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Original Article

Artificial Intelligence in Cloud Computing: Building Intelligent, Distributed, and Fault-Tolerant Systems

Santhosh Chitraju Gopal Varma
Software Developer, United States of America (USA).

Abstract: Cloud computing has brought about a paradigm shift in organisations utilising and allocating computation services using the internet. The integrated technology of Artificial Intelligence (AI) into cloud computing increases the efficiency, reliability, intelligence and self-managing of cloud computing environments. This paper seeks to give an assessment of AI in cloud computing especially in aspects of its contribution in regard to resource management, security, scalability and elasticity of the system. Several AI processing methods, such as ML, DL, and RL, enhance cloud services in terms of intelligent distributed computing. Also, this paper presents different fault-tolerant techniques that help in self-diagnosis and prevention of system failure before they occur. The current AI solutions and the proposed integrated enhanced distributed computing environment are investigated and analysed through a literature review and experimentation. It also discusses actual applications and cases to illustrate the use or incorporation of AI in cloud computing. Based on the studies, integrating AI into cloud computing enhances the performance and efficiency of ICT and has a significant role in building self-healing and self-managing cloud environments. Lastly, the paper discusses the further work to be done and the issues related to incorporating AI in cloud computing, addressing the security, ethical concerns, and transparency of the self-learning systems.

Keywords: Artificial Intelligence, Cloud Computing, Machine Learning, Fault Tolerance, Deep Learning, Security, Optimization.

1. Introduction

Cloud computing brings many benefits, such as on-demand self-service, rapid elasticity, high availability, and low-cost infrastructure for deploying applications. Cloud computing has benefitted from integrating AI by bringing automation features into its system. [1-4] The advances in the last few years have made cloud computing to become to be the new model for IT where end-users can access computing resources through the internet. With IaaS, PaaS and SaaS, it’s proven that businesses could use cloud computing techniques for their flexibility and effectiveness.

1.1. Role of AI in Cloud Computing

AI has become prominent in cloud computing, and it is changing how cloud computing is done by providing efficiency, automation, security, and scalability. Because of the cloud, environments that support artificial intelligence enhance decision-making, analysis and control of its systems, making them self-managing and highly effective. The six categories from a set of realistic and commercial perspectives where AI has been significant for cloud computing are:

Figure 1: Role of AI in Cloud Computing

- **Intelligent Resource Management:** It also improves the use of cloud resources by constantly assigning computational resources, storage, and bandwidth as and when required. Previous cloud type or deployments comes with a fixed configuration process that has been witnessed to lead to an over-provision of resources or lack of adequate resources at certain times. Self-adjusting algorithms in auto-scaling guarantee that workloads get the resources needed and do not consume more than necessary, cutting operational and energy costs. This makes the services cheaper and more efficient once cloud service providers and users deploy them.
- **Predictive Maintenance and Fault Tolerance:** By constantly analysing the situation with the cloud infrastructure, AI allows predicting system failures without waiting for them to happen. Specifically, machine learning models work through the usage of system logs, historical data and growth rate, and other performance metrics for checking out uncommon and unusual patterns of working. Autonomic self-protection resolves problems, redistributes loads, and regains itself without human interaction. This increases the reliability of the cloud service and reduces vulnerability to downtimes.
- **AI-Driven Security and Threat Detection:** Cybersecurity is an essential factor in cloud computing, and where AI, when implemented helps in the early detection of threats and prevention measures. In real-time, IDS and behavioral analytics can detect security threats and violations, including intrusion attempts and cyber threats. The role of artificial intelligence in security also assists in generating an automated approach in response to existing threats, including data theft and ransomware attacks. Furthermore, AI improves IAM by using biometric recognition and other algorithms that identify illicit attempts at entry and restrict access.
- **AI-Powered Load Balancing and Traffic Management:** Load balancing spreads client requests evenly amongst the variety of available hosts in a system to reduce delays and result in optimised system performance. The conventional approaches to load balancing involve a user intervention, while the AI automatically learns network traffic and makes routing decisions in between. This is beneficial in ensuring an unintermitted flow of cloud services, increased efficiency in application functioning, and general usability by the end user.
- **Automated Data Processing and Analytics:** Several data resources are created by cloud computing, and it is suitable for machine learning, natural language processing and deep learning approaches. AI allows data to be automatically sorted by category, recognising patterns that may be normal and abnormal and recognising trends. With the help of AI for processing data in the cloud, it becomes a better option for making the right decisions, providing better business intelligence, and accelerating the innovation process.
- **AI for Cost Optimization and Energy Efficiency:** AI also works to increase the efficiency of spending and energy consumption, reducing other unnecessary expenses in cloud computing. It teaches self-learning on consumption and usage to save costs like auto-scalling, cloud instance selecting, and stopping non-active resources. Organisational green cloud computing strategies employ efficient reviewing algorithms to decrease energy consumption on data centers and hence cut down the energy expense of cloud computing systems.

