

Application of Machine Learning Algorithm in Cloud-to-edge Computing: Analysis and Limitations

Emmanuel A. Adeniyi

Department of Computer Sciences,
Precious Cornerstone University
Ibadan, Nigeria.
emmanueladeniyi@pcu.edu.ng
[0000-0002-2728-0116]

Aminat Omotayo Adebayo

Department of Computer Sciences,
Al-Hikmah University, Ilorin.
Ilorin, Nigeria
ayakub@alhikimah.edu.ng

Sunday Adeola Ajagbe*

Department of Computer Science,
University of Zululand, South Africa
Department of Computer Engineering,
First Technical University Ibadan,
Ibadan, Nigeria.
Saajagbe@pgschool.lautech.edu.ng
[0000-0002-7010-5540]

Olukayode A. Oki

Department of Information Technology,
Walter Sisulu University,
South Africa.
ooki@wsu.ac.za
[0000-0002-6887-9782]

Oyebola Olasupo

Department of Computer Sciences,
National Open University of Nigeria,
Abuja, Nigeria
olasuposunday@ieee.org
[0000-0003-0753-5721]

Abstract—Machine learning (ML) approaches have been shown to be useful in a variety of difficult issues and domains such as managing resources, cloud services, and edge computing when used appropriately. Many cloud services concepts exist, including edge computing, fog computing, and mist computing. Internet of Things (IoT), Software-Defined Networking (SDN), cyber twin, and industry 4.0, have emerged in response to client application needs. These paradigms work together to provide customer-centric services delivered through the cloud server/data centers backend. However, a full review focused on cloud-to-edge computational resources management, technical and analytical features of these concepts, and the role of ML approaches in new cloud-to-edge computing concepts is still lacking, and this topic needs to be researched. As a result, this paper surveys the rising cloud-to-edge computing paradigms integration while taking into account the most dominant problem-solving technology by ML. This study provides a complete literature assessment of new cloud-to-edge computing paradigms, as well as their integration with ML. To carry out this research, articles from the last ten years (2013-2022) are extensively explored and analyzed in order to comprehend the application of various ML approaches in resource management of the cloud-to-edge ecosystem, and the comparison analysis on numerous aspects, including recent developments. Lastly, based on the observed numerous ML resource management issues and deficiencies in present methodologies for addressing these challenges, the paper proposes probable future research topics.

Keywords— Artificial intelligence, Cloud computing, Edge computing, Internet of Things, Machine learning.

1. Introduction

On the basis of information gathered about system operations, artificial intelligence (AI) can be utilized to support and build edge computing and cloud computing applications. For instance, ML approaches can be used to find patterns in the workload and then exploit those patterns to improve resource management. AI can be used in the analysis and planning phases of edge-based applications and cloud computing, which are frequently organized as monitor-analyze-plan-and-execute (MAPE) cycles. Additionally, the application of control theory concepts. The fundamental advantages in supporting cloud computing and edge-based resource management come from the combination of feedback control and AI-driven data-driven model creation. Both for private users and commercial users, cloud computing has significantly transformed how computing is provided. The use of cloud services has increased steadily since they were first

introduced, and it is anticipated that revenue from public cloud services would increase globally by 33% from 266.4 billion dollars in 2020 to 354.6 billion dollars in 2022 [1], [2].

Cloud storage has developed with numerous linked processing and communication concepts like as edge devices, fog nodes, mist computing, the Internet of Things (IoT) [3], Software-Defined Networking (SDN), digital twins, and industry 4.0. Developing with the combination of various cloud services concepts and their archetypes is becoming popular in order to satisfy the processing requirements of the next generations [4]. Furthermore, the use of Machine Learning (ML) approaches in conjunction with combined cloud methodologies is providing academics with new study options to satisfy the future requirements for technological breakthroughs [5]. To the best of the authors' knowledge, there has been no comprehensive research on combined computing systems using ML approaches. To fulfil modern computing needs, scholars from academia and business must do extensive research on cloud-driven integrated developing cloud computing concepts as well as ML approaches.

Edge computing, in general, works with local data and prevents data transmission to the cloud. It analyzes data immediately on the edge nodes, which are linked to adjacent switches or detectors [6]. The ability to interconnect, preserve, and analyze data locally via edge computing technology minimizes bandwidth, latency, and energy needs [7], [8]. Mist computing analyzes data on the network at its most remote point, which includes numerous microcontrollers and sensors. It collects the linked resources by exploiting the sensor's computing and communication features [9]–[11]. IoT can be implemented as sensors, controllers, cellphones, and other devices that engage and engage among themselves using locally or internet-based technologies connectivity [12]. Smart cities, mobility health care, and agriculture are some of the primary IoT applications [13].

