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# Server Less AI: Democratizing Machine Learning with Cloud Functions

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**Abstract**

Large-scale distributive Artificial Intelligence (AI) systems that can cooperatively complete difficult learning tasks must replace traditional centralised AI systems in order to support emerging cross-device applications for AI. Because of its significant impact on cost savings, latency reduction, scalability improvement, and the elimination of server-side management, among other benefits, Server Less computing has become more and more prominent over the past 10 years as an intriguing new sector. Nevertheless, comprehensive surveys that would aid academics and developers in comprehending the importance of server-less computing in various scenarios are still lacking. The idea of server-less machine learning is examined in this study, along with how it can revolutionise the creation and application of AI algorithms. Engineers can concentrate on creating and refining machine learning models instead of worrying about maintaining the fundamental framework by utilising server-less platforms. The study explores the advantages of server-less machine learning, such as lower the time to market, scalability, and cost. It also covers how server-less machine learning may be integrated with widely used platforms and services to provide seamless model deployment and education. The difficulties of data management, performance optimisation, and security assurance in server-less machine learning settings are also covered in the study. The report attempts to shed light on an opportunity of Server Less technology in democratising AI development and speeding cloud innovation through this thorough analysis.

**Keywords: -** Artificial Intelligence (AI), Machine Learning, Large-Scale Distributed, AI Development, Managing Data, Server Less, Transformative Impact, Cloud, Security, Building And Training, Optimizing Performance.

## I. INTRODUCTION

The speedy progress in machine learning and Artificial Intelligence (AI) has created novel opportunities for resolving intricate issues and stimulating creativity in diverse sectors. But historically, creating and implementing AI models required a lot of infrastructural administration, [1, 2], which prevented many organisations from utilising AI technology to its fullest. ServerLess computing has arisen as a paradigm-shifting solution to this problem, transforming the creation and application of AI models on the cloud [1]. A more streamlined and effective method of developing artificial intelligence is provided by ServerLess machine learning, which is the combination of ServerLess technology and machine learning technology [1]. Developers can concentrate on creating and refining machine learning models instead of worrying about the intricacies of overseeing underlying infrastructure when using ServerLess platforms [2, 3]. Organisations can now democratise AI development and make it available to a wider spectrum of developers and companies thanks to this paradigm change [2, 3].

The last few years have seen a rise in the use of ServerLess in both industry and academics. With its straightforward Function-as-a-Service (FaaS) development approach, [3], which fulfilled the cloud's initial promise of elasticity and fine-grained pay-as-you-go for actual consumption, it drew in businesses and developers [2]. Designers do not have command over the code's location while it runs in a FaaS environment, nor do they need to worry about scaling [3]. Server Less cloud providers increase visibility by eliminating servers, or at the very least, by making them more readily available [3]. In systems with distributed components, visibility is a classic problem that remains to be sufficiently resolved. Transparency means hiding the intricacies of systems that are distributed from application programmers and users. Access transparency, according to Colourist, [3, 4], allows for the same processes to be utilised for gaining access local and external resources [4, 5].

However, combining computational and programming frameworks of local and remote computing is not a novel idea. According to them, "a new distributed computing paradigm is announced and a furious bout of language and protocol design takes place" approximately every ten years [4, 5]. Every iteration produces a fresh wave of modern software, [5], and programmes are migrated to the hottest and most recent architecture. We think that the current iteration of the Server Less Compute paradigm will converge at the necessary level of resource abstraction to allow for transparent [5]. Mapping this idea to newly developing disaggregated computing resources (memory, storage, and computation) is what we refer to as the Server Less End Game, and it finally allows for infinitely variable scaling [5, 6].

Doubling Machine Learning (DML) models have several methodology extensions and applications in fields like as banking, economics, and COVID-19 research, [6], and are growing in popularity among statisticians, economics researchers, and data scientists. Through the use of DML models, researchers can take use of the superior predictive ability of algorithms developed using machine learning inside a reliable statistical structure to perform causal estimation of parameters and inference. The Python and R package Double ML, [6, 7], which estimate double machine learning models, have just been released [7, 8]. They have an adaptable object-oriented architecture [6, 7]. According to the Berkeley View on ServerLess Computing, ServerLess cloud computing is expected to become the predominant and standard framework for cloud computing in the ensuing ten years and is gaining traction among researchers and industry participants [8, 9]. The Function as a Service (FaaS) model lowers the barrier to entry for cloud computing technologies by putting nearly all operational and maintenance tasks under the purview of cloud providers [9]. The great elasticity of ServerLess computing in terms of automated on-demand scaling based on the actual volume of computing requests is one of its main advantages [9, 10]. The pricing structure of ServerLess computing is a further significant benefit. Provisioning fees do not apply; [9], only resources that are actually used will be charged [9, 10].