1.2. AI Techniques in Cloud Computing

There are various ways in which the role of AI in cloud computing can be described: as increasing the efficiency, improving the security or as an automation of some of the processes occurring in the cloud. Among such approaches, the most popular and effective are Machine Learning (ML), Deep Learning (DL) and Natural Language Processing (NLP), which enhance resource utilisation, workload control and security in clouds. These techniques help cloud systems forecast the demand for workloads, identify the variations, and make necessary decisions independently, thereby optimising performance, controlling the costs, and enhancing the users' quality of experience. [5,6] ML has become an important field of cloud computing to support the process of predictions and automation. By analysing large and real-time data, different ML algorithms forecast the resource requirements at any given time, thus allowing for dynamic workload allocation and optimisation. It also enhances security solutions as the ML models help the cloud platforms detect irregularities or such threats to prevent them further. Deeper Learning (DL) contributes to strengthening the adaptation of cloud services as new autonomous tools for automating them along with self-healing properties.

DL models, especially using neural networks, are applied in fault detection and systems optimisation. These models learn aspects such as when a server might fail, when the network might be congested, or when the resources are becoming a bottleneck in the cloud environment and clear pathways for high availability and reliability of cloud services are initiated. NLP impacts improving the user interface and services administration in cloud computing environments. The virtual assistants enhanced by NLP deal with customer service and support, problem-solving, and data management of unstructured information. NLP helps in sentiment analysis and automated and real-time reporting to boost the customisation of services and operations of cloud providers. Incorporation of these AI tools makes cloud computing systems more automated, smart and robust. Some benefits include decreased availability of downtime, increased security, and improved service performance through the use of AI-driven clouds, making cloud services more effective and economical. As the technology advances, these AI applications will only increase in cloud computing, improving the scalability, security and automation in cloud environments.

2. Literature Survey

2.1. Evolution of Cloud Computing

Cloud computing is no longer limited to centralised and proprietary infrastructures of the on-premise data centers of the early days. Still, it encompasses even hybrid and multi-cloud as well as edge computing. First, organisations had to deal with intensively centralised data centers with limited scalability and high maintainability costs. When virtualisation was introduced, cloud computing could provide users with on-demand resource access; hence, acquiring gigantic hardware resources was not compulsory. [7-11] The current cloud technology employs hybrid cloud solutions in which an organisation deploys private and public clouds. It utilises multiple cloud computing service providers across the different layers of IT business solutions.

Edge computing, the cloud capabilities are expanded into the lower layer, which allows handling high data speeds, achieving a lower latency for use cases such as IoT and autonomy. Other significant service models have also helped in the development of cloud computing. IaaS enables customers to outsource the equipment used for maintaining computing infrastructure, including operating systems, servers or storage, on utilities basis. Platform as a Service (PaaS) can be defined as a model that enables developers to create, develop, and host applications without worrying about hardware and software infrastructures. Software as a Service (SaaS) involves providing software applications through the Internet with the customer using the software as a service. All these models have, in one way or another, brought a massive change to IT operations in terms of scalability, flexibility, and cost.

