2016) [50] developed a probability regression model. The prototype was tested over the Xen data set for computing downtime and overall immigration time. With the help of this model, predicting the count of dirty pages has an accuracy of 91.74%. With the help of the SVR model, the prediction for predicting the count of dirty pages has an accuracy of 94.61%, which is greater than the previous model.

Changyeon Jo et al. (2017) [31] presented numerous algorithms for live migration that have the following characteristics: volume of data relocated, accomplishment time of the task, virtual machine performance degradation, and virtual machine downtime. Different adaptive machine learning-based models that can predict the critical features of live migration with high accuracy in reliance on the migration algorithm and the load running inside the VM are also part of the paper. Mohamed Esam Duggan et al. (2017) [18] explained a self-directed network responsive to virtual machine migration policies that detect a network's current demand level and execute a suitable action built over its experiences. Table 4 highlights the work done on live migration using machine learning for the betterment of results [22].

3.5. Machine learning techniques for mobile cloud computing

Mobile computing is achieving popularity among various users and large organizations. Each day at least n number of users get connected to the cloud. Thanks to cloud services and wireless connectivity, bonding over the cloud has become one of the easiest and simple tasks. Azharul Karim et al. (2017) [32] proposed an algorithm based on machine learning technologies that reflect user inputs, network conditions, mobile device energy, and device resources. For testing this algorithm, whether it would produce better results or not, the author has applied an image processing app whose results are being compared with the previous algorithm. The proposed algorithm can achieve the total energy and time saved calculations better. Xiaomin Jin et al. (2019) [30] presented the working of offloading choices in the mobile cloud environment to reduce the decision algorithm's intake. Virtual reality explains that the existing algorithm supports various applications, energy and time while crushing out the computing resources used in that.

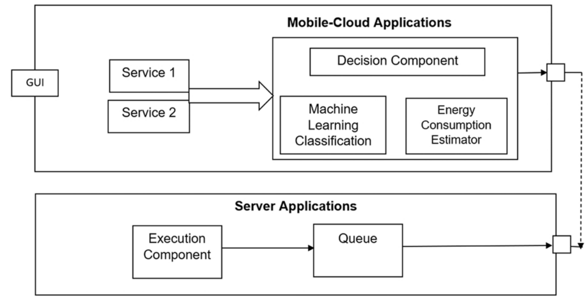

Fig. 4. Machine learning based cloud mobile application development [45].

As shown in Fig. 4, two main modules are presented. One is the mobile application and the other is the server back end. The central part of the structure is a decision component for code offloading. It can adjust task distribution in mobile cloud computing to resourcefully deliver facilities that need multifaceted computations like multimedia processing. On the other hand, the server applications are implemented by the set of FIFO queues. P. Nawrocki et al. (2019) [45] presented a solution by giving a formal method and developed its prototype to check its accuracy. Such technology helps provide hybrid applications, which may be helpful for code transfer on various operating systems like windows, android, or iOS. Such hybrid applications help in decreasing the volume of work required from developers. Piotr Nawrocki et al. (2018) [46] presented different opportunities for using ML on mobile devices to execute services within the framework of mobile cloud computing. Two main learning approaches had been part of this: reinforcement and supervised learning. The explanation projected to influences among various things like network connection potentials and knowledge about mobile device resources etc. Amir Erfan Eshratifar et al. (2019) [23] presented a method that can adjust to any hardware platform, DNN architecture, mobile and server load levels, and wireless network settings. The new network has helped a lot in improving the better accuracy results. Table 5 summarizes various papers for mobile cloud computing using ML and also helps in differentiating amongs the benefits and limitations.

3.6. Secure cloud computing environment using machine learning techniques

In CC, cloud security is the main challenging issue faced by the users. Cloud vulnerabilities have introduced various threats like domain name server spoofing, address resolution protocol, and denial of services. Zina Chkirbene et al. (2019) [14] proposed an enhanced intrusion detection and Classification model that help in securing the cloud computing environment. Kulwinder Kaur et al. (2016) [33] involved its efforts in analyzing the security issues. The author suggested the framework, which helps prevent cloud computing security issues at the storage and authentication level. Before getting into the security process, one should classify what is secured and not guaranteed. Based on this classification,

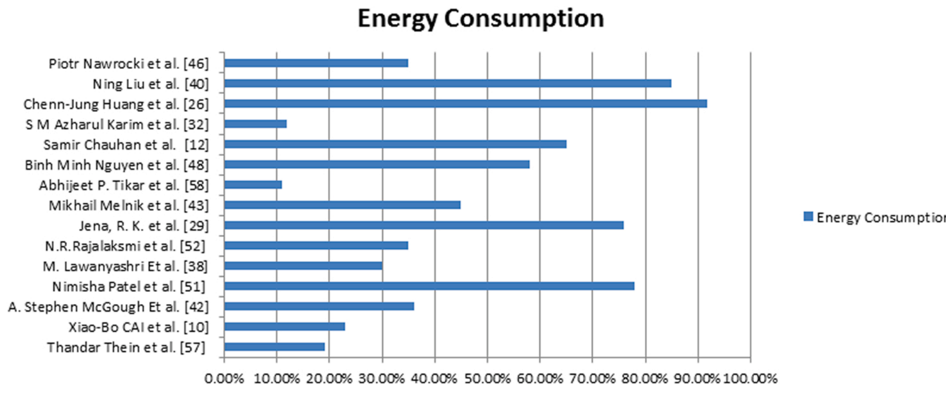

Fig. 5. : Artificial intelligence techniques in cloud for energy consumption.