### 1.1 ServerLess Computing

A fundamental tenet of ServerLess computing is that the user only needs to create a cloud function—typically in an advanced programming language like Python—while the cloud provider handles all server deployment and management [10]. Because the user essentially just defines the function code that needs to be executed and declares what circumstances should trigger those function calls, [10, 11], these server-less cloud function offerings are frequently referred to as Function as a Service (FaaS). In particular, ex-ante supply of computational resources is not necessary [11].

The cloud provider has the authority to automatically increase resources in response to the volume of requests made to the FaaS [11]. Compared to a traditional cloud server, where the user must determine in advance which requirements best suit the impending computing duties, this is one of the main contrasts [11, 12]. You can find general talks about ServerLess computing on this website, including its latest advancements and difficulties [12]. In addition, ServerLess computing is becoming more and more popular for a range of machine learning applications, such as serving models generated by deep learning or, more broadly, for hyper parameter tuning and ML model training [12]. One more fundamental idea in ServerLess computing is the price structure [13]. Typically, billing is based on the resources that are actually used, not the resources that were provided. With AWS Lambda, [13, 14], the billing granular has been lowered to millisecond billing, meaning that the pricing is highly fine-grained and proportionate to the execution time. One important parameter that the user sets while using AWS Lambda is the RAM that the function has access to at runtime [14].

In addition, AWS Lambda scale other resources in proportion to RAM allotted, such as CPU power [15]. The maximum ram allocable has historically been progressively grew, and most recently, it was significantly expanded from a maximum of 3 GB to 10 GB. This translates to a maximum of 6 vCPUs that are available in a single FaaS request, [15], according to AWS. Because of their inherent extreme flexibility, [16], ServerLess computing technologies have quite stringent limits on computing resources for a single request. The maximum runtime while utilising AWS Lambda is fifteen minutes [16]. But with the latest improvements, ServerLess computing is becoming more and more appealing for computationally demanding jobs like machine learning [16, 17].

### 1.2 A Brief Overview of Double Machine Learning

In a number of studies, Double Machine Learning (DML) was created and presented as a general framework. It is discussed how DML can be used to several model types, including interactive regression analysis interactive intermediate variables, [17], as well as partially models based on linear regression. Many model classes, [17], including reinforcement learning, transformation models, generalised additive models, constantly treatment impacts, dynamic treatment effects, Gaussian graphic models, difference between differences designs, and many more, have recently been added to the DML framework and related techniques [16]. The statistical determination for a causal parameter $\theta_0$ is typically of importance in these DML applications.

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$$\begin{aligned} y &= D\theta_0 + g^0(X) + U, \quad E(U|X,D), 0, \\ D &= m_0(X) + V, \quad\;\; E(V|X) = 0, \end{aligned} \quad \text{........1}$$

$$\frac{1}{N}\sum_{k=1}^{K}\sum_{i\epsilon Im,k} \psi\left(W_{i;}\grave{\theta}_{0,m,}\grave{n}_{0,}K\right) = 0. \text{ .......2}$$

