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STUDY OF SUSTAINABILITY OF CLOUD COMPUTING AND ARTIFICIAL INTELLIGENCE

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ABSTRACT

Modern society is increasingly reliant on cloud computing, which supports a wide range of applications from social media to infrastructure. To achieve Quality of Service (QoS) assurances, such a system must be able to handle changing loads and usage that represent how societies interact with and rely on automated computing systems. These systems are made possible by a collection of conceptual technologies that have been merged to fulfil the needs of developing computing applications. To understand the system's current and future difficulties, it is crucial to identify the essential technologies that will enable future applications. We explore how three developing AI paradigms will influence cloud computing systems in the future in this study. Furthermore, we identify major technologies that are powering these paradigms and invite experts to discuss the current state of cloud computing and anticipated future advances. Finally, we suggested a conceptual model for cloud futurology to explore the influence of new paradigms and technologies on the growth of cloud computing.

INTRODUCTION

Cloud computing entails renting hardware and software, only paying for services that are used, and more. It refers to the supply of computer hardware, software, and other information technology services to a customer or client via a network, depending on their needs. Third-party cloud computing service providers who maintain their data centres or network infrastructure commonly provide these services. Cloud computing is another new area of the information technology business that is rapidly expanding. However, security concerns with this evolving technology remain a key source of concern. Economic denial of service (EDoS) attacks on cloud infrastructure are rapidly becoming security issues. In 2008, Hoff and Cohen coined the phrase "economic denial of sustainability". Cohen defined it further in 2011, and the scientific community now widely adopts this concept. Cloud computing infrastructures, which are increasingly important in emerging communication technologies, are regularly the target of denial-of-service (DDoS) attacks. DDoS attacks are thus precisely defined by Singh et al. as "threats that attempt to render the pricing model unsustainable and, as a result, make it difficult for a firm to financially use or pay for its cloud-based infrastructure". According to studies, EDoS threats are also known as reduction of quality (RoQ) threats and fraudulent resource consumption (FRC) attacks. Attackers utilize computational intelligence techniques to take advantage of the bulk of cloud computing firms' "pay-as-you-go" accounting model and auto-scaling features.

The EDoS attack is a new type of distributed denial of service (DDoS) attack. In contrast to a DDoS attack, which may prohibit lawful users from accessing a service for a limited time, an EDoS attack has the potential to prevent a cloud adopter from offering services indefinitely, resulting in insolvency. They are more difficult to detect since they are more intricate and new than DDoS attacks. Figure 1 demonstrates the direct and indirect ways in which EDoS threatens cloud computing. EDoS attacks make use of the auto-scaling functionality of cloud computing, resulting in the unneeded creation of new virtual computers. The cloud service provider bears the cost of this illegal malicious use. Attackers utilizing EDoS can steadily increase illegal traffic. Because EDoS attack traffic mimics difficult traffic, it is difficult to detect.