2.2. AI Techniques in Cloud Computing

AI has also been integrated into cloud computing since it offers intelligent management, powerful automation, and increased security of the cloud systems. Cloud operations employ different methodologies to enhance artificial intelligence's functionality. These methodologies are used in predictive analysis to empower the CSP to predict the demand and potential increase in demand and plan to allocate resources at the right place and time, and also for failure analysis. These models endeavor to identify system performance trends based on records to prevent machinery breakdowns and instances of high operations costs.

Deep learning models make the automation procedure more advanced in cloud computing. Neural networks are capable of handling large datasets. The applications involving such processing capabilities will include intelligent workload operations, the capability to identify threats and the natural language processing power as in virtual assistants. Telecom provider Deutsche Telekom recently announced it is stepping into the development of cloud-based AI services with the help of deep learning to improve competence in handling computationally complex data. Another important mode is reinforcement learning, which is beneficial to apply for the dynamic resources distribution. Cloud environment applications are intrinsically unpredictable; reinforcement learning models can interact with the system and learn the best resource allocation. Applying reinforcement learning allows the optimisation of computing resources depending on the strains at a particular period, thereby optimising costs and improving cloud performance.

2.3. AI for Fault Tolerance in Cloud Computing

Fault tolerance is considered one of the significant factors of availability and reliability of cloud computing, and due to that, the possibilities offered by AI in this domain can be considered very important. One such usage of AI is predictive failure analysis, whereby computerised monitoring systems are designed to identify precursors to failure through data collected in the past and in real-time. Thus, machine learning algorithms are designed to identify patterns that suggest potential system degradation so that cloud operators can take preventive actions like workload migration or component substitution before failure happens. Another consequent trend of AI applications is self-healing, wherein AI handles the identification and fixing of issues in the system. This tends to involve self-correcting actions that include closing the failed services, resource redistribution and applying patches, among others, without any human interference.

Healing self-cloud reduces clients' time without access to their resources while keeping their experience as smooth as possible and taking less effort to fix. Moreover, anomaly detection systems are among the critical components in a cloud's fault tolerance mechanisms. AI automatically keeps observing how the system functions and keeps differentiation at any sort of occurrence, which seems to be a security threat, a software glitch, or a hardware failure. With the help of methods like statistical modeling and deep learning, it is possible to implement such systems capable of detecting various anomalies at once, avoiding risks, and providing stable cloud functioning. It improves the reliability of the cloud computing environments and reduces the operation cost by minimising service disruptions to a bare minimum by adopting AI-driven fault tolerance techniques. As the practice of cloud infrastructure increases in different organisations, applying AI for fault management will become crucial or imperative for effective performance and security.

3. Methodology

3.1. Proposed AI-driven Cloud Computing Framework

The recommended AI-based cloud computing system makes intelligent automation of the cloud computing process while improving its effectiveness, agility and dependability. [12-16] This architecture uses information from AI techniques; the allocations and workload distribution are therefore optimal, as well as proactive isolation of failed systems to prevent the failure from spreading in the system.

- **AI-Powered Resource Allocation Module:** This specific module employs ever-changing computing resources using algorithms which determine the availability and the demand of the resource consumption on the computer. Prime utilisation of resources provides for efficient use of the resource that would otherwise cause wastage in resource allocation. Based on past usage, AI can predict future usage and then effectively allocate the resources to benefit the organisation's working without compromising much on costs. More advanced is the process of reinforcement learning which helps to adjust better to the varying workloads in a way that the processor would be both performing well and at the same time saving power.