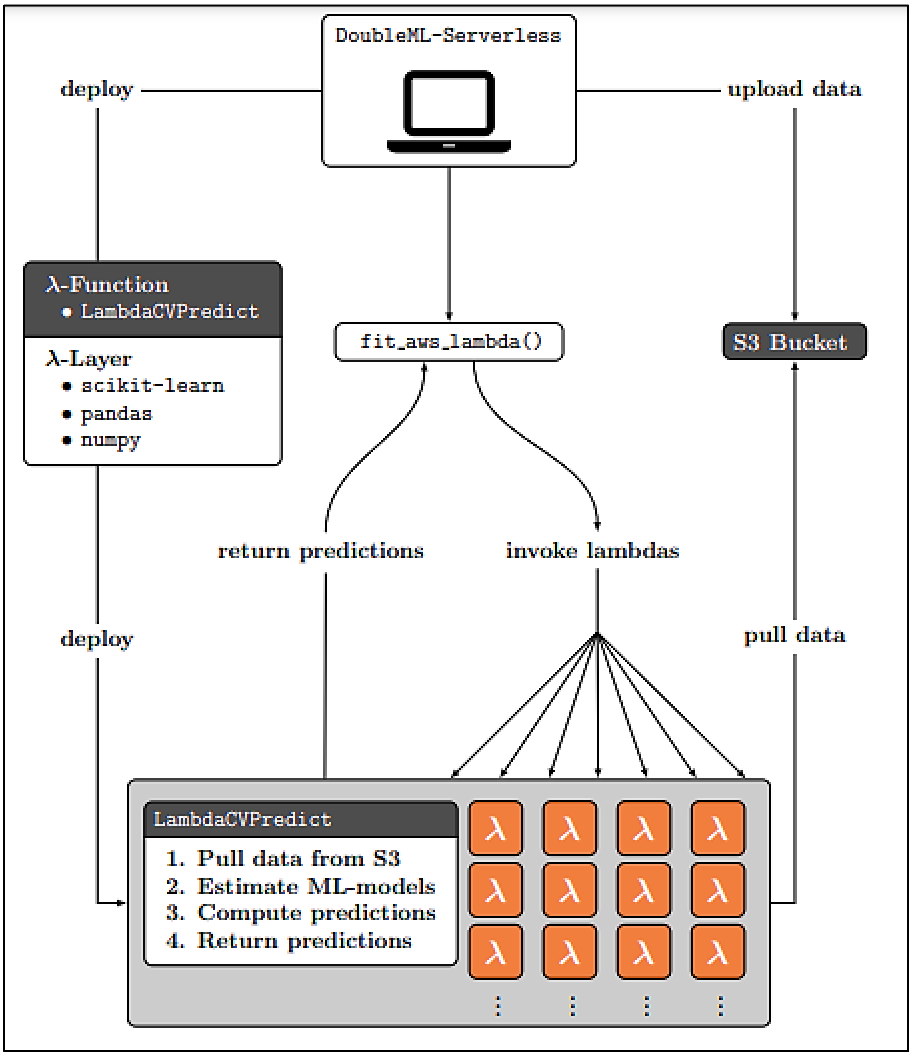


Fig. 1 Architectural Design: Double ML-Server less. [17].

### 1.3 Server Less Double Machine Learning

Like PyWren, our prototype the implementation DoubleMLServerLess is meant to be used in an interactive manner: The user can access a high degree of Parallelism with a on the demand and pay-per-request interaction for the computationally demanding duties during the estimation of DML models, while also running a Python session on a local machine or server [17, 18]. Our version is more tailored to the unique use case of DML models than PyWren, which enables the execution of nearly arbitrary parallel activities, such as map reduce. There are numerous cloud companies that offer ServerLess FaaS [18]. Our AWS Lambda-powered prototype Dual ML ServerLess system is created in Python and is an addition to the Double ML package.

### 1.4 Objectives of the study

- Examine how deploying machine learning solutions can be made easier for individuals and small businesses by examining how Server Less AI can help.
- Determine and suggest best practices for server-less architecture-based machine learning application design, deployment, and management.

- Compare the efficiency parameters (throughput, latency, etc.) of machine learning activities carried out by server-less functions to those carried out by server-based methods.

## II. LITERATURE REVIEW

The increased interest and acceptance of ServerLess computers in the context of AI model creation and deployment is reflected in literature on ServerLess machine learning. Many facets of ServerLess machine learning have been thoroughly investigated by scholars as well as practitioners, including its advantages, difficulties, uses, and influence on cloud-based AI technology.

1. **Features of Serverless Machine Learning:** The benefits of ServerLess machine learning have been emphasised by several research projects. ServerLess computing reduces operational complexity and overhead by releasing developers from the burden of managing infrastructure, [18], allowing them to concentrate entirely on creating and training AI models [18]. Because pay-as-you-go pricing models only charge for the resources used during model training and inference, ServerLess systems guarantee cost-effectiveness [18].
2. **Driving AI innovation in the cloud:** The revolutionary effect of ServerLess computing ML on AI innovation in the cloud has been covered in great detail in the literature. ServerLess computing democratises access to AI by lowering entry barriers for developers, [18, 19], allowing a wider range of entrepreneurs and developers to take advantage of AI capabilities.
3. **Integrate with popular machine learning frameworks:** Scholars have investigated how well-known machine learning frameworks and services can be integrated with ServerLess machine learning [19]. ServerLess platforms facilitate the easy utilisation of pre-existing machine learning libraries by developers by supporting frameworks such as Tensor Flow, PyTorch, and scikit-learn [19, 20].
4. **Challenges and concerns:** The literature has also pointed up ServerLess machine learning-related issues and concerns [19, 20]. The processing and analysis of massive volumes of data in the cloud by organisations raises serious concerns about data management. Successful AI model building requires effective data access, [20], storage, and retrieval [20, 21]. Additionally, it is crucial to guarantee data security and privacy, especially when working with sensitive data in a ServerLess architecture. Building confidence and preserving data integrity require addressing security concerns and adhering to data protection laws.
5. **Application scenarios and case research:** Scholars have investigated a range of practical uses for ServerLess machine learning across many sectors. Successful ServerLess methods have been implemented for tasks like image identification, anomaly detection, processing of natural language, and automated forecasting, as shown by case studies [21]. These papers demonstrate the revolutionary effect of ServerLess computing in democratising AI development and spurring creativity in a variety of fields.

## III. METHOD

The principle of ServerLess machine learning is examined in this study along with its importance in the context of cloud computing. It explores the advantages of ServerLess computing, which are especially helpful when developing and implementing AI models [20]. These advantages include the cost-effectiveness scalability, [21], and shortened time-to-market. Moreover, the smooth training and distribution of models is made possible by the integration of ServerLess machine learning with well-known machine learning frameworks and services, which gives businesses the ability to effectively use AI capabilities [20]. Beyond resource and cost optimisation, ServerLess machine learning has many more advantages. Because ServerLess platforms are flexible, [20, 21], businesses can adjust to changing workloads by dynamically scaling computing resources to match demand and cutting down on idle time. Because training and inference workloads in machine learning can fluctuate greatly over time, this elasticity is very beneficial [20].