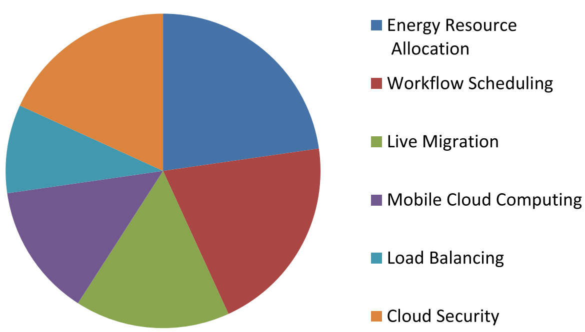

Fig. 6. AI techniques in cloud services.

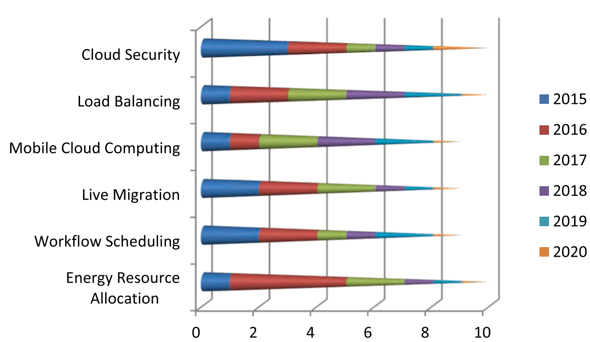

Fig. 7. Year-by-year evaluation prediction studies.

data has been divided into 2 parts first is sensitive and the other is non-sensitive data. Nada Ahmed et al. (2015) [3] attained the feature decline, achieved the best accuracy over the data set, and found the best method applied.

The author has explained the use of various machine learning algorithms to model security in cloud computing environments. Dhivya R et al. (2019) [17] highlighted different attacks caused in a cloud environment such as man-in-the-middle attack, malware injection attack, authentication attack, side-channel attack, and a denial-of-service attack. For detecting such attacks in the cloud, various machine learning algorithms are being used. Many algorithms of ML have been used in the CC for security purposes, are logistic regression, support vector machine, and Naive Bayes. Masroor Khan et al. (2019) [35] proposed a cloud security model which helps in improving data efficiency in the cloud environment. As security is the main issue these days in cloud environments, it is necessary to have good algorithms. The cloud security mechanism has two main algorithms based on neural network and machine learning.

Table 5
Summary of the papers for mobile cloud computing using ML techniques.

Authors	Technique	Benefits of the Work	Limitations
Karim et al. (2017) [32]	Machine Learning Model	• Optimized mobile device resources by offloading computation to the cloud in a strategic way.	• Financial feasibility of offloading computation is high.
Nawrocki et al. (2018) [46]	Reinforcement Learning	• Optimized the video file processing services on a mobile cloud environment.	• Difficult to handle the rapid changes in conditions in the cellular network.
Xiaomin Jin et al. (2019) [30]	Offloading Decision Algorithm	• Presented the work under a mobile cloud environment using runtime decision.	• Offloading decision problems with multiple applications
P. Nawrocki et al. (2019) [45]	Supervised Learning	• offloading enables permitting the facilities which can be optimized on various mobile devices.	• Implementation of the proposed task is difficult for mobile devices.
Eshratifar et al. (2019) [23]	Deep Neural Network	• DNN architecture minimizes end-to-end latency, and server load levels for mobile devices.	• Deep model can be applied further for uploading activities.

Ehsan Hesamifard et al. (2018) [25] proposed a new technique for delivering the solutions by applying deep neural network algorithms to the encrypted data. The study showed that this technique is much more realistic and practical for training the neural networks using encrypted data and help predict the results from the encrypted form. The proposed method is evaluated, and performance has been checked for this scenario. The results are showing better results as compared to other methods. The author has formulated the formula, which is represented in eq

$$SK1 = K1 \odot K2 + K2 \tag{7}$$

$$SK2 = K3 \odot K4 + K3 \tag{8}$$

K = key (divided in 4 parts)

Used logical operations (XOR, XNOR) XOR between every two keys to generate Sub keys (Sk1, Sk2) and XNOR between two sub keys to

Table 6
Machine learning based security solution measures on the cloud platform.