Whereas cloud service was a proven research subject, automation across the cloud-to-edge computing path has received less attention [14]–[18]. Because existing cloud allocation solutions were not created with edge and fog computing in view, there is a shortage of technologies that can enable software utilisation in an enhanced cloud-to-edge context. In such contexts, applications are hosted in a more complicated and diverse architecture, where computing devices are spread over separate networks that span numerous

layers of a design in the cloud-to-edge domain rather than in a centralized node. As a result, it is necessary to investigate computational resource methods in order to expand their competences to the network's edge. Therefore, this research aims to investigate the various literature on the existing cloud-to-edge ecosystem, thus, discuss the research challenges such as the computation resources on the cloud-to-edge environment and provide a future research direction on how to use ML to mitigate the computational resources challenges in the cloud-to-edge environment. To carry out an extensive literature review, the following Research Questions (RQ) in table 1 must be answered:

TABLE I. RESEARCH QUESTION AND ITS MOTIVATION.

ID	Research Question	Motivation
RQ1	What are the various ML algorithms that were implemented for Cloud-Edge computing resource management by previous researchers in the last decade?	Determine cutting-edge methodologies and procedures of ML algorithms implemented for cloud-to-edge computing
RQ2	Are the implemented/ developed ML algorithm well suited for resource management in Cloud-Edge Computing?	Recognize frequently used and cutting-edge terminology ML algorithm in resource management of cloud-to-edge computing
RQ3	Which category of ML algorithms is more effective and efficient in Cloud-Edge Computing resources management?	Identify commonly ML algorithm that are efficient in cloud-to-edge computing
RQ4	What challenges and open research questions exist to resource management in Cloud-Edge computing using ML algorithms	Identify challenges and open research issues in resource management of cloud-to-edge computing.

As a result, in this research, a thorough literature review was proposed for the computational resources of a cloud-to-edge computing environment using ML approaches as utilities. As a result, the purpose of this study is to examine the different literature on the established cloud-to-edge ecosystem, discuss research issues such as computational capabilities on the cloud-to-edge environment, and propose a future research direction regarding the use of diverse ML algorithms to mitigate computational resources challenges in the cloud-to-edge environment.

Moving from the Cloud to the Edge: Accelerator Virtualization in Fog Computing was the focus of [19] study. According to the report, cloud-based hardware accelerators are accessible for improved analytics. By reducing end-to-end latencies and response times, the increased analytics employing accelerators moves user devices closer to the network's edge, increasing the quality of service. The paper discusses obstacles to making accelerators available at the edge as well as potential solutions. To conduct a fruitful study in this field, one must adopt a comprehensive perspective of fog architecture. Based on the preliminary reviewed literature, using AI algorithms to mitigate the resources management challenges in cloud and edge computing has been attempted, but with little achievement, there is still room for further study on the cloud and edge computing systems in terms of their computation resources, the focus of such direction will be identified in this study. The study provides the following contributions:

1. The study gives a thorough examination of the existing methodologies and techniques for implementing machine learning algorithms in cloud-to-edge computing.
2. This analysis provides an insights into the practical factors and potential impediments that must be addressed in order for implementation of ML in cloud resources to be effective.
3. The study investigate model compression and optimization strategies, resource-aware machine learning algorithms, privacy-protection systems, and adaptive learning approaches. These recommended solutions might serve as a roadmap for future field research and development activities.

The remaining parts of this study is arranged as follows. Section 2 discussed the methodology used in this study. Section 3 presents the results of the study using various tables and figures. While section 4 concludes the study giving the scope, recommendation and future works.

2. Methodology

A systematic review (SLR) of qualitative data will be used in the project. Although there is a lot of research on cloud and edge computing in relation to ML, it frequently focuses on a particular application. The implementation of diverse software on cloud services has been the subject of numerous publications, but there are still knowledge gaps in this field in terms of computing resources, which explains the need for the current study. Here, data from a few papers published in the past 10 years (from 2013 to 2022) will be systematically evaluated to examine information regarding cloud and edge computing, highlighting what has been said about the topic in both academic research and literature reviews. Fig. 1 shows the proposed block diagram of the ML for cloud-to-edge computing resources management study. Various scientific repositories were used for this research such as Scopus, ScienceDirect, Web of Science (WoS), Taylor and Francis among others. The two main scientific databases for this research were Scopus and Web of Science (WoS). These databases have very good literature in the domain this research, and the time line are judged to be sufficient for this investigation [20]. RStudio Software/ library in Python was used for the analysis of this study.