Furthermore, ServerLess machine learning speeds up model deployment and experimentation, allowing programmers to rapidly iterate and improve their AI model [22, 23]. Businesses may respond more quickly to changing consumer demands and market trends by implementing AI-driven solutions [23, 24]. But there are also particular difficulties with ServerLess machine learning, such as efficient data management, performance optimisation, and ServerLess environmental security. Data management becoming essential as enterprises use the cloud to analyse and analyse massive volumes of data. Since the ServerLess architecture handles sensitive data, protecting data security and privacy is crucial [23].

Our goal in this study is to examine the transformational potential of ServerLess machine learning, as well as its advantages, drawbacks, and implications for the creation and application of artificial intelligence [23]. Organisations can revolutionise computing through the cloud, accelerate innovation, and democratise access to AI by embracing server-less computing in the context of machine learning. The field of AI development is expected to change as ServerLess machine learning advances, becoming more scalable, efficient, and accessible [23]. This will pave the way for a day when AI-driven solutions will affect enterprises and society at large [22].

## IV. RESULT

Organisations can reap several benefits from the notable advancements in AI model creation and deployment that have resulted from the implementation of server-less machine learning [24]. Engineers may concentrate on creating and refining AI models instead of worrying about the intricacies of managing the infrastructure by utilising ServerLess computing technology. As a result, AI-driven solutions now have lower operating costs, [23, 24], are more cost-effective, and have a faster time to market [24]. Standard machine learning packages and ServerLess platform have seamlessly integrated to accelerate the model construction process, enabling organisations to take advantage of pre-existing AI tools and knowledge in a ServerLess ecosystem [24, 25].

## V. DISCUSSION

The conversation around server-less machine learning revolves around its revolutionary effect on Artificial Intelligence (AI) development, the advantages of scalability and affordability, and the difficulties associated with data management, security, [26], and privacy.

1. **Transformative Impact on AI Innovation:** ServerLess machine learning has made AI development more accessible, which has revolutionised AI innovation. The removal of obstacles related to infrastructure management enables a wider spectrum of developers and enterprises to fully utilise the capabilities of artificial intelligence [27]. This democratisation has sped up the adoption of AI-driven solutions across a range of industries, resulting in creative uses and improved ability to make decisions [26, 27].
2. **Scaling and Cost-Effectiveness:** The benefits of cost-effectiveness and scalability in ServerLess machine learning have been covered in great detail in the literature. Businesses can optimise both cost and performance by dynamically scaling their computing resources in response to changing workloads [28. 29]. Organisations can save money and optimise resources [30], by using the pay-as-you-go pricing model, which guarantees that they only pay for the resources utilised during model instruction and deduction [31, 32].
3. **Challenges in data management, protection, and privacy:** There are additional difficulties with ServerLess machine learning in the areas of managing information, protection, and privacy. In ServerLess contexts, [32, 33], successful AI model development requires efficient data storage, access, and retrieval. To protect confidential information within the ServerLess architecture, organisations need to follow data protection laws and have strong data security safeguards in place [33, 34]. Resolving security issues is essential to gaining the trust of stakeholders and customers.

The field of developing and implementing AI models has changed as a result of the widespread use of ServerLess machine learning [34, 35]. Organisations have benefited from lower operational complexity, cost effectiveness, and quicker time-to-market for AI-driven products by utilising ServerLess computing [35, 36]. A wider range of entrepreneurs and developers are now able to take use of AI capabilities thanks to the democratisation of AI development, which has also encouraged creativity. ServerLess machine learning has shown to be a substantial benefit in terms of scalability and the effectiveness of costs. It has made it possible for organisations to optimise costs and scale computer resources in response to changing workloads. The pay-as-you-go pricing strategy guarantees resource efficiency and cost savings.

## VI. CONCLUSION

A novel paradigm known as ServerLess machine learning has taken off, changing the way AI models are developed and implemented in the cloud. Significant progress has been made as a result of the adoption of ServerLess computing, providing enterprises with scalable, affordable, and effective solutions for developing and implementing AI models. The disruptive power of ServerLess machine learning, along with its advantages, drawbacks, and consequences for AI innovation, have all been examined in this research.

This study investigates the use of ServerLess cloud computing in double machine learning model estimation. Our Double ML-ServerLess prototypes.