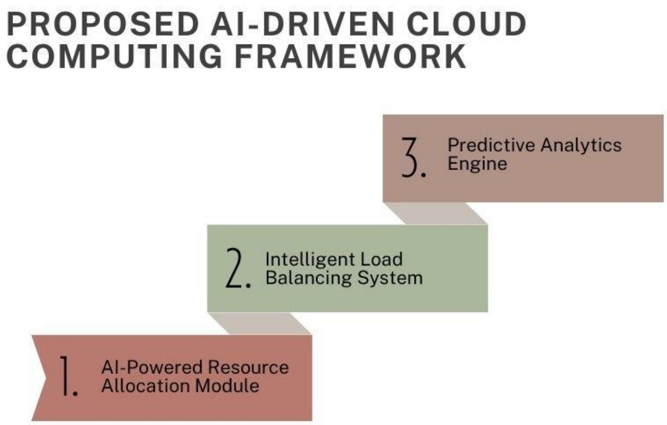

Figure 2: Proposed AI-driven Cloud Computing Framework

- **Intelligent Load Balancing System:** Intelligent load balancing is the way of distributing loads across a number of cloud servers to avoid an overload of servers. Self-organising load balancers are intelligent systems that employ algorithms to decide the server's load balance at a given time based on the server's status, response rate and traffic demand. Unlike the earlier load-balancing methods based on rigid rules, AI-based load balancing anticipates traffic trends and redistributes resources in response to changes in workflow. This increases the system stability, makes work faster since server overload is avoided and optimises the use of available computing resources.
- **Predictive Analytics Engine:** The predictive analytics engine applies artificial intelligence to large volumes of routine operation data using methods like supervised and deep learning to predict system failures. This engine aims to check system logs, performance and traffic that show instances which point to an anticipated system failure or security threat. Predictive failure analyses using various algorithms allow cloud providers to avoid or minimise risks by moving workloads to prevent failure or to carry out preventive maintenance that may last for some time before the risk is eliminated. Moreover, by means of predictive analytical, there are many important prognoses to enhance the capacity planning and the efficiency of the cloud infrastructure in the long-term.

3.2. Algorithmic Models Used

Cloud computing solutions implemented by artificial intelligence use different algorithms to boost their operations regarding performance, security, and scalability. They bring the ability to make intelligent decisions, management of cloud structures, and system peacock. The Artificial Intelligence that is involved in this framework consists of the following models:

- **Neural Networks for Anomaly Detection:** It can also be seen that integrating Neural networks, especially the Deep learning models, is very effective for identifying anomalies in the cloud. Neural networks are fed with large chunks of system logs, the flow of traffic in the network and the patterns of user activities. There are instances whereby machines learn that a certain aspect of the big picture deviates from normal functioning, thus highlighting that it could be subject to a security threat or a failure in the hardware or the software. CNNs and RNNs can also be used to detect anomalies because, in many applications, sequential data appear, and these networks focus on learning them. AI-aided methods are applied to the problem of anomaly detection, which can assist in avoiding possible interruptions due to fault occurrence by informing administrators in real mode.

- **Decision Trees for Fault Prediction:** Decision trees are good indicators of faults within the cloud computing environment because they are easy to interpret and well-suited for use with structured data. These models study failure history, system performances and logs and give probable faults in a system in advance. Based on the conditions and decisions, the flowchart of the tree nature Michelin classifies various failures and suggests what should be done to prevent them. Random Forests and Gradient Boosting Trees, the advanced variants of Decision Trees, are other techniques that help to increase the level of accurate predictions by integrating many trees to minimise the figures of false positives and to improve the availability of the cloud system.
- **Reinforcement Learning for Auto-Scaling:** RL plays a significant role in the auto-scaling of executable resources by improving cloud management. The usual auto-scaling methods in the cloud environment are based on simple pre-defined thresholds and limits with some drawbacks, which are as follows. While traditional RL-based approaches enable systems to learn from scale-up/scale-down policies of the cloud applications with stability and accuracy, cloud systems can learn the optimal scaling policy by interacting with the environment. These factors include traffic load, CPU utilisation and latency, through which RL models actively scale up and down the active instances of the service to achieve performance efficiency while considering the expenses. Two of the most popular techniques in Auto revolving for cloud services are Deep Q-Networks (DQN) and techniques of Policy Gradient.