Security Threats	Machine Learning Security Measures
Malicious attacks and their activities	ML algorithms support businesses in detecting various malicious activities quicker and stopping those attacks before they are started.
Analyze mobile endpoints	ML is also used widely over mobile devices. These activities have been used for improving voice-based practices, for example, Apple's Siri, Amazon's Alexa, Google, etc.
Human analysis	The security provided by machine learning approaches has proved a lot of help in malicious attacks, network investigation and weakness valuation.
Automate repetitive security tasks	The approach of ML is to help in automating the tedious tasks and also empowering staff members to focus on more vital work.
Zero-day vulnerabilities	ML could help in closing the weaknesses.

generate the main key (KK) as shown in equations.

Ahmad Neyaz Khan et al. (2019) [34] explained the capabilities of both supervised and unsupervised machine learning techniques through neural networks over encrypted data. This work helps in getting the base for defining the machine learning performance over the cloud security domain using homomorphic encryption. Algorithm, E. (2020) [5] presented the method called as privacy-preserving clustering fussed with homomorphic encryption schemes. This fusion helps get the high-performance computation platform in the cloud environment. Because of this system does not have to work in a high processing manner as ample work is to be done by the cloud system provider itself.

Machine learning may be defined as "the capability to study without being explicitly encoded". With the help of various mathematical approaches used over large datasets, ML approaches form action and use such types of systems for better results. Also, it is important to note where the system can be at risk. So, here we are discussing machine learning based solutions for security threats on cloud computing in Table 6.

When companies cogitate cloud computing as one of the critical advantages for making the business more secure, in the modern era, various big companies have preferred to migrate to the cloud only for its security aids. So, it is surprising to learn that there are multiple threats related to cyber security that can cause problems for cloud systems. Machine learning helps in providing the most satisfactory solution for handling all such security threats that can disturb the performance of any business over the cloud.

4. Machine learning approaches for different research areas on cloud computing

The machine learning-based solutions for various cloud computing areas and different clouds are presented in Table 7. Table 7 illustrates the purpose of ML classifications for energy-efficient resource allocation, workflow scheduling activities, migrations solutions on cloud platforms, and dynamic load allocation schemes.

Table 7 presents a classification of the schemes discussed by various authors. The observations is the machine learning techniques are used in excess these days. Many researchers have proposed that the ML is very helpful in predicting future workloads. Lots of algorithms have been discussed and used for maximizing energy conservation. The main goal of using ML techniques is to decrease the use of servers required and simply off the machines that are not to use for a particular time to save energy. Various machine learning techniques for optimization are used to get better results in the area of Energy-Resource Allocation, Workflow Scheduling and Live Migration. The prediction results are better as compared to traditional implementation. Using a machine learning approach, the operating cost can be reduced by 60–70%. Training 100,000 samples with more than 4000 routers. High prediction accuracy can be targeted. The overall comparison showing the growth in energy consumption results is shown in the below graph.

5. Discussion and research gaps

This article aims to give a comprehensive summary of the research being conducted in the area of Machine Learning for Energy-Resource Allocation, Workflow Scheduling and Live Migration in Cloud Computing. Furthermore, we addressed machine learning classifications for different cloud research activities. The article provided a compilation of valuable results with sufficient parameters.

1. ***Role of different supervised and unsupervised machine learning models.***

Machine learning uses supervised learning for the majority. There are input and out variables (x) and (y) in supervised learning. Using the algorithm, we know about mapping function through the variables.

$$Y = f(X) \tag{9}$$

The main purpose of supervised learning is to estimate the mapping function so that new input data (x) can calculate the output variable, so we can say that the training dataset can be treated as a teacher who supervises the learning process through algorithm learning. Algorithms make rough calculations repeatedly through training data which will be further accurate by the teacher and when suitable and adequate performance obtained by algorithm learning ends. Further supervised learning problems are classified into classification and regression problems and the following are some famous examples of supervised machine learning:

- For the classification problems, the support vector machine is the primary example.
- For both regression and classification problems, the random forest is the main example.
- Linear regression for the regression problems.

When there are no corresponding output variables and only input data (X) that is unsupervised learning. The main purpose of unsupervised learning is to build structure in such a way so that we understand more about the data. Because like supervised learning, there is no teacher or accurate answer; therefore, these are known as unsupervised learning to generate and present exciting structures in the data algorithm left to their devices. Further, there are two groups of unsupervised learning, i.e., association and clustering problems.

The following two are the most famous examples of unsupervised learning algorithms:

- K-means for clustering problems.
- Apriori algorithm for association rule learning problems.