A wider spectrum of developers and enterprises may now take advantage of AI capabilities thanks to ServerLess machine learning, which has democratised AI development. ServerLess computing democratises access to AI by doing away with the hassles of maintaining infrastructure. This promotes creative applications and speeds up the adoption of artificial intelligence-driven solutions across a range of industries. The two main benefits of ServerLess machine learning are scalability and affordability. Organisations can optimise performance and cost, leading to resource effectiveness and expenditure savings, by having the flexibility to dynamically scale hardware and software based on changing workloads. By matching costs to actual utilisation, the pay-as-you-go pricing approach guarantees that businesses only pay for those assets used during AI model training and inference. But issues with privacy, security, and data management must be carefully considered. In a ServerLess context, developing AI models successfully requires efficient data accessibility, storage, and retrieval.

Furthermore, to protect sensitive data in the ServerLess architecture, strong data security protocols and adherence to data protection laws are essential. To sum up, ServerLess machine learning is a revolutionary method for developing and implementing AI models that allows businesses to fully utilise AI in an economical and expandable way. Organisations may expedite their adoption of AI-driven solutions and increase the impact, efficiency, and accessibility of AI by embracing ServerLess computing.

## FUTURE WORK

The advancement of ServerLess machine learning offers the potential to influence the future in which Artificial Intelligence (AI) will be widely used to solve complicated problems and create new opportunities for businesses and society in the age of intelligent automation.

## REFERENCES

[1] N. Akhtar, A. Raza, V. Ishakian, and I. Matta. 2020. COSE: Configuring Serverless Functions using Statistical Learning. In IEEE INFOCOM 2020 - IEEE Conference on Computer Communications. 129–138.

[2] P. Bach, V. Chernozhukov, M. S. Kurz, and M. Spindler. 2020. DoubleML - Double Machine Learning in Python.

[3] P. Bach, V. Chernozhukov, M. S. Kurz, and M. Spindler. 2020. DoubleML - Double Philipp Bach, Sven Klaassen, Jannis Kueck, and Martin Spindler. 2020. Uniform Inference in High-Dimensional Generalized Additive Models.

[4] Ioana Baldini, Paul Castro, Kerry Chang, Perry Cheng, Stephen Fink, Vatche Ishakian, Nick Mitchell, Vinod Muthusamy, Rodric Rabbah, Aleksander Slominski, and Philippe Suter. 2017. Serverless Computing: Current Trends and Open Problems. Springer Singapore, Singapore, 1–20.

[5] Alexandre Belloni, Victor Chernozhukov, Denis Chetverikov, and Ying Wei. 2018. Uniformly valid post-regularization confidence regions for many functional parameters in z-estimation framework. Ann. Statist. 46, 6B (2018), 3643–3675.

[6] L. Barroso, M. Marty, D. Patterson, P. Ranganathan, "Attack of the killer microseconds", Communications of the ACM, pp 48–54, 2017.

[7] C. Lee, J. Ousterhout, "Granular Computing", Proceedings of the Workshop on Hot Topics in Operating Systems, 2019.

[8] P. Gao, A. Narayan, S. Karandikar, J. Carreira, S. Han, R. Agarwal, S. Ratnasamy, S. Shenker, "Network requirements for resource disaggregation", USENIX Symposium on Operating Systems Design and Implementation, 2016.

[9] E. Jona et al, "Cloud programming simplified: A berkeley view on serverless computing", [Online].

[10] J. Gu, Y. Lee, Y. Zhang, M. Chowdhury, K. Shin, "Efficient memory disaggregation with infiniswap", USENIX Symposium on Networked Systems Design and Implementation, 2017.

[11] A. Dragojevic, D. Narayanan, M. Castro, O. Hodson, ´ "FaRM: Fast remote memory", USENIX Symposium on Networked Systems Design and Implementation, 2014.