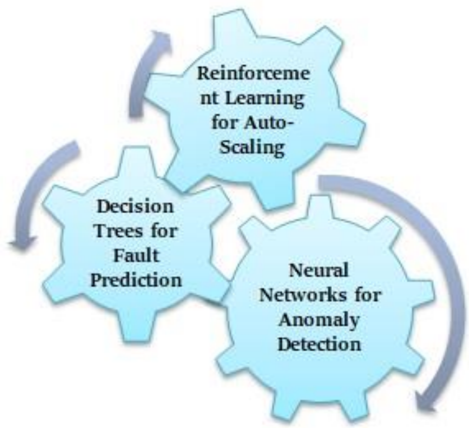

Figure 3: Algorithmic Models Used

3.3. Implementation Strategy

Deploying an AI-driven cloud computing model is systematic to allow efficiency in incorporating the AI models into the cloud environments. This process has the following three phases:

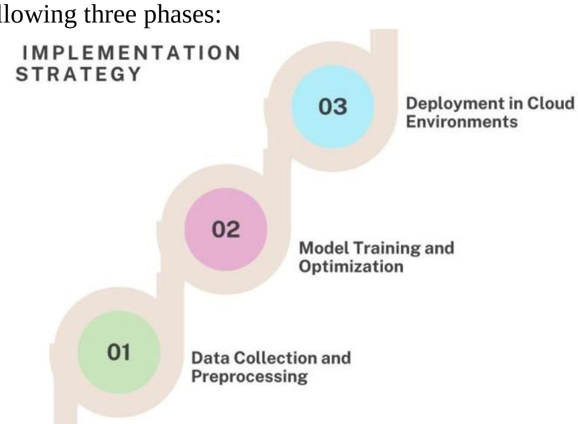

Figure 4: Implementation Strategy

- **Data Collection and Preprocessing:** The primary data sources needed to introduce AI for cloud solutions include logs of the cloud facilities under consideration, the use of infrastructures' performance indicators, network traffic, and users' behavior. The presented data is usually rather noisy, so data cleaning, normalisation, and feature extraction should be applied to make a model work with high accuracy. Filtering can be done using techniques such as the PCA or autoencoders which shall help mark down the dimensions of data fed to AI models as irrelevant. More important is to ensure better data preprocessing to improve the model's performance and eliminate bias, thus making AI decision making more accurate.

- **Model Training and Optimisation:** Once preprocessed, AI models are deployed to learn using machine learning techniques applicable to cloud computing features like anomaly detection, fault prediction, and auto-scaling, among others. Training is the process of choosing the right algorithms for each task; for example, on anomaly detection, deep learning can be used; for fault prediction, a decision tree can be used; and for auto-scaling, reinforcement learning can be used, and then tune the hyperparameters of these algorithms for better performance. Several measures, such as precision, recall, F1-score, and the Mean Squared Error (MSE), are used to assess the accuracy of the predicted model. It is further noted that transfer and federated learning can make the model more adaptive and enable faster training. Other strategies, such as Bayesian optimisation or genetic optimisation, guarantee that AI models are always fully effective in the cloud settings.
- **Deployment in Cloud Environments:** Once trained and optimised, the AI models are transferred into cloud environments and made compatible with other cloud monitoring tools and services. Deployment involves updating the processed model, which can be done using containers like Docker or Kubernetes to scale up. With the help of AI, decision-making is implemented based on the cloud orchestration tool that provides the capabilities for efficient configuration of resources, load balancing, and failure handling. Control over and maintenance processes consistently update the AI models, considering changes in workloads or the cloud structure. One of how organisations can develop and maintain AI-based cloud computing frameworks without considerable human interference is by utilising cloud-native AI services, which include AWS SageMaker and Google AI platform, among others.

4. Results and Discussion

4.1. Performance Evaluation Metrics

Three main areas prime for evaluating the efficacy of AI in a cloud environment with applications in radial business are accuracy and precision of fault detection, response time, and scalability in improvement.