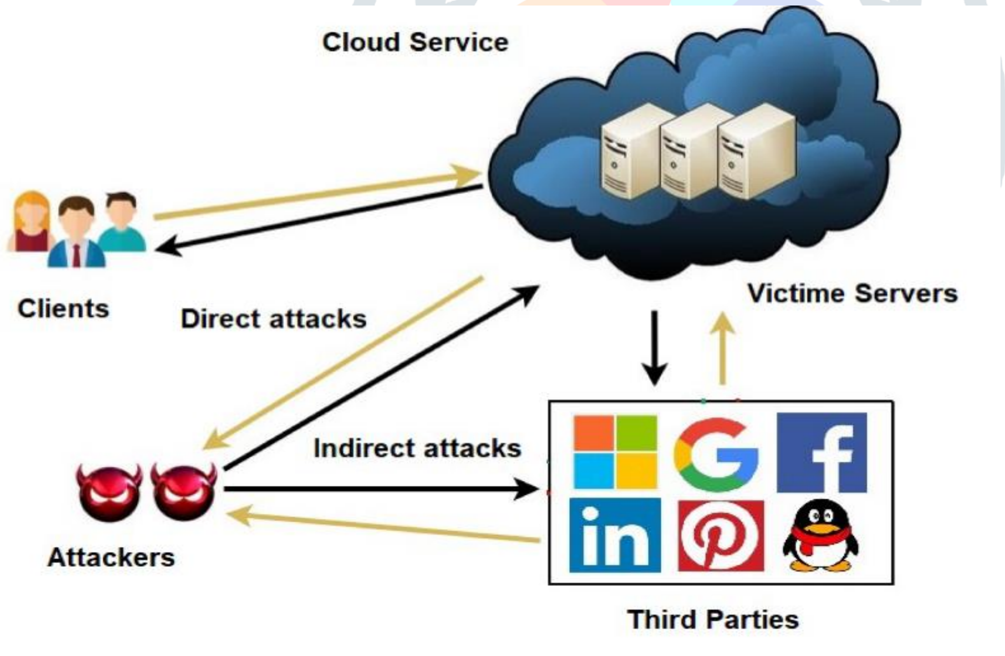

Figure 1. Economic denial of sustainability threat to cloud computing service providers

The challenge of detecting EDoS has been addressed in several ways. DDoS attacks have been identified using the self-organizing map (SOM) and SVM machine learning algorithms. However, because they rely heavily on feature engineering and selection, traditional machine learning algorithms struggle to interpret large amounts of EDoS data in network applications. Deep learning (DL), a type of machine learning technique that uses neural layers, can be used to improve information extraction, increase detection accuracy and resilience, and overcome the disadvantages of machine learning (ML). DL algorithms use a variety of neural network models fashioned after the human brain, as well as various nonlinear processing units, to address complicated issues. Many models and processes that use flow-based detection approaches require a time series model that can reliably recall the most recent input and predict the output of the sequence data. The recurrent neural network can detect DDoS attacks (RNN). A memory gate, a built-in mechanism in the long short-term memory (LSTM) RNN model, can be used to circumvent the vanishing gradient issue in RNNs by regulating the flow of input sequences.

Cloud computing

Cloud computing refers to the technique of using a network of remote computers hosted on the internet to store, manage, and process data rather than a local server or personal computer. Cloud computing can be deployed on-premises, on the cloud, or in a hybrid deployment. Furthermore, it provides three core service models that reflect different cloud computing components: Software as a Service (SaaS), Platform as a Service (PaaS), and Infrastructure as a Service (IaaS), which is designed for system administrators. Figure 1 depicts a detailed visualization of the various cloud computing service and deployment models.

Cloud computing is commonly used in aquaculture to collect and store data generated by production, processing, and sales before processing and analysis. Aquaculturists usually follow sets of rules and principles when creating fish. Cloud computing and big data technology enable massive volumes of data to be collected for process optimization and traceability. Cloud computing provides an excellent platform for application system integration, with CIA integration being the key to developing a smart aquaculture system that promotes optimal performance, feasibility, and flexibility (water quality monitoring system, data intelligent processing system, and fish pest knowledge base). One example is Aqua cloud, a cloud-based platform developed by the Norwegian Seafood Innovation cluster in conjunction with IBM and several other companies. The platform was built on IBM Clouds to collect data from aquaculture firms, such as sea lice counts and other information. The data is then entered into a prediction system to forecast sea lice outbreaks over time. Farm managers are then given this information so that they may understand the risks and take safeguards before an outbreak occurs.

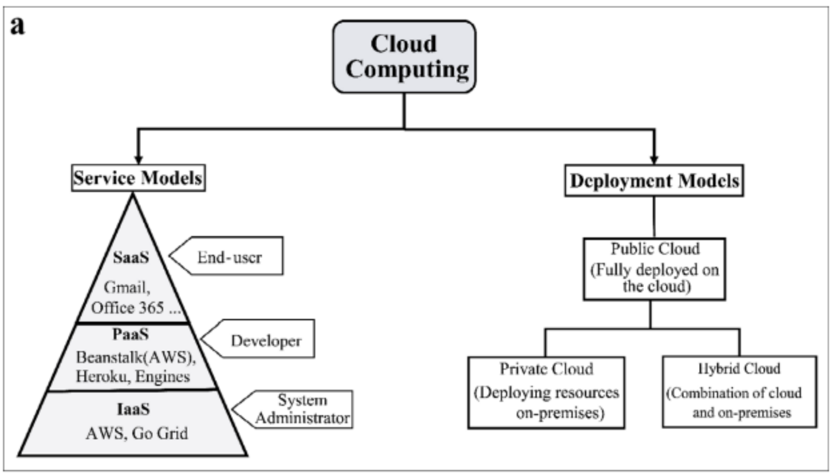

Figure 2 Cloud computing architecture

Artificial intelligence (AI)