The review methodology was developed in accordance with the indicated research questions and study objectives. It is critical to seek for the most relevant papers linked to the study subject in a research review. Cloud services, internet of things, mist computing, edge computing, cloud technology, industrial internet of things, cybertwin, SDN, IoT, ML in public cloud, ML and computation power were explored for appropriate inclusions in ACM Digital Library, IEEE Xplore, Web of Science Core Collection, Scopus, ScienceDirect, Google Scholar, and electronic scholarly databases. The survey established inclusion and exclusion criteria to limit the study to recent works and future breakthroughs in ML methodologies for cloud-to-edge computing computational resources. A search phrase filter was implemented in order to find peer-reviewed literature, conference papers, journal papers, blogs, and scientific book chapters published in English. The survey excluded research articles unrelated to the above-mentioned study themes, as well as articles that did not investigate the methodologies, posters, references, non-English, preliminary studies, proof-of-concept, Powerpoint presentations, venue impact factor, and so on.

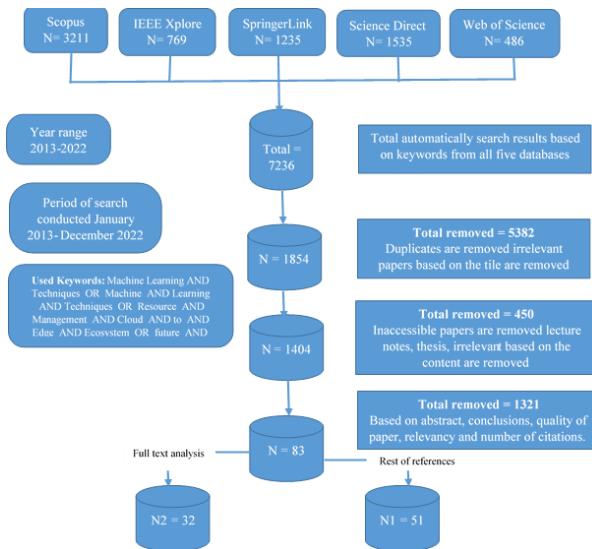


Fig. 1. The proposed block diagram of PRISMA used for selecting research papers.

TABLE II: Inclusion and Exclusion criteria used

I/E	CRITERIA	EXPLANATION
INCLUSION	Review Paper	The study suggests many sorts of reviews, such as literature reviews, systematic reviews, surveys, and so on.
	Research Paper	The paper aimed to survey specific research problems related to ML application in computational resources of cloud-to-edge computing.
EXCLUSION	Duplicated papers	The same paper that appears multiple times
	Non-research papers	This is not a scientific article. It could be editorial notes, remarks, or something else.
	Non-related papers	The issue under investigation extends beyond the scope of this work's research.
	Non English papers	The paper was not written in English
	Implicitly related papers	The paper does not directly express the research focus cloud-edge-computing and the use of ML in cloud-edge computing system.
	Non research paper	The paper was not a research paper. It might be editorial notes, comments, etc.

3. Results and Presentation

Using the inclusion and exclusion criteria, each article title is reviewed individually, yielding 7,236 publications. 5382 papers were removed because they were unrelated to the research topic (some excluded because they were focused on other aspects of ML and resource management in cloud-to-edge computing). Based on their abstracts, introductions, and conclusions, 1854 of them were chosen for additional evaluation. Endnote X8 was used to delete 450 duplicate papers. Several publications were eliminated because their complete contents were difficult to understand or their summaries revealed that they were irrelevant to the investigation. A total of 83 publications were chosen for evaluation as journal articles; each was reviewed for completeness, independently, and again using the inclusion

979-8-3503-3621-4/23/\$31.00 ©2023 IEEE

and exclusion criteria. The statistics of the publications per year is contained in Table III.