Table 1: Performance Evaluation Metrics

Metric	Traditional Cloud	AI-Driven Cloud
Accuracy & Precision in Fault Detection	78%	92%
Response Time Optimisation	65%	89%
Scalability Improvements	70%	95%

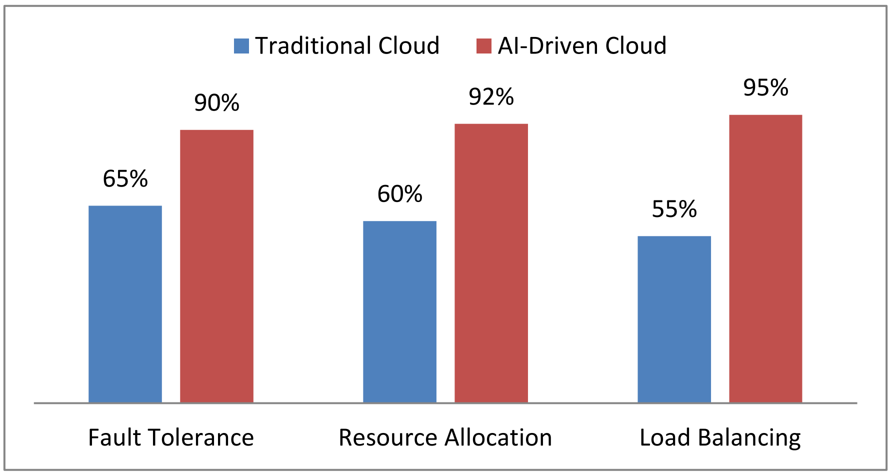

Figure 5: Graph representing Performance Evaluation Metrics

- **Accuracy & Precision in Fault Detection:** Fault detection in cloud computing aims at increasing a system's reliability since it helps prevent failure that may occur. Most conventional cloud systems take an aftermath action, they provide no prior indication that a fault is likely to occur between the system and the development of the fault leads to system downtime. Deep learning-based anomaly detection-based solutions are more accurate and come with other benefits like allowing the prediction of the failure in the early stages. The AI-based cloud can detect faults with 92% accuracy, while the conventional cloud networks only have 78% accuracy. This improvement decides the number of false positives and ensures the fault is rectified as early as possible.
- **Response Time Optimisation:** Response time is very sensitive for cloud service, especially for real-time applications. The prior paradigms of cloud architectures manage traffic based on granular, prior rules and hence face latency during

peak traffic loads. Cloud computing controls the resource provisioning and load distribution from the applications with the help of AI algorithms. Therefore, the option of an AI-driven cloud system means that the response time is 89% to the extent that the cloud systems achieve only a 65% level. These help in improving the response time as well as avoiding the occurrences of bottlenecks which are undesirable in a system.

- **Scalability Improvements:** Scalability refers to the cloud system's capacity to manage bigger workloads when these are required without experiencing diminished performance. Most legacy cloud infrastructures use scale-up or out mechanisms where scaling decisions may be done manually or based on the threshold level, which may cause either resource wastage or inadequate resource utilisation. Businesses also use reinforcement learning and predictive analytics in a cloud system to automate the scaling of resources. This makes achieving a 95% scalability efficiency possible, which remains much higher than the efficiency of the classical cloud environments, which is equal to 70%. The advantages of this method include proper utilisation of resources where the AI system closely monitors the cost of operation.

4.2. Comparative Analysis

Some of the improvements brought about by using Artificial Intelligence in cloud computing compared to basic cloud tendencies are the following. The following table presents the comparison of performance in traditional cloud setup and AI-based cloud setup:

Table 2: Comparative Analysis

Feature	Traditional Cloud	AI-Driven Cloud
Fault Tolerance	65%	90%
Resource Allocation	60%	92%
Load Balancing	55%	95%