A subfield of computer science that attempts to duplicate the cognitive processes of living beings in computers by mimicking learning mechanisms that allow them to make decisions based on prior experiences. Mimicking that machine learning and AI are two distinct yet connected fields of science. One of the specific scientific techniques now used for AI research is the study of the algorithms and statistical models that computer systems utilize to perform specific tasks with little interference from humans. In machine learning, algorithms are used to perform mathematical models based on learned data to create predictions without being specifically programmed to do so. The majority of industries that work with large amounts of data have recognized the value of machine learning technology in increasing productivity. Although there are other classification schemes for machine learning techniques, the most common divisions are supervised and unsupervised learning. Unsupervised learning, in contrast to supervised learning, involves no human intervention and involves feeding training data—data that includes inputs and intended outputs—to the learning algorithm.

The fundamental acknowledged AI paradigm is to solve problems by comprehending an automated intelligent task. Other industries are developing AI models at a rapid pace (like contemporary data science approaches). They have not been sufficiently utilized in the aquaculture business at the same time. Digitalization, big data, and deep learning (DL) enable the use of machine learning approaches in developing aquaculture models that can forecast unforeseen events and ensure decision-making efficiency. DL analyses, evaluates, and breaks down large data of data into smaller concepts. When it comes to live fish identification, species classification, behavioural analysis, food selection, size or biomass estimation, and water quality prediction, DL in smart fish farming has been intensively investigated, yielding more accurate findings than conventional techniques.

In practice, to use AI and machine learning, challenges are recognized and fed into machine learning processes as intelligent tasks. These processes are then processed and interpreted to make decisions. Because machine learning can process and interpret multiple tasks faster than humans, there will be less stress associated with processing multiple tasks. a method for defining operational limits in aquaculture using data from multiple sources to support businesses, particularly service providers, in making safe operational planning and decisions for both coastal and offshore fish farms. They used machine learning techniques such as Bayesian networks, Tree Augmented Nave Bayes (TAN), and algorithms to create a prediction model to determine operational limits under a specific scenario.

Because AI provides the opportunity to solve problems based on experience and background knowledge to obtain relevant information and make discoveries that previously relied on experts' experience. To ensure high prediction accuracy (99.99%) by removing outside influences, research and development are required to improve statistical models and algorithms used in AI and machine learning. We cannot, however, avoid trade-offs when implementing machine learning technologies. As a result, we must be prepared to deal with unforeseen events throughout the transition period, at least temporarily.

How Cloud Computing works:

A cloud computing system's workload is changing dramatically. Applications can now be run remotely without overburdening local PCs. Instead, they are managed by the cloud's computer network. Hardware and software user expectations are declining. The only software required to interface with the cloud computing system, which can be as simple as a web browser, must be able to run on the user's computer; the rest is handled by the cloud's network. A web-based email account, such as Gmail or Outlook, is an example. When you use a web browser to connect to a webmail account, the software maintains the account on the service's cloud web rather than on the computer, where a computer program would ordinarily be running.

