

Study on the Design of Algorithm Based on Machine Learning to Improve Cloud Computing

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Abstract. The on-demand availability of end-user resources, in particular data storage and processing power, without a direct or customer-defined organization is referred to as "cloud computing." Distributed computing is a term widely used yet may have different meanings to different people. Customers may access both public and private data using the cloud computing model. The potential of simultaneously requesting data from several clients of the same source, which slows down the source's response time, is the most significant security risk with cloud computing. Other security concerns with cloud computing include weaknesses in the client and connection. By reducing the delay between a client's request for data and the cloud source's answer, a method was developed in our recent research to enhance the performance of cloud computing. By requesting data from several clients from the same source at once or from multiple clients from the same source or from other sources at various times in the same network, four instances were shown. By testing request and response times while protecting data from loss and noise, the findings demonstrated the system's robustness.

Keywords. Cloud computing, Virtual machines (VMs), Cloud service, Machine Learning.

1. Introduction

"Cloud computing" is a new Internet service architecture [1]. Budgetary limitations and increased computer costs for data storage, processing, and presentation have changed the cloud model [2]. "Cloud computing" is the on-demand availability of end-user resources without client organization, such as data storage and processing power. Distributed computing is a common term with multiple meanings. Distributed computing allows Internet access to public and private data [3]. Cloud computing's client and association vulnerabilities slow its adoption [4].

Edge computing, a sort of cloud computing used to analyze time-sensitive data, gives application developers and service providers dispersed processing capacity [5]. Current edge processing uses virtualization to transfer and operate more edge servers. This paradigm requires distributed computing security and storage to evolve. Encryption is necessary because data may travel via several Web-connected hubs before reaching the cloud. Asset-obligated edge hubs reduce security options. Keep information at the margins to transfer ownership from service providers to end users [6].

The goal is to allow computers to modify themselves and adjust required processes. Cloud computing offers deployment options, including public, private, community, and hybrid cloud services like IaaS, PaaS, and SaaS. Cloud computing security threats include integrity, availability, and confidentiality. Cloud services include data storage and software service management. Cloud architecture, services, and computing power are often intended to be impermeable and available on demand [7]. The cloud architecture supports enormous infrastructure and hardware applications for service delivery [9]. Cloud

computing has drawbacks as a revolutionary computer model. Not every cloud deployment approach benefits every service, provider, customer, or party [8].

ML algorithms improve data handling, security, and capacity [9]. ML is used to learn and enhance frameworks [10] automatically. Machine learning aims to create self-learning programs [11]. The learning process starts with perceptions or facts, such as models, direct comprehension, or heading, to the channel for informational structures and chooses better possibilities based on the models [12].

By leveraging data that has been saved in the cloud and applying Radial basis function networks, one of the machine learning methods, to predict new values without requiring local storage, the performance of cloud computing will be enhanced in the current article using machine learning approaches.

Problem statements: Cloud computing has helped big data management at the industrial level. But there are several issues that still limit the usage of cloud computing. The issues of higher latency and bigger data streaming arose with increasing audiovisual data usage of the users. The increasing demand for big data and extensive usage of bid data across the globe needs a more comprehensive and efficient algorithm that needs to be designed and tested for effective application. This current study aims to fulfill this demand by designing and validating a new proposed algorithm that might be contributing to mitigating these issues mentioned above.

Aims of the paper:

- 1- To introduce high-performance computing with machine learning and artificial intelligence on cloud platforms.
- 2- Validate and classify performance patterns to verify system performance and resiliency decisions.

Research questions:

1. Whether there can be an improvement in the time of obtaining the requested data from cloud to device and vice versa.
2. How the whole proposed system can be efficient in preserving data loss and noise?

Significance of the paper: Although cloud computing has helped facilitate our big data management, there are significant delays in the request time of data both during sending and retrieval. This proposed system is the need of the hour in the computing field which would contribute to reducing the time of data transfer from device to cloud and vice versa while minimizing the noise and loss of data by employing auto-correcting the performance in real-time instances. This would further validate the pattern of performance and ensure continuous flow decisions. Hence, this proposed paper can highlight a proposed system that would contribute to shaping cloud computing for future development.