2. How artificial intelligence techniques are embedded in cloud computing for different services.

AI helps in various fields like uplifting the IT infrastructure and throughput. The fusion of AI and CC results in providing many volumes of data. Various tools like Google Cloud Vertex, IBM Watson, Microsoft Azure AI and AI services portfolio are easy to use. Various benefits of AI in cloud computing are Lower costs, Intelligent automation, Deeper insights, Improved data management and Increased security.

In AI techniques, machine learning offers a lot of wider acceptance in industries. Its use has indicated a better future for this fusion. Numerous cloud and machine learning approaches have made tremendous contributions to the body of knowledge. The fusion of machine learning and the cloud has put forward users with many benefits. Different cloud providers use this fusion in their environments to get better results. Various fields where cloud and machine fusion are done have been

Table 7
Machine learning approaches in the cloud.

Authors	Area/Purpose	Platform	Machine Learning Techniques / Optimization Method	Result Achieved
Thandar Thein et al. [57]	Energy-efficient resource allocation in cloud data centers	CloudSim Simulator	Reinforcement learning and fuzzy logic	Power usage effectiveness range= 1.91–1.92 for 50 VMs and 1.92–1.88 for 100 VMs
Xiao-Bo CAI et al. [10]	Energy efficiency optimization on cloud	Hadoop MapReduce framework	K-Means and page rank applications	Energy consumptions= 23% for K-Mean and 20% for Page Rank
A. Stephen McGough Et al. [42]	Reducing the energy wasted in volunteer computing environments	HTC-Simulator	Random forest and multi-layer perceptron	Energy consumption= 3.6MWh Overhead= 4.9%
Nimisha Patel et al. [51]	Energy-efficient workload consolidation with minimal migration	CloudSim Toolkit	Host utilization aware (HUA) algorithm	Energy consumptions= 7.83 kWh and Avg. SLA Violation= 11.03.
M. Lawanyashri Et al. [38]	Energy efficiency and load balancing	CloudSim Toolkit	Multi-objective hybrid and fruitfly optimization	Energy consumption= 3.08 for 400 tasks
N.R.Rajalakshmi et al. [52]	Energy efficiency and VM consolidation	CloudSim Toolkit	Reinforcement learning agent learns (RLAL)	Energy consumption= 25 kWh for RLAL, 38 kWh for IQRRS and IQRMC= 36 kWh.
Jena, R. K. et al. [29]	Energy-efficient task scheduling	CloudSim Toolkit	Clonal selection algorithm (TSCSA)	Energy consumptions= 0.28–3.45 kWh for up to 360 tasks.
Mikhail Melnik et al. [43]	Workflow scheduling	Workflow Simulator	Neural network scheduling	Average effective scheduling improvement= 76% for NNS
Atul Vikas Lakra et al. [60]	Tasks scheduling	CloudSim Toolkit	Multi-objective task scheduling algorithms	Turnaround time= 4.5% for 100 tasks and 10 VMs
Abhijeet P. Tikar et al. [58]	Task scheduling using machine learning	CloudSim Toolkit for Simluation WEKA Tool for testing datasets	Supervised learning	Execution of tasks for FCFS using machine learning= 3.1 for data centers= 2
Binh Minh Nguyen et al. [48]	Optimize task scheduling Problems over IoT	FogSim Simulator	Modified particle swarm optimization (MPSO) and bee life algorithm (BLA)	Avg. time and cost execution = 11.04% for MPSO and 15.11% for BLA
Samir Chauhan et al. [12]	dynamic load balancing on the cloud using machine learning	CloudSim Toolkit	Dynamic load balancer with linear regression technique	Response time= 0.58% Data transfer cost= 0.65% Make-span processing time= 170
Bakul Panchal et al. [49]	Dynamic load balancing on cloud	AWS cloud platform	Machine learning classifications for load balancing	Execution time= 12 ms Upper threshold= 1.10%
Changyeon Jo et al. [31]	Live migration modeling on cloud	Quick EMUlator for Virtual Machine Manager	Linear regression, support vector regression, and support vector regression with bagging	Total migration time for pre-copy= 0.16% for LR, 0.06 for SVR and for 0.06 for SVR with Bagging Total migration time for post-copy= 0.12% for LR, 0.03% for SVR and 0.03% for SVR with Bagging
Mohamed Esam Elsaid et al. [22]	Network VM migration	CloudSim toolkit for VM Migrations	Reinforcement, learning agent, and migrate-first algorithm	Avg. migration cost= $88.44 for MF Algo. and $60.63 for RLA. Improved avg. migration time= 35%
Minal Patel et al. [50]	Statistical prediction model	Improved Xen server for performing live migrations	autoregressive integrated moving average and support vector regression	Dirty page prediction Accuracy= 91.74% for ARIMA Model and 94.61% for SVR model
S M Azharul Karim et al. [32]	Mobile cloud offloading for energy consumption and device latency	Python Sockets for offloading	Proposed machine learning (decision tree) based algorithm for offloading	Execution time= 0.855 ms
Piotr Nawrocki et al. [46]	Service management in mobile cloud Computing	Mobile device-LG Nexus 5	Supervised and reinforcement learning with Q-learning	Average execution time (s)= 262 ms for supervised learning and 265 ms for reinforcement learning and Q-learning algorithm
Chenn-Jung Huang et al. [26]	Resource Management in cloud computing	CloudSim Toolkit	Support vector regressions (SVRs) and genetic algorithm	Mean difference= 1.61
Ning Liu et al. [40]	Resource allocation and power management on cloud	CloudSim Toolkit	Deep reinforcement learning and round robin	Power consumptions for 40 VMs= 561.13 kWh for RR and 273.41 kWh for DRL
Swati Agarwal et al. [1]	Resource provisioning in fog computing	Cloud Analyst Simulator	Efficient resource allocation (ERA), reconfiguring dynamically with load balancing (RDLB), optimize response time policy (ORT)	Response time= 632.87 ms for RDLB, 630.11 ms for ORL, 63.11 for ERA