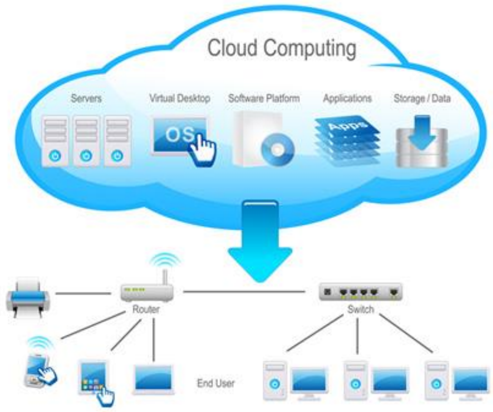

Figure 3 Cloud Computing working

This is one type of cloud computing. Due to a scarcity of available hard drive storage capacity, cloud storage devices such as G-drive, Microsoft drive, Mega drive, and others have also been seen. This is a type of cloud computing in which data is saved on the cloud (servers of cloud providers instead of data in a server of a hard drive). This is what happens with cloud computing, where all data or servers that may be running are stored on the cloud provider's server. Because there isn't just one server, but rather a network of connected servers, the same data is duplicated across all of them, making it considerably more secure and safe if one of the servers fails.

The main characteristics of Cloud computing

Cloud computing makes it possible to have shared, convenient, on-demand network access to a pool of configurable computing resources (such as networks, servers, storage, applications, and services) that can be quickly provisioned and released with little management work or service provider involvement.

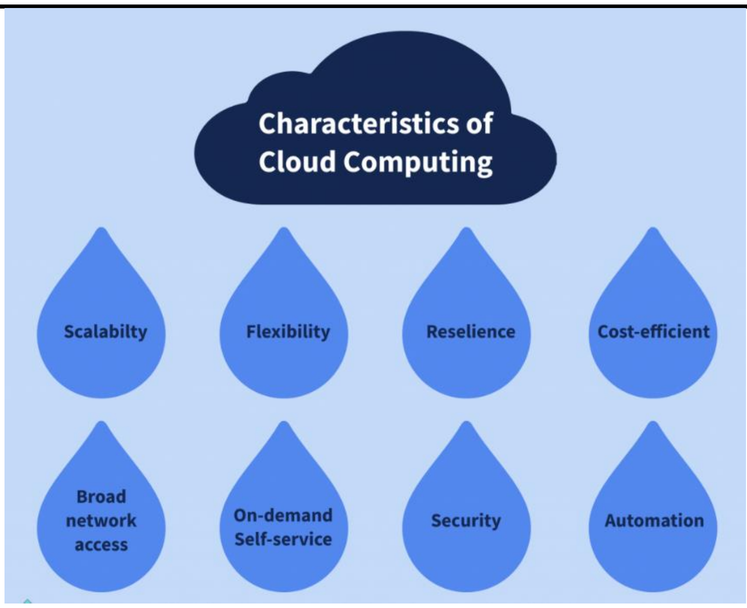

Figure 4 Characteristics of cloud computing

Types of cloud services: Iaas, PaaS, SaaS (Service Models)

The majority of cloud computing services fall into three categories. These are sometimes known as cloud computing stacks since they stack one on top of the other: Infrastructure as a service (IaaS): As we descend the stack, we approach the key building blocks for cloud services. Cloud storage and network capabilities that can be self-provisioned, metered, and made available on demand round out IaaS's highly automated and scalable computing resources. This service provides infrastructure such as servers, operating systems, virtual machines, networks, and storage on a rental basis. Microsoft Azure, Amazon Web Service, and other services are examples.

B. PaaS (Platform as a Service): PaaS performs at a lower level than SaaS and typically provides a platform for the design and deployment of software. This service is used in software development, testing, and maintenance. The PaaS service is identical to IaaS, but it also includes additional tools such as DBMS, BI services, and so on. PaaS abstracts much of the work associated with managing servers and provides clients with an environment in which the operating system and server software, as well as the underlying server hardware and network infrastructure, are taken care of, allowing users to focus on the business side of scalability and application development of their product or service. Other examples are Heroku, Google App Engine, and Red Hat Open Shift.