2. Related works

Moving virtual machines (VMs) is becoming a serious challenge in a cloud computing environment. The technology offered by virtualization technology has an impact on how well the cloud performs. Virtual machine migrations must be optimized since the distribution of virtual machines during resource allocation is imbalanced, and moving virtual machines from one server to another might result in higher network overhead and power usage. A machine learning prototype for virtual device migration is represented by Ali Belgacem, Sa'd Mahmoudi, and Mohamed Amine Ferrag in their paper. Power use and virtual machine migrations were reduced to improve selection. Numerical results showed that the proposed solution might considerably improve the goals [13].

In the study given by Muhammed YILDIRIM, Ahmet INAR, and Emine CENGL, large data brought on by cloud technology and this data's classification utilizing machine learning techniques and algorithms were first looked at [14].

Ali Al-Zahrani et al have proposed a hybrid approach for storage solutions that combines replication and token erasure to improve stability and recovery. They have also developed learning and training methods to create a dynamic architecture for developing and testing the data model. To evaluate their proposed hybrid framework, the researchers employed a RAID architecture and divided it into two groups, each consisting of different RAID configurations. They evaluated the reliability and recoverability of both the server-side and virtual-level data based on FTT, parity, failure range, and capacity. The results showed that the RAID-6c configuration on the server side was the best for

maximizing performance and that RAID-6 mirroring and complete coherence encryption for erase and recovery produced good results. The researchers also noted that their proposed approach presents interesting research prospects for the future [15].

Alvaro López-Garça and his team proposed a distributed architecture called the DEEP-Hybrid-DataCloud framework, which aims to provide machine learning practitioners with a comprehensive set of tools and cloud services covering the entire machine learning development cycle. This includes model creation, training, validation, testing, deployment, and sharing. The framework allows for the optimal use of distributed resources, enabling the most computationally intensive activities during the machine learning development cycle. It also provides transparent access to existing cyber infrastructures. By using a serverless architecture and DevOps methodology, the framework allows scientists to publish their models and make them easily shareable and distributable [16].

In our contemporary research, the execution of cloud computing was enhanced by using device learning methods.

3. Cloud Computing

cloud computing is a technology that provides users with access to computing resources and data storage without requiring active maintenance [17]. It relies on a distributed architecture and resource sharing to achieve coherence and improve efficiency [18].

The subsequent important traits are illustrated in cloud computing:

A. Cloud service providers offer savings by transforming capital expenses into operational costs, as a third party provides the framework and does not require a significant upfront investment [19]. This reduces access barriers and enables fine-grained utility computing costs with usage-based invoicing options. Cloud computing projects require fewer in-house IT resources, but the extent of cost savings depends on the specific activities and infrastructure available. The e-FISCAL undertaking's cutting-edge repository examines cost considerations and concludes that expense savings rely on the types of actions and infrastructure available [20].

B. Users can use the enter strategies using an internet browser regardless of their area or the instrument they are employing thanks to appliance and area freedom [21] (e.g., PC, mobile phone). Consumers can relate to infrastructure from anywhere because it is off-site (usually furnished by a third party) as well as available through the Internet [22].

C. Cloud computing makes it easier to manage the computing environment as the data is stored on an external server maintained by a provider, eliminating the need to invest in data hub infrastructure. This also reduces IT supervision and update costs compared to on-premises data hubs. As a result, cloud computing can be less expensive [23].

D. When resources and expenses are communicated across a vast amount of consumers, it is possible to:

- Concentrating infrastructure in affordable locations.
- Peak-load capability grows.
- Efficiency and effectiveness gains for methods that are typically only used 10%-20% of the time.

E. Website aid builds consistent, loosely connected structures while IT experts from the assistance provider monitor execution.

F. Multiple users working on the same data may boost productivity instead of waiting to be stored and emailed. Consumers don't have to enter information again or install application software updates when fields match.