[12] S. Peter et al, "Arrakis: The operating system is the control plane", ACM Transactions on Computer Systems (TOCS), 2015. (Journal)
[13] S. Angel, M. Nanavati, S. Sen, "Disaggregation and the Application", USENIX Workshop on Hot Topics in Cloud Computing, 2020.
[14] J. Sampe, P. Garcia-Lopez, M. Sanchez, "Towards Multicloud Access Transparency in Serverless Computing", IEEE Software, 2020.
[15] S. R. Pandey, N. H. Tran, M. Bennis, Y. K. Tun, A. Manzoor, and C. S. Hong, "A crowdsourcing framework for on-device federated learning," IEEE Trans. Wireless Commun., vol. 19, no. 5, pp. 3241–3256, Feb. 2020.
[16] A. T. Dinh et al., "Federated learning over wireless networks: Convergence analysis and resource allocation," IEEE/ACM Trans. Netw., vol. 29, no. 1, pp. 398–409, Feb. 2021.
[17] M. Chen, Z. Yang, W. Saad, C. Yin, H. V. Poor, and S. Cui, "A joint learning and communications framework for federated learning over wireless networks," 2019, arXiv:1909.07972.
[18] A. Fallah, A. Mokhtari, and A. Ozdaglar, "Personalized federated learning: A meta-learning approach," 2020, arXiv: 2002.07948.
[19] Y. Deng, M. M. Kamani, and M. Mahdavi, "Adaptive personalized federated learning," 2020, arXiv: 2003.13461.
[20] W. Y. B. Lim et al., "Federated learning in mobile edge networks: A comprehensive survey," 2019, arXiv: 1909.11875.
[21] A. Dinh, N. Tran, and T. D. Nguyen, "Personalized federated learning with Moreau envelopes," in Proc. Adv. Neural Inf. Process. Syst., vol. 33, 2020, pp. 21394–21405.
[22] M. N. H. Nguyen et al., "Distributed and democratized learning: Philosophy and research challenges," IEEE Comput. Intell. Mag., vol. 16, no. 1, pp. 49–62, Feb. 2021.
[23] K. Jain, M. N. Murty, and P. J. Flynn, "Data clustering: A review," ACM Comput. Surv., vol. 31, no. 3, pp. 264–323, Sep. 1999.
[24] H. Mengistu, J. Huizinga, J.-B. Mouret, and J. Clune, "The evolutionary origins of hierarchy," PLOS Comput. Biol., vol. 12, no. 6, Jun. 2016, Art. no. e1004829.
[25] F. Pedregosa et al., "Scikit-learn: Machine learning in Python," J. Mach. Learn. Res., vol. 12 no. 10, pp. 2825–2830, 2011.
[26] S. Dasgupta and P. M. Long, "Performance guarantees for hierarchical clustering," J. Comput. Syst. Sci., vol. 70, no. 4, pp. 555–569, 2005.
[27] J. Shore and R. Johnson, "Properties of cross-entropy minimization," IEEE Trans. Inf. Theory, vol. IT-27, no. 4, pp. 472–482, Jul. 1981.
[28] T. Li, A. K. Sahu, M. Zaheer, M. Sanjabi, A. Talwalkar, and V. Smith, "Federated optimization in heterogeneous networks," in Proc. Mach. Learn. Syst., 2020, pp. 429–450.
[29] Muralidhara, P. (2017). THE EVOLUTION OF CLOUD COMPUTING SECURITY: ADDRESSING EMERGING THREATS. INTERNATIONAL JOURNAL OF COMPUTER SCIENCE AND TECHNOLOGY, 1(4), 1-33.
[30] Muralidhara, P. (2017). IoT applications in cloud computing for smart devices. INTERNATIONAL JOURNAL OF COMPUTER SCIENCE AND TECHNOLOGY, 1(1), 1-41.
[31] Serrano, N., Gallardo, G., & Hernantes, J. (2015). Infrastructure as a service and cloud technologies. IEEE Software, 32(2), 30-36.
[32] Muralidhara, P. (2019). Load balancing in cloud computing: A literature review of different cloud computing platforms. 7. Elmurzaevich, M. A. (2022, February). Use of cloud technologies in education. In Conference Zone (pp. 191-192).
[33] Fang, B., Yin, X., Tan, Y., Li, C., GAO, Y., Cao, Y., & Li, J. (2016). The contributions of cloud technologies to smart grid. Renewable and Sustainable Energy Reviews, 59, 1326- 1331.
[34] G'ayratovich, E. N. (2022). The Theory of the Use of Cloud Technologies in the Implementation of Hierarchical Preparation of Engineers. Eurasian Research Bulletin, 7, 18-21.
[35] Ekanayake, J., Gunarathne, T., & Qiu, J. (2010). Cloud technologies for bioinformatics applications. IEEE Transactions on parallel and distributed systems, 22(6), 998-1011.
[36] Aziz, M. A., Abawajy, J., & Chowdhury, M. (2013, December). The challenges of cloud technology adoption in e-government. In 2013 International Conference on Advanced Computer Science Applications and Technologies (pp. 470-474). IEEE.

[37] Ashok : "Ashok Choppadandi, Jagbir Kaur, Pradeep Kumar Chenchala, Akshay Agarwal, Varun Nakra, Pandi Kirupa Gopalakrishna Pandian, 2021. "Anomaly Detection in Cybersecurity: Leveraging Machine Learning Algorithms" ESP Journal of Engineering & Technology Advancements 1(2): 34-41.")

[38] Kaur, J. (2021). Big Data Visualization Techniques for Decision Support Systems. Jishu/Journal of Propulsion Technology, 42(4). https://propulsiontechjournal.com/index.php/journal/article/view/5701

[39] Ashok : "Choppadandi, A., Kaur, J.,Chenchala, P. K., Nakra, V., & Pandian, P. K. K. G. (2020). Automating ERP Applications for Taxation Compliance using Machine Learning at SAP Labs. International Journal of Computer Science and Mobile Computing, 9(12), 103-112. https://doi.org/10.47760/ijcsmc.2020.v09i12.014

[40] Chenchala, P. K., Choppadandi, A., Kaur, J., Nakra, V., & Pandian, P. K. G. (2020). Predictive Maintenance and Resource Optimization in Inventory Identification Tool Using ML. International Journal of Open Publication and Exploration, 8(2), 43-50. https://ijope.com/index.php/home/article/view/127

[41] Kaur, J., Choppadandi, A., Chenchala, P. K., Nakra, V., & Pandian, P. K. G. (2019). AI Applications in Smart Cities: Experiences from Deploying ML Algorithms for Urban Planning and Resource Optimization. Tuijin Jishu/Journal of Propulsion Technology, 40(4), 50-56.