Software as a service (SaaS). Consumers are most familiar with the sort of cloud service known as SaaS. SaaS outsources software management and deployment to a third-party service. Among the most well-known SaaS services for enterprises include customer relationship management tools like Salesforce, productivity software bundles like Google Apps, and store solution siblings like Box and Dropbox. The use of SaaS applications tends to minimize the cost of software ownership by eliminating the need for technical employees to manage, install, manage, and upgrade software as well as lowering the cost of software licensing. The majority of SaaS apps are available on a subscription basis. Salesforce, for example, or Google application

LITERATURE REVIEW

Mustapha, U. F., Alhassan, A. W. et al,(2021) Rising worldwide populations and a corresponding demand for protein have resulted in steadily rising demands for the world's food supply. Considering that fish is a popular protein source all over the world, this places a strain on the capture fishery industry. However, the faster the fisheries stock is depleted, the more effort we put into the capture fisheries to obtain maximum catch. Aquaculture technology advancements are currently our best bet for producing enough fish to meet demand. While the agricultural and manufacturing sectors have benefited greatly from technological progress, the aquaculture sector has seen only a limited effect. As new technologies like the Cloud, IoT, and CIA have emerged, there have been a plethora of new opportunities to apply and integrate IT into all facets of human endeavour.

Aldhyani, T. H., & Alkahtani, H. (2020) Providing business and consumer IT services via the internet is a growing industry, and cloud computing is the most cost-effective method at the moment. However, it is vulnerable to emerging problems. When a cloud customer is subjected to an economic denial of sustainability attack (EDoS), the attacker takes advantage of the pay-per-use model to gradually increase the number of resources they consume. We provide a practical method for protecting cloud infrastructure from distributed denial of service attacks. Methods for detecting these kinds of distributed attacks on various cloud computing smart grids have been proposed as a way to lessen their impact.

Goralski, M. A., & Tan, T. K. (2020) A new era of innovation in business, corporate practices, and public policy is emerging rapidly as a result of advancements in artificial intelligence (AI). The deep learning capabilities of machines and robotics have had far-reaching disruptive and enabling effects on the business world, national governments, and social and political systems. They are having a greater impact on the overall global sustainability movements. The advent of a brave new world ushered in by the AI revolution could either be the beginning of a utopian era in which humans and machines live in peace and prosperity together, or the beginning of an era of widespread war, poverty, and misery. To put it another way, would the advent of AI hasten our achievement of the United Nations' Sustainable Development Goals (SDGs) or lead us down a path toward even greater economic instability, ecological devastation, and social unrest? What does this mean for the future of business leadership and how do we train the leaders of tomorrow? To answer these questions, this article will examine the effects of AI in three different scenarios.

Lytras, M. D., & Chui, K. T. (2019) Eleven original papers (and a review article) cover a wide range of topics and approaches to artificial intelligence (AI) for smart and sustainable energy systems and applications in this special issue. Many interesting perspectives on recent events and beyond have been provided by the contributors. The guest editors have provided concise summaries of each piece and drawn attention to four categories of emerging topics in the energy sector. The guest editors appreciate everyone's hard work and feedback. We anticipate a dramatic increase in the use of actual AI methods in the energy sector in the not-too-distant future.

Gill, S. S., Tuli, S., et al,(2019) From basic societal functions like infrastructure maintenance to more niche uses like social networking, cloud computing is indispensable in today's world. Quality of Service (QoS) guarantees are essential for such a system to function reliably under unpredictable loads and changing usage patterns that reflect society's engagement with and dependence on automated computing systems. All of this is made possible by a group of conceptual technologies that have been synthesized to fulfil the needs of advanced computing applications. We need to identify essential technologies enabling future applications to comprehend the existing and future challenges of such a system.

Yoo, S. K., & Kim, B. Y. (2018) Sustainable progress and increased corporate competitiveness are the results of using big data, artificial intelligence, and modern information and communication technology. Before the advent of more modern cloud computing architectural layers such as infrastructure, platform, and software as a service, cloud services were categorized as having unique system requirements for businesses. To keep up with the ever-shifting landscape of IT services, businesses must reevaluate their strategies and determine whether or not a cloud computing infrastructure would be beneficial.

Nishant, R., Kennedy, M. et al,(2020) Business as usual will be radically altered by AI, and major societal issues, such as environmental degradation, may finally be tackled. Environmental decline and the climate crisis are extremely intricate phenomena that call for cutting-edge strategies. Specifically, we argue that AI can help derive culturally appropriate organizational processes and individual practices to lessen the strain on the planet's natural resources and energy infrastructure. At a higher level, the true value of AI will be in how it facilitates and fosters environmental governance rather than in how it enables society to reduce its energy, water, and land use intensities. The sustainability of our planet is threatened primarily by human actions.