TABLE II. STATISTICS OF THE PUBLICATIONS PER YEAR

SN	Year	Number of Publication
1	2022	470
2	2021	352
3	2020	371
4	2019	244
5	2018	175
6	2017	67
7	2016	73
8	2015	45
9	2014	38
10	2013	19
	Total	1854

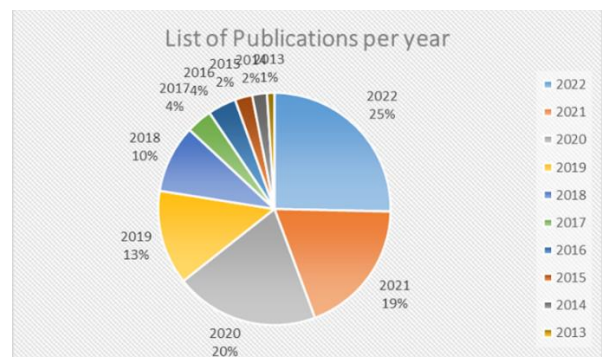


Fig. 2. Graphical representation of publications per year.

The survey article search outcome includes 277 review articles, 1521 journal articles and 56 chapters in books. The subject areas include Computer Science, Engineering and Decision supports in Open access & Open archive access.

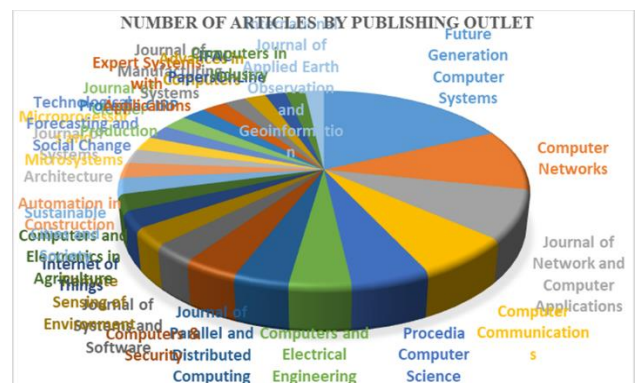


Fig. 3. Graphical representation of Articles by publishing outlet

3.1 Search Techniques/Review/ Investigation

The general search string for this study was: (“(“Machine Learning AND Techniques OR Machine AND Learning AND Techniques OR Resource AND Management AND in AND Cloud AND to AND Edge AND Ecosystem OR future AND research AND direction”). The chosen data sources were Scopus, Taylor and Francis, and ACM Computing surveys. The filtering range was set from 2013 to

2022 to include the important discovery algorithm, known as the Alpha algorithm or Alpha miner. Table IV shows the search phrase that was customized for each repository collection and was used to evaluate all fields accessible in each database.

TABLE III. VARIOUS REPOSITORIES AND SEARCH KEYWORD

Database	Search Keyword
Scopus	("Machine Learning AND Techniques OR Machine AND Learning AND Techniques OR Resource AND Management AND Cloud AND to AND Edge AND Ecosystem OR future AND research AND direction AND (LIMIT-TO (EXACTSRCTITLE , "Scopus"))
ScienceDirect	("Machine Learning AND Techniques OR Machine AND Learning AND Techniques OR Resource AND Management AND Cloud AND to AND Edge AND Ecosystem OR future AND research AND direction AND (LIMIT-TO (EXACTSRCTITLE , "ScienceDirect"))
Taylor and Francis	("Machine Learning AND Techniques OR Machine AND Learning AND Techniques OR Resource AND Management AND Cloud AND to AND Edge AND Ecosystem OR future AND research AND direction AND (LIMIT-TO (EXACTSRCTITLE , "TandF"))
ACM Computing Surveys	("Machine Learning AND Techniques OR Machine AND Learning AND Techniques OR Resource AND Management AND Cloud AND to AND Edge AND Ecosystem OR future AND research AND direction AND (LIMIT-TO (EXACTSRCTITLE , "ACM Computing Surveys"))

3.2 Published Papers and Data Extraction

Data extraction starts with a general overview of the most active nations for resource management of cloud-edge-computing. The data was retrieved after the inclusive and exclusive search criteria were applied. The number of articles on application of ML in cloud-to-edge computing has risen year after year. In recent years, this suggests that it is a rising knowledge field.

In further explaining the research question, the paper was also distributed based on subject areas of cloud-to-edge computing. Because this survey categorized publications relating to learning algorithms, applications, and technology, the category with the most papers is the subject areas. The distribution of papers by subject area is shown in Figure 4.