[42] Case Studies on Improving User Interaction and Satisfaction using AI-Enabled Chatbots for Customer Service . (2019). International Journal of Transcontinental Discoveries, ISSN: 3006-628X, 6(1), 29-34. https://internationaljournals.org/index.php/ijtd/article/view/98

[43] Kaur, J., Choppadandi, A., Chenchala, P. K., Nakra, V., & Pandian, P. K. G. (2019). Case Studies on Improving User Interaction and Satisfaction using AI-Enabled Chatbots for Customer Service. International Journal

[44] of Transcontinental Discoveries, 6(1), 29-34. https://internationaljournals.org/index.php/ijtd/article/view/98

[45] Choppadandi, A., Kaur, J., Chenchala, P. K., Kanungo, S., & Pandian, P. K. K. G. (2019). AI-Driven Customer Relationship Management in PK Salon Management System. International Journal of Open Publication and Exploration, 7(2), 28-35. https://ijope.com/index.php/home/article/view/128

[46] Ashok Choppadandi, Jagbir Kaur, Pradeep Kumar Chenchala, Akshay Agarwal, Varun Nakra, Pandi Kirupa Gopalakrishna Pandian, 2021. "Anomaly Detection in Cybersecurity: Leveraging Machine Learning Algorithms" ESP Journal of Engineering & Technology Advancements 1(2): 34-41.

[47] Ashok Choppadandi et al, International Journal of Computer Science and Mobile Computing, Vol.9 Issue.12, December- 2020, pg. 103-112. ( Google scholar indexed)

[48] Choppadandi, A., Kaur, J., Chenchala, P. K., Nakra, V., & Pandian, P. K. K. G. (2020). Automating ERP Applications for Taxation Compliance using Machine Learning at SAP Labs. International Journal of Computer Science and Mobile Computing, 9(12), 103-112. https://doi.org/10.47760/ijcsmc.2020.v09i12.014

[49] Chenchala, P. K., Choppadandi, A., Kaur, J., Nakra, V., & Pandian, P. K. G. (2020). Predictive Maintenance and Resource Optimization in Inventory Identification Tool Using ML. International Journal of Open Publication and Exploration, 8(2), 43-50. https://ijope.com/index.php/home/article/view/127

[50] AI-Driven Customer Relationship Management in PK Salon Management System. (2019). International Journal of Open Publication and Exploration, ISSN: 3006-2853, 7(2), 28-35. https://ijope.com/index.php/home/article/view/128

[51] Narukulla, Narendra, Joel Lopes, Venudhar Rao Hajari, Nitin Prasad, and Hemanth Swamy. "Real-Time Data Processing and Predictive Analytics Using Cloud-Based Machine Learning." Tuijin Jishu/Journal of Propulsion Technology 42, no. 4 (2021): 91-102.

[52] Narukulla, Narendra, Joel Lopes, Venudhar Rao Hajari, Nitin Prasad, and Hemanth Swamy. "Real-Time Data Processing and Predictive Analytics Using Cloud-Based Machine Learning." Tuijin Jishu/Journal of Propulsion Technology 42, no. 4 (2021): 91-102.

[53] Big Data Analytics using Machine Learning Techniques on Cloud Platforms. (2019). International Journal of Business Management and Visuals, ISSN: 3006-2705, 2(2), 54-58. https://ijbmv.com/index.php/home/article/view/76

[54] Shah, J., Prasad, N., Narukulla, N., Hajari, V. R., & Paripati, L. (2019). Big Data Analytics using Machine Learning Techniques on Cloud Platforms. International Journal of Business Management and Visuals, 2(2), 54-58. https://ijbmv.com/index.php/home/article/view/76

[55] Cygan, Kamil J., Ehdieh Khaledian, Lili Blumenberg, Robert R. Salzler, Darshit Shah, William Olson, Lynn E. Macdonald, Andrew J. Murphy, and Ankur Dhanik. "Rigorous Estimation of Post-Translational Proteasomal Splicing in the Immunopeptidome." bioRxiv (2021): 1-24. https://doi.org/10.1101/2021.05.26.445792

[56] Shah, Darshit, Ankur Dhanik, Kamil Cygan, Olav Olsen, William Olson, and Robert Salzler. "Proteogenomics and de novo Sequencing Based Approach for Neoantigen Discovery from the Immunopeptidomes of Patient CRC Liver Metastases Using Mass Spectrometry." The Journal of Immunology 204, no. 1_Supplement (2020): 217.16-217.16. American Association of Immunologists.