Wong, S., Yeung, J. K. W. et al, (2021) Designing a blockchain architecture based on cloud infrastructure is proposed in light of the difficulties in maintaining and manipulating ever-increasing numbers of immutable transaction records in a blockchain network of various supply chain parties, as well as the advantages to be gained from using sophisticated analyses on the big data generated from these records. The technological sustainability of this approach is discussed in this work concerning issues of scalability and large data processing and analytics.

Kumar, P. R. A. M. O. D. (2020) Technology in the present day is characterized by a trend toward digitalization, which is reshaping business practices all over the globe. A new business computational ecosystem is emerging as a result of the rapid development of new technologies and innovations. Digitization, Industry 4.0, Big Data, Blockchain Technologies, cloud computing, 3D Printing, Machine Learning, Automation, Artificial Intelligence (AI), Internet of Things (IoT), Data mining, etc. are among the most frequently used terms in professional conversations around the world. One of the most rapidly developing cutting-edge technologies, Cloud Computing combines the scalability of a large-scale computing system with the ease of use and virtually infinite resources of the cloud.

Yoo, S. K., & Kim, B. Y. (2019) The study's goal is to test, through Fit and Viability, how task characteristics for business and technological characteristics, economic feasibility, technology readiness, organizational factors, and environmental elements of cloud computing affect performance. The study's stated goal is to validate the Fit-Viability model's predicted association between the various success elements for adopting cloud computing. Workers from South Korean IT firms that make use of cloud computing were polled for this study. The structural equating model examined the data. Therefore, Task characteristics and Technology characteristics influenced Fit positively, while Technology readiness, Organizational factors, and Environmental factors influenced Viability positively. The adoption of cloud computing was similarly impacted by Fit and Viability.

The emergence of AI in the Age of Sustainable Development

According to Jeffrey Sachs, a Columbia University professor of health policy and management, the world is entering a new world known as the Age of Sustainable Development, in which all countries must collaborate to address the most difficult issues such as persistent extreme poverty, social exclusion, economic injustice, poor governance, and environmental degradation (Sachs, 2015). Sachs is the current director of the United Nations Sustainable Development Solutions Network and has acted as a key counsellor to the UN on both the SDGs and the Millennium Development Goals (UNSDSN). At the UN World Summit on Sustainable Development (WSSD) in Johannesburg in 2002, he presented a paradigm for assessing sustainable development through the four pillars of economic development, social development, environmental protection, and good governance. The world's sustainable development is dependent on all four of these factors, which are individually distinct pillars that support one another (World Summit of Sustainable Development [WSSD], 2002, p. 2). Sachs addressed difficulties with sustainable development, proposed solutions, and provided reams of information on global sustainability events via the UNSDSN. However, because AI is such a novel, dynamic, and rapidly evolving phenomenon, its consequences on the work of promoting the SDGs are only now becoming apparent and have not been thoroughly investigated.

The research of artificial intelligence from its inception to the present day has been extensively researched. As documented in industry trade magazines and academic journal articles, the number of research has expanded as a result of the experimental integration of AI into theory, thought processes, and feasible solutions to difficulties by innovators across a variety of sectors. Initially, there was a dramatic rise in AI investment, but after receiving limited returns, it reduced, increased, and declined in a cycle that has appeared intermittently throughout the history of AI (Munoz & Naqvi, 2018). On a roller coaster, AI has encountered both success and disaster.

Elon Musk, Stephen Hawking, and Bill Gates warn that increased AI use will exacerbate global economic inequality and presage an existential crisis for humanity. While some people hail the increased use of AI as a vision of increased economic prosperity, improved leisure, and more free time, others disagree (Sainato, 2015). It might signal the beginning of a brand-new, 40–60-year-long wave known as the Kondratiev Wave, which heralds a fresh cycle of enduring industrial innovation and economic expansion. In his 1925 book, The Major Economic Cycles, Russian economist Nikolai Kondratiev described this phenomenon of business cycles that feature booms and busts, and Joseph Schumpeter gave these economic cycles the term Kondratieff waves in his honour (Barnett, 2002). Unquestionably, AI has the potential to be a potent force that ignites decades of economic expansion, one of the four pillars of sustainable development.