G. With multiple redundant locations, cloud computing is suitable for business continuity and disaster recovery [24].

H. Scalability and elasticity through near-real-time "on-demand" resource supply. Peak loads do not need to be engineered (VM startup time varies by VM type, location, OS, and cloud provider) [25]. This allows scaling up or down depending on resource utilization. Cloud scaling reduces time to market and

increases company agility and flexibility [26]. Machine learning can suggest appropriate elasticity models [5].

I. Data centralization, safety resources, and other measures may protect sensitive data. However, issues regarding kernel storage and data loss may remain. Security is often better than other traditional systems because service providers can invest money in correcting security flaws that many customers cannot pay for or lack the technical competence to handle [17]. However, data dispersed over a larger territory, across more instruments, or in multi-tenant approaches shared by irrelevant users increases safety sophistication. Protection audit documents may also be difficult to access. Private clouds are driven by users' need to control infrastructure and data security.

4. Improve cloud computing performance

Optimal application performance is something that businesses and organizations aim for, but getting there is no accident. Organizations must supply correctly configured resources to achieve performance objectives in on-premises, host-based IT systems. These issues are constructed more complicated by cloud computing, which determines how much a consumer may personalize the infrastructure and other benefits. Many assistance and methods can enhance cloud execution, even though no particular architecture may ensure ultimate execution for every application [15].

4.1. Choose acceptable situations

Understanding their workload's resource requirements and preparing an example variety with suitable attributes might impact a corporation. Most cloud instances are VMs, but container variants are growing fast.

The goal is to size the instance to optimize memory, vCPUs, and specialized features. If the instance is too large, the extra resources will not influence cloud workload performance, making them a beneficial investment. If the task executes all, performance will degrade.

Cloud providers offer many instance types with varied vCPUs, memory, storage, and networking. These VMs are versatile. AWS A1 instances support scale-out and ARM applications. M4 instances share resources among multiple programs. Cloud instances can handle AI, memory-intensive apps, and more. Choosing wisely is vital, given the many options [27].

4.2. Implement autoscaling services

Companies scale arbitrarily. Because IT resources must be upgraded and under supervision, scaling fast, dynamic, or independent was needed. Public cloud computing changes. Public cloud partnerships count or distribute instances and resources. AWS, GCP, and Azure offer load balancing and autoscaling.

Businesses must set rules to scale when and what to improve cloud performance. Monitoring systems often track load characteristics like vCPU utilization. The controlling alert activates autoscaling when work pressure exceeds a state usage threshold. It counts resources and makes load-balancing options using a specified mechanism. Autoscaling easily maintains a workload's performance and reactivity for users while reducing cloud costs.

4.3. Implement cache services

Data-dependent applications may be slower to respond if the assets are far away or heavily used by multiple tenants. Caching stores a copy of frequently used data near the program. Data storage speeds up data activities. Azure caching for Redis, ElastiCache, and Memcache are cloud-based caching solutions. Changes to the cached data may cause problems. To ensure caching and primary data repository consistency, application developers should evaluate how to refresh and invalidate cache data. Cloud service providers help designers with lots of information and standard designs [28].

4.4. Microservices architectures should be used.

Monolithic apps have one executable structure with all the essential features and functionalities. Monoliths can hinder cloud scalability and performance. When a monolithic application reaches its performance limit, it must be reinstalled.

Interconnected microservices can be deployed, run, and scaled separately. Several API-connected services supply the program's features and functioning. When strained to its performance limit, that service must scale out. Modern program management may be faster and more resource-efficient. Orchestrated container platforms like Azure Service Fabric are utilized more often than tiny VMs for microservices components.

4.5. Adopt event-driven architectures

Using cloud hosting cloud computing services like AWS Lambda, Azure Functions, and Google Cloud Functions, event-driven systems can be implemented. The adoption of cloud services computers among programmers has been tremendous.