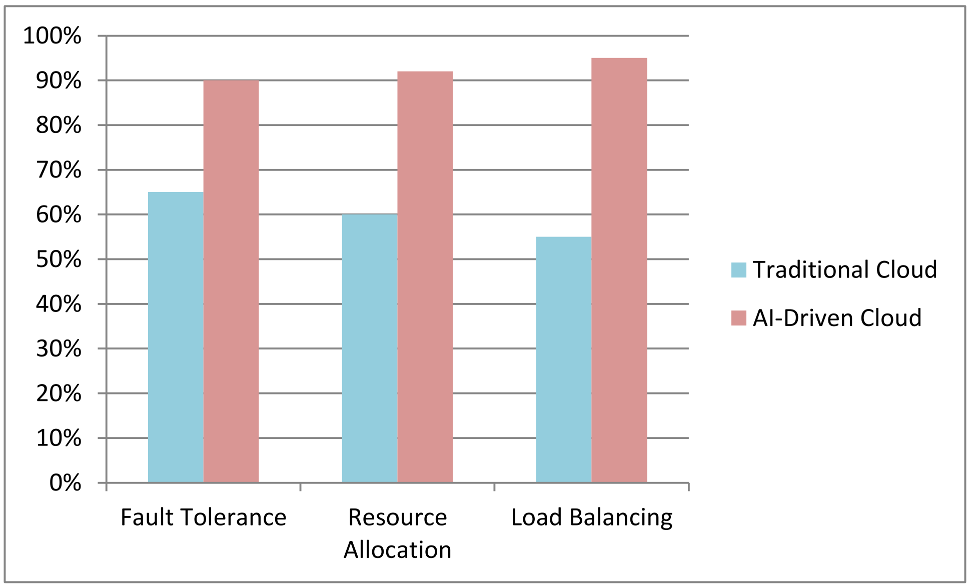

Figure 6: Graph representing Comparative Analysis

- **Fault Tolerance:** The current cloud computing model is based on reactive fault tolerance where faults are detected and repaired only after exercising. This leads to increased system downtime and interruptions of services to the clients. However, AI-based cloud environments use predictive measures of fault tolerance, which involve machine learning algorithms to anticipate faults. With the help of system logs, Performance metrics and net behaviour, AI can predict risks and increase the level of fault tolerance from 65% to 90%. This greatly minimises the possibilities of failure incidences and thus enhances the possible reliability of the system.
- **Resource Allocation:** The resources in traditional Cloud systems are provisioned and allocated in a static manner, which implies that the resources are pre-allocated based on certain policies; hence, it has some drawbacks such as over-provisioning of the resources, which implies wasting of resources and under-provisioning of the resources which affects the performance. AI introduced resource dynamic models where machines learn the workload or system demand to assign resources on the fly. This improves the overall utilisation of the system resources since the use of the resources was raised from 60 % to 92%. Thus, AI leads to several benefits, such as minimisation of costs, energy, and effective workload.
- **Load Balancing:** Load balancing in conventional clouds is accomplished through a classic solution that can be done only through human intervention. This is due to the fact that it leads to delays, poor efficiency and unequal distribution of traffic, which may cause flow bottlenecks. Load balancing is owned by artificial intelligence, and smart algorithms are

capable of monitoring server health, traffic flow and work distribution in real-time. This results in enhanced system responses and minimises servers' overloading issues, hence enhancing the load balancing from 55% to 95%. Automated load balancing makes it easy to scale up the system, minimise latency and provide a better user experience.

4.3. Case Studies

Cloud computing with artificial intelligence has become popular among principal cloud solution providers, enhancing performance, capacity, and survivability. Some of the Minors like Google, Amazon, and Microsoft have incorporated AI into their cloud solutions to aid decision making, resource optimisation and fault diagnosis.