discussed in the figure below.

3. The most thoroughly investigated Machine Learning for Energy-Resource Allocation, Workflow Scheduling, Live Migration and others in Cloud Computing and year-by-year evaluation prediction studies.

Since machine learning has been used tremendously in every aspect of human life. Many efforts have been made so far where machine learning can be used without human interactions till it's not necessary. AI that uses ML for learning the data have come forward a lot in science these days – ML is one of the next levels in this evolution. When ML and CC are clubbed together, they provide much more benefits in every field. This fusion is termed as "Intelligent Cloud".

The cloud involves storage, computing and networking applications. But when CC is fussed with ML, the proficiency of the cloud increase vastly. The intelligent cloud helps learn the massive amount of data stored in the cloud, building up predictions and analyzing situations. Various articles have been discussed in this research year-wise, which helps find better results for Machine Learning for Energy-Resource

Table 8
Description of metrics.

Metrics	Description	Formula
E_{WS}	Energy efficiency metrics	$Ews(p)\Delta\Sigma k\varepsilon Kwk\Sigma u\varepsilon UkRku(p)/gk(p)$
TT(i,j)	Transfer Time T T(i,j)	$TT(i,j) = datai,j/Transferrate(p,k)$
L	Total load	$L = \Sigma_{i=1}^{k} l_i$
LPC	Load per unit capacity	$LPC = L/\Sigma i = 1ci$
X	Elementary operations for the migration time	$X = k\Sigma Ti/tmin$
K	KEY	$SK1 = K1© K2 + K2$

Allocation, Workflow Scheduling, and Live Migration in Cloud Computing. The graph given below represents the papers used in these fields.

4. Metric and evaluation models used by machine learning based cloud services.

Evaluation of prediction models is critical for determining their performance. These metrics assist in comprehending prediction accuracy and in comparing different models. Table 8 summarizes the evaluation metrics used to evaluate the prediction models.

6. Conclusion and future direction

The intelligent cloud is new progress that appeals to lots of researchers in the field of cloud computing. Providing acceptable computation results is one of the biggest dares in cloud computing using machine learning. The detailed survey explores the different cloud research activities in energy consumption, workflow scheduling, live migration, load balancing on the cloud, mobile cloud computing, and privacy policy using machine learning methods. From the survey, we try to highlight the critical areas of cloud computing using machine learning algorithms. This article has covered machine learning-based cloud services and the importance of AI and machine learning in cloud computing.

The survey also described the comparative analysis based on ML techniques in the different cloud computing research areas. Machine learning is likely to help increase data center utilization and resource scheduling competence. For future directions, Deep understanding can help learn better, optimize the solution, and provide the best results for cloud computing tasks. Further improvement can be made by combining the meta-heuristics approaches with machine learning algorithms for cloud resource allocation, better scheduling decisions, and energy optimization.

Funding

The authors declare that they do not have any funding or grant for the manuscript.

CRediT authorship contribution statement

Yogesh Kumar: Conceptualization, Methodology, Visualization, Investigation, **Surabhi Kaul**: Software, Data curation, Writing – original draft preparation, **Yu-Chen Hu:** Investigation, Supervision, Validation, Writing – reviewing and editing.

Code availability

Not applicable.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Availability of data and material

Not applicable.