3.3 Machine Learning Integration in Cloud-to-edge Computing

To address question raised earlier in this study, table VII shows problem, ML algorithms, field, topic, methods/tools used, dataset, attribute/parameters related to cloud and fog computing. Figure 4 depicts the distribution of various ML techniques according to the first research question. The ML algorithms account for 79.30% of the contributions in the cloud-to-edge field. Since the initial articles in 7236, the most interesting research area has been Generalized Linear Model (GLM), Gaussian Processes (GP), Multilayer Perceptrons (MLP), Random Forests (RF), which have received 25.50% of the attention and 258 articles. The second most active ML techniques are artificial neural network (ANN), support vector machine (SVM), k-nearest neighbour (KNN), decision tress (DT) and bayesian networks (BN), with 15.35% and 162 articles. At 8.20%, particle swarm clustering, Hidden Markov Model are used in the Smart Grid, Intelligent Transportation System and Smart Manufacturing implementations are the third most essential group, trailed by resource management at

6.47%, and papers concentrating on ML projects, which describe practical and theoretical structures to perform and implement ML at 5.52%.

TABLE IV. ANALYSIS VARIOUS ML ALGORITHMS USED IN CLOUD-TO-EDGE COMPUTING OVER THE YEARS

Various Machine Learning	No of Articles
GLM	334
GP	252
MLP	129
RF	86
ANN	85
SVM	70
KNN	54
DT	50
BN	35

The report was also provided depending on ML application in various research fields to further elucidate the study question. The section with the most papers is subject domains, which may be justified since we gathered articles relating to projects, applications, and methods under this topic. Figure 4 depicts the distribution of papers by subject area.

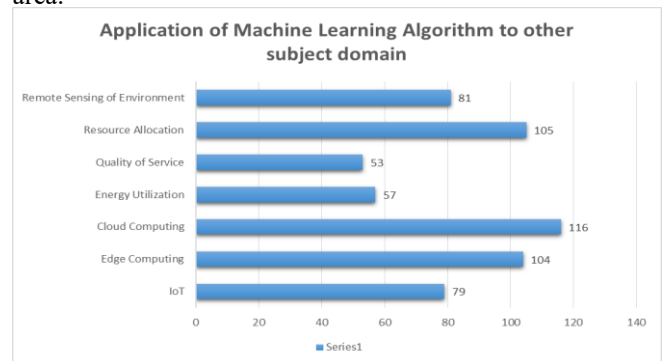


Fig. 4. Analysis of ML in other subject domain.

3.3.1 Machine learning contribution in Cloud-to-edge Computing

The evaluation of paper used by document type is given the Figure 5 below.

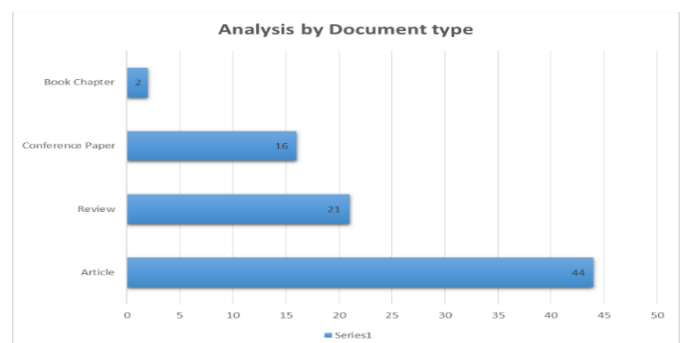


Figure 5: Graphical representation of Document type used to carry-out the various analysis. Journal article carry the large percentage of materials used from the various journal repository.

This sub-section briefs the solution to research question 2 asked about the ML techniques implemented in the cloud-to-edge computing domain. The major algorithms available in the literature include SVM, KNN, hidden Markov model,

linear SVM, collaborative filtering, linear regression (LR), bayesian networks, and k-means clustering for various cloud-to-edge computing-based applications. Table VI presents the category of ML algorithms and resource management.

TABLE V. CATEGORY OF ML ALGORITHMS AND RESOURCE MANAGEMENT

Authors and Year	ML Algorithm	Resource Management	Accuracy
[30]	SVM	Computational Capacity, Sensor, Battery Life	93.6%
[31]	Markov model	Bandwidth consumption, latency	90%
[32]	Bayesian Networks, K-Means clustering	Latency, Bandwidth	80% to 90%
[11]	GMM, KNN	Resource allocation detection rate	98% to 100%
[34]	SVM	Security	90%
[35]	LR	Communication efficiency, computation overhead	90%
[7]	SVM	-	98.75%
[17]	GBM, XGBoost, RF	Network traffic	99.281%