The goal is to stop people from using ordinary VM or container instances over the long term, even when they are necessary for event-driven back-end functions. The code for specific software behavior or functions, however, is uploaded by business programmers to the cloud service, where it only runs in response to an actual or planned event. This task is discharged once finished; at this point, internet services are no longer used. Instead of the user, the cloud service loads, runs, and unloads the program. Even while relatively few systems are truly event-driven, programmers can use functions to quickly implement defenses against actual technological events, like streaming data from the Internet of Things. Cloud hosting services enable the software to be more accomplished, streamlined, and simplified.

4.6. Choosing a monitoring service

When enhancing cloud performance, monitoring cannot be undervalued. A number of monitoring services are provided by public cloud providers, such as Amazon CloudWatch, GCP Stackdriver Monitoring, and Azure Monitor.

Although monitoring doesn't have a direct effect on workload execution, these services are an essential part of every public cloud operation. Performance indicators, which serve as the foundation for decisions about services like autoscaling and assist enterprises in making sure their cloud investments are profitable, can only be tracked objectively through monitoring.

5. The proposed system

5.1. Methodology

The main challenge in cloud computing is ensuring effective and secure data management. The primary pillars of the cloud computing system are dispersion, power management, and delay management.

Connectivity in cloud hosting is achieved through various strategies, with backup, recovery, and erasure coding being the most effective for data accessibility, reliability, and profiling. Replication and erasure coding can be combined to achieve the best data integrity, resulting in fewer failures, fewer data losses, and quick recoveries. However, the choice of technology used for data storage and the latency can affect data recovery speed and may have advantages and disadvantages.

5.1.1. Code manager

To ensure data reliability, we compared replication and erasure coding. Replication using mirroring is more reliable but takes up more space, while erasure coding uses less storage but has stronger fault tolerance and recovery capabilities. To help ease the challenges and hassles of repairing a system problem, most manufacturers now provide system restoration disc PC system restoration discs for repairing system problems and using CNI (cloud network interface) or CSI (cloud storage interface) to detect competent networks for virtual machine configuration. The server is managed using cloud-based Kubernetes settings.

5.1.2. Replication manager

The configuration manager manages all virtual machine ruin configurations. The CSI and CNI interfaces also translate the virtual machine's dynamic state into health status. If virtual machine number 3's storage is dynamically priced, erasure coding is triggered during a recovery instance. The VM health controller gets information from the CSI and CNI interfaces. If space is made available for dynamic replication or erasure coding by launching an instance on another virtual machine, load balancing will begin to make room for the present instance.

Instead of deleting the machine, the current example would be stored in the cache queue. Thus, the scheduled restoration or replication operation will begin if the virtual machine has sufficient processing, storage, and networking.

5.1.3. The physical Layer

The physical resource surface is made up of different kinds of hardware resources, such as racks, nodes, disks, and so on. Even though people are talking about the cloud platform, this surface is hosted by the cloud-based service provider in a general populace, society, or hybrid cloud. Whenever people have a cloud infrastructure or a business information centre, this layer will be called "in-prime hardware services." As was previously established, the physical resource layer controls both erasure coding and replication, which employ RAID-5/6 and RAID-1, respectively. Through the use of several virtual computers, virtualization enables access to this layer. Although each virtual machine may be configured differently thanks to the cloud platform, the total capacity of all virtual machines depends on the actual resources that are available. This component is intended to provide information about the health of a data group and the possibility of a device failing. It does this by using a fabric agent for host planning, which lets users choose among two storage solutions: reversal coding and reproduction.

It is noteworthy that in this case, predictions of device failure are predicated on the likelihood that the replication or erasure coding mechanism will fail. To explain, the network agents can provide a health alert for the current data clusters and determine the probability of failure in advance whenever replication uses HDFS for reflecting and faces a hardware, connectivity, or logical problem.

A relatively similar method applies to implicit bias coding; for example, the fabric agent will perform the mentioned previous action when loss coding employs hyper-convergent memory for streaming content and encounters high latency, equipment failures, or a split modulating issue. The goal of this module is to convert to the other technique within a short amount of time without interfering with data operations and administration, as shown in Figure 1.