References

[1] S. Agarwal, S. Yadav, A.K. Yadav, ‘An efficient architecture and algorithm for resource provisioning in fog computing’, Int. J. Inf. Eng. Electron. Bus. 1 (2016) 48–61.
[2] Agavanakis, K.N. et al. (2019) ‘Practical Machine Learning Based on Cloud Computing Resources’, AIP Conference Proceeding 2123, Article ID 020096.
[3] Agavanakis, K., et al. (2018) ‘Energy Trading Market Evolution to the Energy Internet a Feasibility Review on the Enabling Internet of Things (IoT) Cloud Technologies’, AIP Conference Proceedings, 1968(1), Article ID 030077.
[4] Alani, M.M. (2019) ‘Applications of Machine Learning in Cryptography: A Survey’, Proceedings of the 3rd International Conference on Cryptography, Security and Privacy, pp. 23–27.
[5] Algorithm, E. (2020) ‘Practical Implementation of Privacy Preserving Clustering Methods Using a Partially Homomorphic’, Electronics, 9, Article ID 229.
[6] J. An, et al., ‘EiF: toward elastic IoT fog framework for AI services’, IEEE Commun. Mag. 57 (5) (2019) 28–33.
[7] A.S. Gowri, P.S. Bala, ‘Fog resource allocation through machine learning algorithm’, IGI Glob. (2020) 7178–7198.
[8] Kumari Uma. (2017) ‘Soft Computing Applications: A Prospective View’, 2nd IEEE International Conference on Communication and Electronic Systems, pp. 787–789.
[9] Bhamare, D., Salman, T., Samaka, M., Erbad, E. and Jain R. (2016) ‘Feasibility of Supervised and Reinforcement based Machine Learning for Cloud Security’, 2016 International Conference on Information Science and Security, Pattaya, Thailand.
[10] X. Cai, Y. Ji, K. Han, ‘Energy efficiency optimizing based on characteristics of machine learning in cloud computing’, ITM web of conferences 12, Artic. ID (2017) 03047.
[11] S. Chandan, et al., ‘An enhanced deadline constraint based task scheduling mechanism for cloud environment’, J. King Saud. Univ. - Comput. Inf. Sci. (2018) 2415–2426.
[12] P.S. Chauhan, J. Patel, ‘Load balancing in cloud computing using machine learning, Techniques’, J. Appl. Sci. Comput., VI(Iv) (2019) 3533–3541.
[13] J. Chen, Y. Wang, ‘A hybrid method for short-term host utilization prediction in cloud computing’, Journal of electronic and computer engineering, 2019, Artic. ID (2019) 2782349.
[14] Chkirbene, Z., Erbad, A. and Hamila, R. (2019) ‘A Combined Decision for Secure Cloud Computing Based on Machine Learning and Past Information’, 2019 IEEE Wireless Communications and Networking Conference, Marrakesh, Morocco, Morocco, pp. 1–6.
[15] Di, S., et al. (2012), ‘Host Load Prediction in a Google Compute Cloud with a Bayesian Model’, In SC’12: Proceedings of the International Conference on High Performance Computing, Networking, Storage and Analysis, pp. 1–11.
[16] M. Deiab, et al., ‘Energy efficiency in cloud computing’, Int. J. Mach. Learn. Comput. 9 (1) (2019) 771–778.
[17] R. Dhivya, R. Dharshana, V. Divya, ‘Security attacks detection in cloud using machine learning algorithms’, Int. Res. J. Eng. Technol. 6 (2) (2019) 223–230.
[18] M. Duggan, et al., ‘A multitime-steps-ahead prediction approach for scheduling live migration in cloud data centers’, Softw.: Pract. Exp. 49 (4) (2018) 617–639.
[19] M. Duggan, ‘A reinforce-ment learning approach for the scheduling of live migration from underutilised hosts”, Memetic Comput. 8 (2016) 111.
[20] Duggan, M., Duggan, J. Howley, E. and Barrett, E. (2016) ‘An Autonomous Network Aware VM Migration Strategy in Cloud Data Centres’, 2016 International Conference on Cloud and Autonomic Computing, Augsburg, Germany, pp. 352–358.
[21] H.M. El-boghdadi, R.A. Ramadan, ‘Resource scheduling for offline cloud computing using deep reinforcement learning’, Int. J. Comput. Sci. Netw. Secur. 19 (4) (2019) 54–60.
[22] Elsaid, M.E. (2019) ‘Machine Learning Approach for Live Migration Cost Prediction in VMware Environments’, International Conference on Cloud Computing and Services Science, At Heraklion, Crete, Greece.
[23] Eshratifar, A.E., Esmaili, A. and Pedram, M. (2019) ‘BottleNet: A Deep Learning Architecture for Intelligent Mobile Cloud Computing Services’, 2019 IEEE/ACM International Symposium on Low Power Electronics and Design, Lausanne, Switzerland, Switzerland, pp. 1–7.
[24] Berral, J. et al. (2012) ‘Toward Energy-aware Scheduling Using Machine Learning’, Energy-Efficient Distributed Computing Systems, Chapter: 8, Publisher: John Wiley & Sons, Editors: A. Zomaya, Y. Lee, pp. 215–244.
[25] Hesamifard, E., Jones, C. and Carolina, N. (2017) ‘Privacy-preserving Machine Learning in Cloud’, 2017 ACM Cloud Computing Security Workshop, Nov. 2017, pp. 34–43.
[26] C. Huang, et al., ‘Applications of machine learning to resource management in cloud computing’, Int. J. Model. Optim. 3 (2) (2013) 148–152.
[27] John J., et al. (2011). ‘Prediction of Cloud Data Center Networks Loads Using Stochastic and Neural Models’, 6th International Conference on System of Systems Engineering, pp. 276–281.
[28] R.K. Jena, ‘Multi objective task scheduling in cloud environment using nested PSO framework’, Procedia Comput. Sci. 57 (2015) 1219–1227.