In answering research question 3, Table VII SVM, DT, bayesian network, bagged tree, naive bayes, logistic regression, and KNN are among the most extensively used ML methods in the cloud-to-edge ecosystem. Bagged tree and KNN algorithms are the most commonly utilized techniques in these methods of cloud-to-edge ecosystem. Research question 3 was also provided answer to in table VII. That table analysis shows that SVM is the most efficient and effective ML algorithm used in cloud-to-edge computing environments considering its application and achieve accuracies. The use of ML approaches in cloud integrated computing paradigms is on the rise in order to fulfill a variety of QoS needs. ANN and other soft computing approaches are being utilized to optimize numerous QoS parameters in the cloud-based cloud-to-edge ecosystem to handle dynamic scheduling [21]. Forecasting Query Run-time (PQR) tree modeling is using ML approaches such as closest neighbor and classification trees for workload management in cloud-based databases [22]–[29]. Moreover, ANN, SVM, Random Forest (RF), and Decision Tree (DT) algorithms are frequently utilized to increase strategic planning correctness in a cloud-to-edge context.

3.3.2 Distribution of articles based on research questions

Relying on the study's research questions, the publications were divided into five classes. Several of the chosen articles responded to the questions in a unique way by tackling one specific aspect of ML techniques and Resource Management in cloud-to-edge ecosystem based on search area, application area, and geographical area among others. While other articles mostly re-emphasized what was written in other articles.

3.4 The Reviewed Outcome

This research examines the goals and issues surrounding the use of ML algorithms for resource management in cloud and edge computing. Given the potent forces at work and it's critical to comprehend the unique needs and traits of cloud

and edge computing in order to guarantee that research is properly directed to fill in specific gaps. Additionally, because information systems at the network's edge can guarantee quicker reaction times and improved reliability, cloud services are being delivered to the cloud's edge. More data might be consumed domestically rather than sent to the cloud, potentially saving traffic. The rise of IoT, sensors and standardized mobile devices transformed the function of the edge from a data consumer to a data producer/consumer in the computing paradigm. Data manipulation or processing at the network's edge would be more effective. This study ultimately carried out a systematic literature review on the computational resources of cloud-edge computing with the aims of causing edge computing will thrive as a result of cloud offloading to a smart environment such as a house or city. Finally, it is hoped by the researcher that this research study will spur researchers in the area of applicability of cloud-edge computing. Cloud-to-Edge Computing applications have been facing many challenges in the past, one of the prominent challenges of cloud-to-edge is resources management, ML algorithms have been helpful in this regard. The idea for this research arose from the need to enumerate the contributions of ML algorithms to cloud-to-edge resource management and identify open research areas for improvement

4. Conclusion

Cloud-to-Edge In the past, computing applications faced several obstacles; one of the most significant issues of cloud-to-edge is resource management; ML algorithms have proven useful in this area. The necessity to list the contributions of ML algorithms to cloud-to-edge resource management and identify open research topics for development prompted the concept for this study. Cloud computing has arisen in the recent decade, with numerous developing paradigms such as edge, fog, and mist leveraging ML techniques. This review first presents all cloud services paradigms that are briefly discussed, and then possible interaction among them is highlighted according to current state-of-the-art research. To accomplish this, investigation, and research publications over the recent ten years (2013-2022) are extensively examined. In addition, numerous tables and charts are utilized to examine the research papers retrieved from each journal repository's search queries for each ML approach in the resource management of the cloud-to-edge computing ecosystem. Based on the research, a crucial comparison study on numerous aspects is made for the readers to comprehend the summary with the least effort. This study focuses on the growing notion of cloud-to-edge computing, resource management, and the extent of ML in the application.

The scope of this research is confined to the research topics mentioned in the review technique. Because the interaction among developing Cloud-to-edge computing models is too broad, this survey does not include all potential combinations of emerging Cloud computing paradigms and their designs. Thus, an in-depth study was conducted to comprehend the function of ML -based approaches in the successful use of computational resources management, as well as which ML algorithm is effective and efficient in the area of cloud-to-edge ecosystem for managing resources. This study demonstrates that ML algorithms are broadly used in the cloud-to-edge environment for numerous activities such as threat detection, cloud security, and resource management. SVM, DT, Bayesian network, bagged tree, naive bayes, logistic regression, and KNN are all examples of ML techniques which are widely used in the cloud-to-edge ecosystem for resource management. Bagged

tree and KNN algorithms are the most often utilized algorithms in the SDN arena. One of the study's shortcomings is that no experiment is provided to evaluate the use of the investigated algorithms to validate their usability and competitiveness. Additionally, hybrid algorithms that use ML in the same area are being developed only beginning to be used, which will require further investigation. These survey study constraints provide fresh research directions for future possible survey investigations.