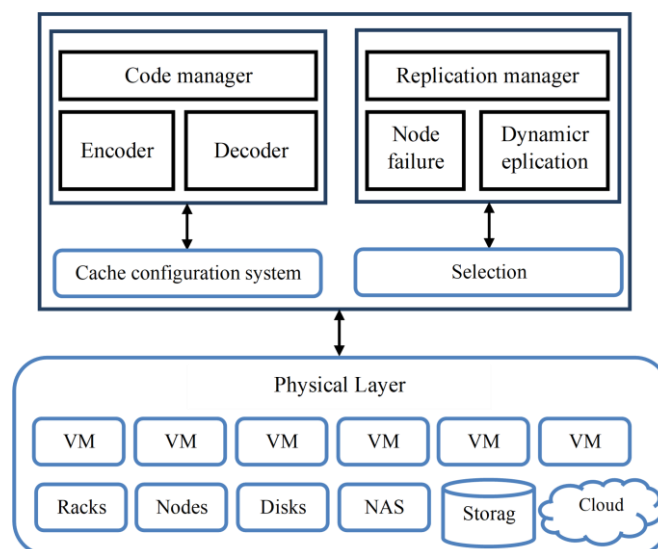


Figure 1. The proposed system conceptual.

5.2. Results

In our current work, the cloudsim3.0.3 tool was used, and the simulation code was programmed using the Java programming language, as this language offers great capabilities in the field of networks. The initial justification is related to data structuring and evaluation in accordance with the situation presented in the previous section. Before moving forward with learning and testing the mirroring and recovery system, it is necessary to rationalize the type and source of the data since it is assumed that the data is connected with various protocols and that various communication methods are linked to the cloud. The outcomes of structuring the data on several recurrent correlations to assess various hypotheses are seen below. By transmitting files to and from cloud storage and calculating the time it takes to send and receive data, the findings demonstrate how cloud computing works.

5.2.1. Example 1

The first illustration made use of cloud data kept in a calculator named Data Center 2. Additionally, broker technology was applied. A Cloud Broker is a company that negotiates contracts between cloud providers and customers and controls the use, performance, and delivery of cloud services. As cloud computing develops, cloud users may find it difficult to manage the integration of cloud services on their own. Table 1 lists the results of example 1.

Table 1. Example 1 results.

Cloudlet ID	STATUS	Data center ID	VM ID	Start Time	Time	Finish Time
0	hit	2	0	400	0.1	400.1

The results table above shows a significant improvement in the sending and receiving process, as the process was completed at a speed of 0.1 seconds.

5.2.2. Example 2

In this model, data was asked by two instruments, VM0 and VM1, from the identical data center simultaneously, as in the next table:

Table 2. Example 2 results.

Cloudlet ID	STATUS	Data center ID	VM ID	Start Time	Time	Finish Time
0	hit	2	0	1000	0.1	1000.1
1	hit	2	1	1000	0.1	1000.1

We note in the above table that data was requested from two different devices at the same time per second, 1000 seconds, which is the beginning of the transmission time, and the request and response process took 0.1 seconds, bringing the total time to 1000.1 seconds.

5.2.3. Example 3

In this instance, data was invited by two appliances, VM0 and VM1, from two separate databases simultaneously, as in the subsequent table:

Table 3. Example 3 results.

Cloudlet ID	STATUS	Data center ID	VM ID	Start Time	Time	Finish Time
0	hit	2	0	1000	0.1	1000.1
1	hit	2	1	1000	0.1	1000.1

5.2.4. Example 4

In the fourth instance, the issue was involved, as data was ordered from the cloud from further machines at further and similar periods, as in the next table:

Table 4. Example 4 results.