[29] R.K. Jena, 'Energy efficient scheduling in cloud environment energy efficient task scheduling in cloud environment', Energy Procedia 141 (2017) 222–227.
[30] X. Jin, Z. Wang, W. Hua, 'Cooperative runtime offloading decision algorithm for mobile cloud computing', Mobile, Inf. Syst., 2019, Artic. ID (2019) 8049804.
[31] Jo, C. and Egger, B. (2017) 'A Machine Learning Approach to Live Migration Modeling', Proceedings of the 2017 Symposium on Cloud Computing, pp. 351–364.
[32] Karim, S.M.A. and Prevost, J.J. (2017) 'A Machine Learning based Approach to Mobile Cloud Offloading', 2017 Computing Conference, pp. 675–680, London, UK.
[33] K. Kaur, V. Zandu, 'A secure data classification model in cloud computing using machine learning approach', Int. J. Grid Distrib. Comput. 9 (8) (2016) 13–22.
[34] Khan, A.N. and Fan, M.Y. (2019) 'Learning from Privacy Preserved Encrypted Data Machine Learning', 2nd International Conference on Computing, Mathematics and Engineering Technologies (iCoMET), pp. 1–5.
[35] M. Khan, 'A cloud security model based on machine learning and neuron network', Int. J. Sci. Res. Publ. 9 (2) (2019) 463–467.
[36] R. Kumar, 'Secure cloud model using classification and cryptography', Int. J. Comput. Appl. 159 (6) (2017) 8–13.
[37] Kumar, Y., Kaul, S. and Sood, K. (2019) 'Effective Use of the Machine Learning Approaches on Different Clouds', Proceedings of International Conference on Sustainable Computing in Science, Technology and Management (SUSCOM), pp. 892–897, Amity University Rajasthan, Jaipur - India, February 26–28, 2019.
[38] M. Lawanyashri, B. Balusamy, S. Subha, 'Energy-aware hybrid fruit fly optimization for load balancing in cloud environments for EHR applications', Inform. Med. Unlocked 8 (2017) 42–50.
[39] L. Liu, et al., 'A task scheduling algorithm based on classification mining in fog computing, Environment', Wirel. Commun. Mob. Comput., 2018, Artic. ID (2018) 2102348.
[40] Liu, N. et al. (2017) 'A Hierarchical Framework of Cloud Resource Allocation and Power Management Using Deep Reinforcement Learning', 2017 IEEE 37th International Conference on Distributed Computing Systems, Atlanta, USA.
[41] B.H. Malik, et al., 'Efficient energy utilization in cloud fog environment', Int. J. Adv. Comput. Sci. Appl. 10 (4) (2019) 617–623.
[42] Mcgough, A.S. et al. (2018) 'Machine Learning to Reduce the Energy Wasted in Volunteer Computing Environments', 2018 Ninth International Green and Sustainable Computing Conference (IGSC), Pittsburgh, PA, USA.
[43] M. Melnik, D. Nasonov, 'Workflow scheduling scheduling using neural neural networks networks and reinforcement reinforcement learning learning', Procedia Comput. Sci. 156 (2019) 29–36.
[44] A. Nair, S. Anand, S. Sinha, 'A performance booster for load balancing in cloud computing with my load balancer techinique', Int. J. Recent Technol. Eng. 8 (1) (2019) 1815–1818.
[45] P. Nawrocki, B. Sniezynski, 'Autonomous context-based service optimization in mobile cloud computing', J. Grid Comput. 15 (2017) 343–356.
[46] P. Nawrocki, B. Sniezynski, 'Adaptive service management in mobile cloud computing by means of supervised and reinforcement learning', J. Netw. Syst. Manag. 26 (1) (2018) 1–22.
[47] P. Nawrocki, B. Sniezynski, H. Slojewski, Adaptable mobile cloud computing environment with code transfer based on machine learning', Pervasive Mob. Comput. 57 (2019) 49–63.
[48] B.M. Nguyen, et al., 'Evolutionary algorithms to optimize task scheduling problem for the iot based bag-of-tasks application in cloud – fog computing, Environment', Appl. Sci., 9(9), Artic. ID (2019) 1730.
[49] B. Panchal, S. Parida, 'An efficient dynamic load balancing algorithm using machine learning technique in cloud environment', international journal of scientific research in science, Eng. Technol. 4 (4) (2018) 1184–1186.
[50] M. Patel, S. Chaudhary, S. Garg, 'Machine learning based statistical prediction model for improving performance of live virtual machine migration', journal of engineering, 2016, Artic. ID (2016) 3061674.