REFERENCES

- [1] [1] H. U. Khan, F. Ali, & S. Nazir (2022). "Systematic analysis of software development in cloud computing perceptions". *Journal of Software Evolution and Processes*, 1-26. J. Clerk Maxwell, A Treatise on Electricity and Magnetism, 3rd ed., vol. 2. Oxford: Clarendon, 1892, pp.68–73.
- [2] Y. Zhang, & K. Xu. (2020). "Network Management in Cloud and Edge Computing". Springer. doi:10.1007/978-981-15-0138-8
- [3] A. Ghasempour. (2019). "Internet of things in smart grid: Architecture, applications, services, key technologies, and challenges". *Inventions*, 4(1), 22.
- [4] P. Metri, & G. Sarote. (2011). "Privacy issues and challenges in cloud computing". *International Journal of Advanced Engineering Sciences and Technologies*, 5(1), 5-6.
- [5] X. Wang, Y. Han, V. Leung, C., Niyato, D., Yan, X., & Chen, X. (2020). "Convergence of edge computing and deep learning: A comprehensive survey". *IEEE Communications Surveys & Tutorials*, 22(2), 869-904.
- [6] J. Ferreira, E. Carvalho, B. Ferreira, V., de Souza, C., Suhara, Y., Pentland, A., & Pessin, G. (2017). "Driver behavior profiling: An investigation with different smartphone sensors and machine learning". *PLoS One*, 12(4), e0174959.
- [7] Y. Meidan, M. Bohadana, A. Shabtai, J. D. Guarnizo, M. Ochoa, N. O. Tippenhauer and Y. Elovici, "ProfilIoT: a machine learning approach for IoT device identification based on network traffic analysis," *Proceedings of the symposium on applied computing*, pp. 506-509, 2017.
- [8] C. Byers, & P. Wetterwald. (2015). "Fog computing distributing data and intelligence for resiliency and scale necessary for IoT: The internet of things (ubiquity symposium)". *Ubiquity*, (pp. 1-12).
- [9] D. Liu, Z. Yan, W. Ding, & M. Atiquzzaman (2019). "A survey on secure data analytics in edge computing". *IEEE Internet of Things Journal*, 6(3), 4946-4967.
- [10] X. Li, T. Chen, Q. Cheng, S. Ma, & J. Ma, (2020). "Smart applications in edge computing: Overview on authentication and data security". *IEEE Internet of Things Journal*, 8(6), 4063-4080.
- [11] S. Talari, M. Shafie-Khah, P. Siano, V. Loia, A. Tommasetti, & J. P. Catalão (2017). "A review of smart cities based on the internet of things concept". *Energies*, 10(4), 421-431.
- [12] C. H. Hong, & B. Varghese (2019). "Resource management in fog/edge computing: a survey on architectures, infrastructure, and algorithms". *ACM Computing Surveys (CSUR)*, 52(5), 1-37
- [13] T. Qiu, J. Chi, X. Zhou, Z. Ning, M. Atiquzzaman, & D. O. Wu, (2021). "Edge computing in industrial internet of things: Architecture, advances and challenges". *IEEE Communications Surveys & Tutorials*, 22(4), 2462-2488.
- [14] B. Varghese, C. Reano, & F. Silla. (2018). "Accelerator virtualization in fog computing: Moving from the cloud to the edge". *IEEE Cloud Computing*, 5(6), 28-37.
- [15] R. Rawat, O. A. Oki, K. S. Sankaran, O. Olasupo, G. N. Ebong and S. A. Ajagbe, "A New Solution for Cyber Security in Big Data Using Machine Learning Approach," in *Mobile Computing and Sustainable Informatics. Lecture Notes on Data Engineering and Communications Technologies*, vol. 166, Springer, Singapore, 2023, pp. 495-505
- [16] D. Liu, Z. Yan, W. Ding, & M. Atiquzzaman, M. (2019). "A survey on secure data analytics in edge computing". *IEEE Internet of Things Journal*, 6(3), 4946-4967.
- [17] A. Tuama, F. Comby and M. Chaumont, "Camera model identification based machine learning approach with high order statistics features," in *2016 24th European Signal Processing Conference (EUSIPCO)*, 2016.
- [18] Y. Zhang, & K. Xu, (2020). "Network Management in Cloud and Edge Computing". Springer. doi:10.1007/978-981-15-0138-8