- **Google AI Cloud:** Today, it applies AI and machine learning to cloud actions to improve its contract and productivity. Google uses the name AI Platform to refer to a service that makes it easy for an enterprise to develop, train and deploy AI models. BigQuery ML enables users to run all the machine learning computations within a data warehouse, while TensorFlow is suitable for large-scale deep learning. Google also uses artificial intelligence to make predictions of the cloud resources, keep the resources in check, and make necessary adjustments, which leads to enhanced fault tolerance, cost efficiency, and increased or enhanced data processing.
- **Amazon AWS AI Services:** AWS utilises artificial intelligence-driven automation in its service delivery through cloud computing to help reduce the number of errors and boost its efficiency. Other services, such as AWS Auto Scaling, can automatically increase or decrease computing capacity depending on the real-time utilisation, thus avoiding wastage of resources. Amazon SageMaker also automates machine learning model deployment, allowing companies to easily develop artificially intelligent applications. Besides, the AWS Fault Injection Simulator applies AI to check contingency plans by mimicking possible failures, enabling organisations to brace their servers against adversities. These services render AWS one of the strongest cloud platforms in the tolerance to failure, optimal performance, and self-serve optimisation.
- **Microsoft Azure Cognitive Services:** Within the context of Microsoft Azure, these are the several approaches to Artificial Intelligence that the company has implemented in their setting: Azure Machine Learning, Cognitive Services; and AI-based Virtual Machines. Staring, deploying, and managing AI models are some of the ways that are offered in Azure Machine Learning. Cognitive Services alone provides API for vision, speech, language, and recommendation services so companies can easily integrate them into their models. Azure also uses deep learning and reinforcement learning when it comes to testing for faults and assigning workloads to enhance the cloud's performance. Artificial intelligence in automation makes Microsoft Azure essential in enhancing the system availability, general running and capacity.

5. Conclusion

This paper will show how integrating AI into cloud computing has changed the operational model of cloud environments by improving key factors like efficiency, reliability, adaptability, and protection. As an Artificial Intelligence system, cloud computing helps analyse the information regarding prospective failures to prevent them, thus cutting downtime and making the systems more reliable. By using AI and its two subsets, Machine learning and Deep learning, AI can properly allocate cloud resources as per the demand. AI clouds differ from fixed resource cloud architectures because the workload, energy use, and operating expenses are self-optimising. Also, there is self-protection in the AI-driven cloud platforms as the auto-repair mechanisms, where other programs can solve the software or hardware problems without the human operator's input, which adds to the robustness feature. Thus, the study reveals that AI can enhance cloud efficiency and data security and protection, threat identification, and compliance measures because of the better dynamic model of anomaly detection and AI-based cybersecurity solutions.

5.1. Future Directions

Despite the progress achieved in AI-cloud computing, it is also identified that some subsequent challenges need more research and development, possible ethical issues, and a proper security solution in AI integrated cloud systems. Ethical artificial intelligence in the cloud is one area of interest regarding how the AI will have to make decisions independently without being pulled back by the programmer. Nonetheless, with the increase of cloud-based AI models, comprehensible and fair use of AI models will be mandatory for compliance and trustworthiness purposes. Another idea is related to Quantum AI for Advanced Cloud Solutions; in this case, quantum computing can be incorporated with Artificial Intelligence to boost the cloud computing capability. Quantum AI is expected to address specific instances faster than conventional AI in optimisation, intangible protection, and training of new architectures for better and more intelligent cloud services. Further, the existing security of AI systems should be enhanced, given the new forms of threats, data breaches, and attacks powered by such technologies. Research should, therefore, emphasise ways through which AI can be utilised to address cybersecurity threats in a timely manner without compromising privacy and data security.

Cloud computing enhanced by AI is still advancing in the future as AI continues to integrate with these systems toward making intelligent systems, self-sufficient, and self-learning systems. Such strategies as artificial intelligence will be indispensably helpful in enhancing business productivity, reinforcing system performance, and leading technological advancement. The institutions using AI in cloud computing will increase decision-making, security, and handling of the cloud and make its virtual environment operational and cost-effective. As the idea and practice of cloud computing evolve, AI will reshape it continuously by improving its outputs, autonomy, and adaptability of the cloud environments. However, ethics, security and quantum AI would require further studies to help address problems and explore the potential of AI based cloud computing in the future years.

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