Cloudlet ID	STATUS	Data center ID	VM ID	Start Time	Time	Finish Time
4	hit	2	4	3	0.2	3.2
16	hit	2	4	3	0.2	3.2
28	hit	2	4	3	0.2	3.2
5	hit	2	5	3	0.2	3.2
17	hit	2	5	3	0.2	3.2
29	hit	2	5	3	0.2	3.2
6	hit	3	6	3	0.2	3.2
18	hit	3	6	3	0.2	3.2
30	hit	3	6	3	0.2	3.2
7	hit	3	7	3	0.2	3.2
19	hit	3	7	3	0.2	3.2
31	hit	3	7	3	0.2	3.2
8	hit	3	8	3	0.2	3.2
20	hit	3	8	3	0.2	3.2
32	hit	3	8	3	0.2	3.2
10	hit	3	10	3	0.2	3.2
22	hit	3	10	3	0.2	3.2
34	hit	3	10	3	0.2	3.2
9	hit	3	9	3	0.2	3.2
21	hit	3	9	3	0.2	3.2
33	hit	3	9	3	0.2	3.2
11	hit	3	11	3	0.2	3.2
23	hit	3	11	3	0.2	3.2
35	hit	3	11	3	0.2	3.2
0	hit	2	0	4	0.2	4.2
12	hit	2	0	4	0.2	4.2
24	hit	2	0	4	0.2	4.2
36	hit	2	0	4	0.2	4.2
1	hit	2	1	4	0.2	4.2
13	hit	2	1	4	0.2	4.2
25	hit	2	1	4	0.2	4.2
37	hit	2	1	4	0.2	4.2
2	hit	2	2	4	0.2	4.2
14	hit	2	2	4	0.2	4.2
26	hit	2	2	4	0.2	4.2
38	hit	2	2	4	0.2	4.2
3	hit	2	3	4	0.2	4.2
15	hit	2	3	4	0.2	4.2
27	hit	2	3	4	0.2	4.2
39	hit	2	3	4	0.2	4.2

In accordance with the above findings, this article has presented an in-depth discussion of the study

issue. In this section, a model API application was used to emulate the methodology suggested and built, and JMeter technologies were used to carry out the API calls [29]. The Internet API instance compiles with a bigger proportional usage of both the CPU and memory, and the results are recorded using contemporary cloud API monitoring technologies. Training and personal development are becoming increasingly important due to the rapid growth of intelligent technologies and the growing labour shortage. Companies use skills and knowledge to maintain adaptability and competitiveness in their respective industries. In this paper, researchers offer a method for managing competence throughout an entire business segment to stay up with the ever-changing demands of clients as well as advances in technological innovation. E-learning and artificial technology are the driving forces behind this approach [30]. A hybrid recommender that is based on machine learning is what researchers propose as a methodology that may be used to customize a learning roadmap for a person. Managers are able to determine and improve the skills necessary to carry out a company's business strategy when they make use of the approach. Emulation of networking loads was performed in table 1 using cloud data from the Data Center 2 calculator. This was accomplished by increasing the API output to 4K bytes per second and higher. There was a utilization of broker technology. Cloud brokers are responsible for managing the use, performance, and delivery of cloud services in addition to negotiating contracts between cloud providers and clients [31]. Customers of cloud computing may have difficulty integrating cloud services as cloud computing technology advances. When there is a greater demand on the CPU, there is an increase in the number of HTTP error codes. In this investigation, the cloudsim3.0.3 tool was used, and the simulation code was built in Java, a programming language that provides rich network-related features. The results of this study are presented in this article. In accordance with the situation described in the preceding section, the initial reason relates to data structuring and evaluation. VM0 and VM1 both asked for data from the same data centre at the same time, as shown in Table 2 demonstrates that when the API component is not used much, it works as expected and meets customer queries [32]. Within the circumstance that table 2 experiences an error, there will be a greater demand placed on either the CPU or the previous memories. A request for data was initiated simultaneously from two distinct devices at the rate of one per second for the first one thousand seconds, which is the beginning of the transmission time. The time it took to both send the request and get the response was 0.1 seconds, making the total time 1000.1 seconds. The reporter provided a description of the processes for restoring base traffic had been, which were developed on the conceptual framework that represented the highest point of these base traffic restoration approaches [33]. People are required to complete 15 cycles of testing, during which they must find solutions to overcome obstacles and get back on track. As can be seen, the findings were evaluated in light of the mobility model that is currently being used. The auto-correct adaptive approach that was proposed shows significant improvement when measured against the script-based implementation that was carried out after a failure. The recommended framework necessitates an amount of time equal to approximately 1000.1 milliseconds in order to take immediate corrective action before the system fails [34]. This improves the system's resilience and makes sure there is no free time. This means that it has proposed machine learning forecasting and classifying mechanism models that perform better and can restore an estimate of 1000.1 seconds faster than the lower limit healing time and 1000.1 seconds faster than current systems. The Multiple relationships Regressor is used in the 5XX situations, with 20% of the data sources used for training and 80% of the sets of data used for test results [35]. This can be seen in the table that follows, Virtual Machine 0 (VM0) and Virtual Machine 1 (VM1) simultaneously requested data from two distinct data centres. It is clear that both the network-sent packets and the network-received parcels are processed as expected, and the HTTP status code 2XX is attained without any issues [36]. The 5XX errors had begun to manifest themselves at precisely the correct moment, which was when the dimensions of the packets being sent and retrieved were growing. It needs to demonstrate that a 5xx HTTP status software, as well as a 2XX HTTP status password, are both visible when a significant number of packets are obtained and sent. The HTTP Status number 2XX has been observed in other places, and the graphical depiction may be found in table 4 [37]. For instance, it was difficult to find a solution to the problem due to the fact that various devices requested data from the cloud at various times. In this circumstance, the amount of network traffic caused by sending and