AI for sustainability research

The term artificial intelligence (AI) is used to describe computerized abilities to solve problems and achieve goals. This ability can be regrouped into three categories:

AI for sustainability research relies primarily on ML models and algorithms to demonstrate how computers can analyse and learn from data. ML learning methodologies include reinforcement, transduction, multitasking, supervised, unsupervised, and semi-supervised learning, Supervised learning is divided into regression and classification for numerical and categorical results. Popular supervised learning models include generalized linear models (GLM), support vector machines (SVM), and decision trees (DT) including random forests, artificial neural networks (ANN), and Bayesian networks (BN). Some models are used for both regression and classification Deep learning is gaining traction as a type of ANN with more layers of units

Natural computing (NC), which overlaps with AI, is a broad field. However, we view the application of NC algorithms to optimize ML models or find information to be a subset of ML. NC frequently comprises constructing algorithms inspired by the natural world, using natural materials as computational media, and simulating natural phenomena in computers. Biological phenomena such as evolution, ecology, and swarm, for example, stimulate the development of optimization algorithms. Genetic algorithms are the most common use of evolutionary computation (EC). EC is frequently used to optimize machine learning models.

AI for sustainability

In 1987, the concept of sustainability gained traction when the Brundtland Commission conceptualized it as “development that meets the needs of the present without compromising the ability of future generations to meet their own needs” (WCED, 1987). The environment, economy, and society are identified as the three elements interrelated dimensions that contribute to achieving sustainability. The literature commonly takes a reductionist approach to deal with each element independently.

Environmental sustainability

Environmental sustainability is defined as "meeting the resource and service needs of current and future generations without jeopardizing ecosystem health". Some of the concepts and topics covered include low-impact transportation, sustainable agriculture, and combinations of environmental asset conservation (e.g., biodiversity, water resources, energy use, renewable energy, raw materials such as food and minerals, and sustainable land use), waste management, and pollution control (e.g., waste reduction, recycling, reuse, repair, using environmentally responsible material, pollution monitoring, pollutant treatment Many of these concerns have been addressed in research on AI for sustainability, with a focus on specific AI applications for increasing biodiversity. ARIES1 is a popular rule-based system for modelling ecosystem services. The software employs several machine learning (ML) models for data analysis to understand researchers in comprehending complex, nonlinear relationships. ANN and BN are two popular ML models for biodiversity, with GA being used as an optimization approach.

AI and smart cities

AI applications for smart cities were studied, as well as applications related to resource conservation and the environmental effects of activities such as transportation. Although various attempts have been made to define smart cities and their dimensions, they are usually viewed as a more "avoidable and appealing urban environment under a smart and agile administration". A smart city has six dimensions: economy, mobility, the environment, people, lifestyle, and governance. It is a critical component of the infrastructure required to improve both public and commercial services, such as sustainability, business innovation, and governance effectiveness. AI may be used to assess data generated by the Internet of Things (IoT) to support smart city governance, culture, and metabolism.

Challenges in studying AI for sustainability

AI applications address environmental sustainability, but are challenged by tendencies to rely on historical data in ML, uncertain human behavioural responses to AI-based interventions, increased cybersecurity risks, adverse impacts of AI applications, and inadequate measurements of performance or intervention strategies.

Reliance on machine learning

According to the review of literature, machine learning (ML) has been widely applied in AI solutions for sustainability. Machine learning (ML) uses patterns and relationships found in historical data to learn and make predictions. Many research organizations, including the Intergovernmental Panel on Climate Change (IPCC), are developing simulation models to forecast potential future scenarios with 1 to 6-degree Celsius increases in global average temperature. Researchers have proposed generating benchmark datasets that include additional climate model components for more accurate climate predictions. However, the fact that historical datasets reflect ages and climate cycles from before substantial human activity may limit their utility. The Anthropogenic epoch has arrived, and a human-caused climate emergency is unfolding. Human-related variables are difficult to integrate into ML models since they can be unpredictable at times and are still emerging. As a result, adopting a deterministic strategy in which results can be foreseen is difficult because we are unable to predict upcoming climate changes with sufficient accuracy. When stochastic techniques are applied, which allow for intrinsic unpredictability with probability for various scenarios, the resulting models are more speculative.