- [19] S. Islam, J. Keung, K. Lee, & A. Liu, (2012). "Empirical prediction models for adaptive resource provisioning in the cloud". *Future Generation Computer Systems*, 28 (1), 155–162.
- [20] B. I. Ismail, E. M. Goortani, M. B. Ab Karim, M. B., Tat, W. M., Setapa, S., Luke, J. Y., & O. H. Hoe, (2015). "Evaluation of docker as edge computing platform". 2015 IEEE conference on open systems (ICOS) (pp. 130-135). IEEE.
- [21] H. A. Kholidy. (2020). "An intelligent swarm based prediction approach for predicting cloud computing user resource needs". *Computer Communications*, 151, 133-144.
- [22] S. A. Ajila, & A. A. Bankole. (2013). "Cloud client prediction models using machine learning techniques". 2013 IEEE 37th Annual Computer Software and Applications Conference (pp. 134-142). IEEE.
- [23] M. A. Al Faruque, & K. Vatanparvar. (2016). "Energy management-as-a-service over fog computing platform". *IEEE Internet Things Journal*, 3(2), 161–169.
- [24] J. B. Awotunde, M. O. Arowolo, A. L. Imoize, Y. Farhaoui, & A. E. Adeniyi (2023). "A Machine Learning-Based Model for Energy Efficiency Classification of an Unmanned Aerial Vehicle". In *Artificial Intelligence and Smart Environment: ICAISE'2022* (pp. 54-63). Cham: Springer International Publishing.
- [25] F. Wang, M. Zhang, X., Ma, & J. Liu. (2020). "Deep Learning for Edge Computing Applications: A State-of-the-Art Survey". *IEEE Access*, 8, 58322- 58336. doi:10.1109/ACCESS.2020.2982411
- [26] X. Wang, Y. Han, V. C. Leung, D. Niyato, X Yan, & X. Chen. (2020). "Convergence of edge computing and deep learning: A comprehensive survey". *IEEE Communications Surveys & Tutorials*, 22(2), 869-904.
- [27] S. A. Ajagbe, S. Misra, O. F. Afe, & I. K. Okesola, (2022). "Internet of Things (IoT) for Secure and Sustainable Healthcare Intelligence: Analysis and Challenges". In: Florez, H., Gomez, H. (eds) *Applied Informatics. ICAI 2022*. Pp. 45-59, Communications in Computer and Information Science, vol 1643. Springer, Cham. https://doi.org/10.1007/978-3-031-19647-8_4
- [28] S. A. Ajagbe & M. O. Adigun. (2023) "Deep learning techniques for detection and prediction of pandemic diseases: a systematic literature review". *Multimedia Tools Application* (2023). <https://doi.org/10.1007/s11042-023-15805-z>
- [29] S. A. Ajagbe, A. A. Adegun, A. B. Olanrewaju, J. B. Oladosu and M. O. Adigun, "Performance investigation of two-stage detection techniques using traffic light detection dataset," *IAES International Journal of Artificial Intelligence (IJ-AI)*, vol. 12, no. 4, pp. 1909-1919, 2023.
- [30] I. Azimi, A. Anzanpour, A. M. Rahmani, T. Pahikkala, M. Levorato, P. Liljeberg and N. Dutt, "HiCH: Hierarchical fog-assisted computing architecture for healthcare IoT," *ACM Transactions on Embedded Computing Systems (TECS)*, vol. 16, no. 5, pp. 1-20, 2017.
- [31] U. Drolia, K. Guo, J. Tan, R. Gandhi and P. Narasimhan, "Towards edge-caching for image recognition," in *2017 IEEE International Conference on Pervasive Computing and Communications Workshops (PerCom Workshops)*, 2017.
- [32] M. Hogan and F. Esposito, "Stochastic delay forecasts for edge traffic engineering via Bayesian networks," in *2017 IEEE 16th International Symposium on Network Computing and Applications (NCA)*, 2017.
- [33] D. Zisis, "Intelligent security on the edge of the cloud," in *2017 International Conference on Engineering, Technology and Innovation (ICE/ITMC)*, 2017.
- [34] J. Wan, J. Yang, Z. Wang and Q. Hua, "Artificial intelligence for cloud-assisted smart factory," *IEEE Access*, vol. 6, pp. 55419-55430, 2018.
- [35] O. A. Fonseca-Herrera, A. E. Rojas and H. Florez, "A model of an information security management system based on ntc-iso/iec 27001 standard," *IAENG International Journal of Computer Science*, vol. 48, no. 2, p. 213–222, 2021.