[51] N. Patel, H. Patel, 'Energy efficient strategy for placement of virtual machines selected from underloaded servers in compute cloud', J. King Saud. Univ. - Comput. Inf. Sci. 32 (6) (2017) 700–708.
[52] N.R. Rajalakshmi, G. Arulkumaran, J. Santhosh, 'Virtual machine consolidation for performance and energy efficient cloud data center using reinforcement learning', Int. J. Eng. Adv. Technol. 8 (3) (2019) 779–784.
[53] A. Revar, 'Load balancing in grid environment using machine learning - innovative load balancing in grid environment using machine learning - innovative approach', Int. J. Comput. Appl. 8 (10) (2010) 31–34.
[54] Series, C. (2019) 'A New Dynamic and Enhanced Resource Allocation Algorithm in Cloud Computing', Journal of Physics: Conference Series 1228 012033.
[55] G. Singh, M. Mahajan, 'A green computing supportive allocation scheme utilizing genetic algorithm and support vector machine', Int. J. Innov. Technol. Explor. Eng. 8 (9) (2019) 760–766.
[56] G. Shyam, et al., 'Virtual resource prediction in cloud environment: a bayesian approach', J. Netw. Comput. Appl. 65 (2016) 144–154.
[57] Thein, T. et al. (In Press) 'Reinforcement Learning Based Methodology for Energy-efficient Resource Allocation in Cloud Data Centers', Journal of King Saud University - Computer and Information Sciences.
[58] Tikar, A.P. (2015) 'Task Scheduling in the Cloud Using Machine Learning Classification', iPGCON-2015. SPPU, Pune. 24th & 25th March 2015. Fourth Post Graduate Conference, pp. 1–6.
[59] M. Trivedi, 'A survey on resource provisioning using machine learning in cloud computing', Int. J. Eng. Dev. Res. 4 (4) (2016) 546–549.
[60] A. Vikas, D. Kumar, 'Multi-objective tasks scheduling algorithm for cloud computing throughput optimization', Procedia Comput. Sci. 48 (2015) 107–113.
[61] J. Wang, et al., 'A machine learning framework for resource allocation assisted by cloud computing', IEEE Netw. 32 (2) (2018) 144–151.
[62] J. Yang, et al., 'AI-powered green cloud and data center', IEEE Access 7 (2019) 4195–4203.
[63] M. Ghose, A. Sahu, S. Karmakar, 'Urgent point aware energy-efficient scheduling of tasks with hard deadline on virtualized cloud system', Sustain. Computing', Inform. Syst. 28 (2020), 100416.
[64] S. Jangiti, V.S., S. Sriram, 'EMC2: Energy-Effic. Multi-Resour. -Fairness Virtual Mach. Consol. Cloud Data Centres', Sustain. Comput.: Inform. Syst. 27 (2020), 100414.
[65] M. Sharma, R. Garg, 'An artificial neural network based approach for energy efficient task scheduling in cloud data centers', Sustain. Comput.: Inform. Syst. 26 (2020), 100373.
[66] C. Stergiou, K.E. Psannis, B.B. Gupta, Y. Ishibashi, 'Security, privacy & efficiency of sustainable cloud computing for big data & IoT', Sustain. Comput.: Inform. Syst. 19 (2018) 174–184.
[67] I. Ahmad, S. Shahabuddin, H. Malik, E. Harjula, T. Leppänen, L. Loven, A. Anttonen, A.H. Sodhro, M.M. Alam, M. Juntti, A. Ylä-Jääski, Machine learning meets communication networks: current trends and future challenges, IEEE Access 8 (2020) 223418–223460.
[68] T. Zhang, A.H. Sodhro, Z. Luo, N. Zahid, M.W. Nawaz, S. Pirbhulal, M. Muzammal, A joint deep learning and internet of medical things driven framework for elderly patients, IEEE Access 8 (2020) 75822–75832.
[69] Sodhro, A.H., Obaidat, M.S., Pirbhulal, S., Sodhro, G.H., Zahid, N. and Rawat, A., 2019, July. A novel energy optimization approach for artificial intelligence-enabled massive internet of things. In 2019 International symposium on performance evaluation of computer and telecommunication systems (SPECTS), pp. 1–6.
[70] A.H. Sodhro, N. Zahid, L. Wang, S. Pirbhulal, Y. Ouzrout, A.S. Seklouli, A.V. L. Neto, A.R.L. de Macedo, V.H.C. de Albuquerque, Toward ML-based energy-efficient mechanism for 6G enabled industrial network in box systems, IEEE Trans. Ind. Inform. 17 (10) (2020) 7185–7192.