Adverse effects of AI

Even though artificial intelligence (AI) is a powerful and promising technology for sustainability, its use leaves a huge carbon footprint, which is a direct type of rebound impact. One AI model training can emit the equivalent of five vehicles' worth of carbon dioxide (Hao, 2019). If energy sources remain constant, the carbon footprint of AI models grows considerably as they progress. They have not, however, been widely adopted or used for AI. New approaches for analysing the environmental sustainability of software programs have been developed (e.g., Furthermore, because AI models rely strongly on data, they unwittingly raise their worldwide carbon footprint. AI models can be used to energize large data centres and energy-intensive datasets. New frameworks and techniques are being developed to provide more comprehensive lifecycle models for measuring data centre sustainability, going beyond typical data centre efficiency indicators such as PUE (power usage effectiveness). To anticipate potential environmental risks from AI, the research and practice communities must capitalize on advances in green software and infrastructure.

CONCLUSION

AI has a wide range of applications that have the potential to change the pursuit of sustainable development, which will involve different actors from various nations, cultures, and industries. Through the UN Global Compact, businesses from all around the world have been invited to contribute to the achievement of the SDGs. The three case studies stated above show how AI may be a powerful enabler of the global effort to stimulate economic development while simultaneously addressing the sustainable-term repercussions of our production and consumption on society, governance institutions, and the environment. Inventors, activists, and global development advocates who use AI-enabled applications have pushed to the forefront of the subject of sustainable development. Their innovations have improved industry and sector efficiency, helped to preserve priceless, non-renewable resources, spread knowledge and expertise, closed global resource and technological gaps, and aided in the formation of successful multi-sector partnerships (between governments, business, civil society, and citizens) that support global sustainability.

The pursuit of Global Goals and the implementation of the SDGs' bold plan for a sustainable future must battle powerful and entrenched forces. They range from people's apathy, lethargy, and ignorance to governments' lack of political will and resources, firms' pursuit of short-term profit, nation-states' short-sighted focus on particular national interests, and abandonment of the global common good. To fight for global sustainability and the future of humanity on the planet, a wide range of public and private sector organizations, national governments, and civil society will need to contribute all of their resources. They would, however, gain from exploiting an entirely new set of resources and tools made available by artificial intelligence.

Many firms are undeniably undergoing a digital transformation as they innovate traditional processes and services through digital transformation efforts and technologies. This is done not only to ensure their survival, but also to enable profitable business growth during the fourth industrial revolution, which includes technologies such as artificial intelligence (AI), self-driving cars, 3D printing, robots and drones, the internet of things (IoT), big data analytics and cloud, and social media solutions. Cloud computing services, in particular, have grown in popularity since their launch in 2006. In the beginning, the primary service was infrastructure as a service (IaaS), which provided physical computing power such as servers, storage, and networks. Platform as a Service (PaaS), which provides developers with a programming environment, has come to be an important part of cloud services. Furthermore, software as a service has accounted for a sizable part of cloud services (SaaS). When building an IT infrastructure paradigm, hybrid IT has also been considered. Total public cloud computing spending will rise from $67 billion in 2015 to $162 billion in 2020 as a result of the IT spending rate, which has grown at a rate of 4.5 times since 2009 and is predicted to grow at a rate of more than 6 times until 2020.

Considering this research, its purpose is to suggest a hierarchical decision structure model with the decision areas, factors and attributes based on the underlying decision factors of cloud computing adoption. The model will support the decision prioritization for cloud computing service adoption and system management. Regarding prior research, the challenges and risk factors of cloud computing adoption were initially looked at in its application to specific industries or countries.

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