receiving data is significant. The 5xx instances in the simulation model are to blame for both the high outgoing and the high receive loads. This system has worked normally during the other three circumstances and returns HTTP provides the reference 2xx. Table 4 has actually shown several examples through the test set of data in the ML model [38]. Therefore as a direct result of this, the value of both the root mean square error and the mean square error itself is 3.84, and the value of the mean square error's square root is 1.96. Table 4, which makes use of the collection of test data, provides a comparison of the actual forecast with several of the possible outcomes. As the number of requests increases, it is clear from examining Tables 2 and 3 that the proposed model is able to achieve an increasingly high level of classification accuracy. All of the different kinds of HTTP response numbers, such as the Cloudlet ID, the Status, the data centre ID, the VM ID, and the start time, the time, and the finish time, have been utilized to carry out the validity checks [39]. On the other hand, because numerous protocols and communication methods are linked to the cloud, it is essential to rationalize the data type and source before learning and testing the mirroring and recovery system. This is because the cloud is linked to numerous communication techniques and protocols. In the previous section, a number of recurrent correlations were utilized in order to test hypotheses., it was found that a classification performance [40]. Additionally, high-performance computer technology is rapidly becoming a major field, which necessitates persistently superior efficiency from both businesses and processing technology in order to satisfy the requirements of real-time operations and maintain company stability. This necessitates that businesses and processing technology work together in order to maintain company stability. The use of cloud computing exemplifies this point more than any other [41].

6. Conclusion

This proposed system concentrates on data availability, dependability, and profiling to guarantee the security and integrity of the data. The proposed system ensured higher accuracy, minimized data loss, minimized latency, and reduced hardware failure. Cloud computing suffers from delays in the time of requesting and sending data, in addition to the loss of that data. After applying the proposed system, which is a system based on improving the performance of cloud computing based on machine learning techniques, an improvement was observed in the time of requesting data from devices to the cloud and the time of sending data from the cloud to devices, while preserving data from loss and noise. Cloud computing can be further improved by integrating more than one artificial intelligence technology because artificial intelligence technologies have proven effective in solving most network problems, especially in the field of cloud computing.

7. Recommendations

Although the proposed system has advantages over the existing status of cloud computing, there are other issues that can arise in the future. So, this proposed system must have experimented with different conditions and requirements with bigger data than used in this current research. Extensive research should be carried out to include more cloud computing metadata for effective handling capacity and testing of video and audio streaming and heterogeneous traffic. Further validation should be done in the future for optimizing categorically based on different traffic data and loads in the multi-clouds environment.

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