[57] Mahesula, Swetha, Itay Raphael, Rekha Raghunathan, Karan Kalsaria, Venkat Kotagiri, Anjali B. Purkar, Manjushree Anjanappa, Darshit Shah, Vidya Pericherla, Yeshwant Lal Avinash Jadhav, Jonathan A.L. Gelfond, Thomas G. Forsthuber, and William E. Haskins. "Immunoenrichment Microwave & Magnetic (IM2) Proteomics for Quantifying CD47 in the EAE Model of Multiple Sclerosis." Electrophoresis 33, no. 24 (2012): 3820-3829. https://doi.org/10.1002/elps.201200515.

[58] Big Data Analytics using Machine Learning Techniques on Cloud Platforms. (2019). International Journal of Business Management and Visuals, ISSN: 3006-2705, 2(2), 54-58. https://ijbmv.com/index.php/home/article/view/76

[59] Cygan, K. J., Khaledian, E., Blumenberg, L., Salzler, R. R., Shah, D., Olson, W., & ... (2021). Rigorous estimation of post-translational proteasomal splicing in the immunopeptidome. bioRxiv, 2021.05.26.445792.

[60] Mahesula, S., Raphael, I., Raghunathan, R., Kalsaria, K., Kotagiri, V., Purkar, A. B., & ... (2012). Immunoenrichment microwave and magnetic proteomics for quantifying CD 47 in the experimental autoimmune encephalomyelitis model of multiple sclerosis. Electrophoresis, 33(24), 3820-3829.

[61] Mahesula, S., Raphael, I., Raghunathan, R., Kalsaria, K., Kotagiri, V., Purkar, A. B., & ... (2012). Immunoenrichment Microwave & Magnetic (IM2) Proteomics for Quantifying CD47 in the EAE Model of Multiple Sclerosis. Electrophoresis, 33(24), 3820.

[62] Raphael, I., Mahesula, S., Kalsaria, K., Kotagiri, V., Purkar, A. B., Anjanappa, M., & ... (2012). Microwave and magnetic (M2) proteomics of the experimental autoimmune encephalomyelitis animal model of multiple sclerosis. Electrophoresis, 33(24), 3810-3819.

[63] Salzler, R. R., Shah, D., Doré, A., Bauerlein, R., Miloscio, L., Latres, E., & ... (2016). Myostatin deficiency but not anti-myostatin blockade induces marked proteomic changes in mouse skeletal muscle. Proteomics, 16(14), 2019-2027.

[64] Shah, D., Anjanappa, M., Kumara, B. S., & Indiresh, K. M. (2012). Effect of post-harvest treatments and packaging on shelf life of cherry tomato cv. Marilee Cherry Red. Mysore Journal of Agricultural Sciences.

[65] Shah, D., Dhanik, A., Cygan, K., Olsen, O., Olson, W., & Salzler, R. (2020). Proteogenomics and de novo sequencing based approach for neoantigen discovery from the immunopeptidomes of patient CRC liver metastases using Mass Spectrometry. The Journal of Immunology, 204(1_Supplement), 217.16-217.16.

[66] Shah, D., Salzler, R., Chen, L., Olsen, O., & Olson, W. (2019). High-Throughput Discovery of Tumor-Specific HLA-Presented Peptides with Post-Translational Modifications. MSACL 2019 US.

[67] Big Data Analytics using Machine Learning Techniques on Cloud Platforms. (2019). International Journal of Business Management and Visuals, ISSN: 3006-2705, 2(2), 54-58. https://ijbmv.com/index.php/home/article/view/76

[68] Fadnavis, N. S., Patil, G. B., Padyana, U. K., Rai, H. P., & Ogeti, P. (2021). Optimizing scalability and performance in cloud services: Strategies and solutions. International Journal on Recent and Innovation Trends in Computing and Communication, 9(2), 14-23. Retrieved from http://www.ijritcc.org

[69] Challa, S. S. S., Tilala, M., Chawda, A. D., & Benke, A. P. (2021). Navigating regulatory requirements for complex dosage forms: Insights from topical, parenteral, and ophthalmic products. NeuroQuantology, 19(12), 971-994. https://doi.org/10.48047/nq.2021.19.12.NQ21307

[70] Fadnavis, N. S., Patil, G. B., Padyana, U. K., Rai, H. P., & Ogeti, P. (2020). Machine learning applications in climate modeling and weather forecasting. NeuroQuantology, 18(6), 135-145. https://doi.org/10.48047/nq.2020.18.6.NQ20194

[71] Santhosh Palavesh. (2021). Business Model Innovation: Strategies for Creating and Capturing Value Through Novel Business Concepts. European Economic Letters (EEL), 11(1). https://doi.org/10.52783/eel.v11i1.1784