Challenges and Experiences of Iranian Developers with MLOps at Enterprise

Mohammad Heydari
School of Industrial and Systems Engineering
Tarbiat Modares University
Tehran, Iran
m_heydari@modares.ac.ir

Zahra Rezvani
School of Computer Science
Institute for Research in Fundamental Sciences (IPM)
Tehran, Iran
zrezvani@ipm.ir

Abstract— Data is becoming more complex, and so are the approaches designed to process it. Enterprises have access to more data than ever, but many still struggle to glean the full potential of insights from what they have. This research explores the challenges and experiences of Iranian developers in implementing the MLOps paradigm within enterprise settings. MLOps, or Machine Learning Operations, is a discipline focused on automating the continuous delivery of machine learning models. In this study, we review the most popular MLOps tools used by leading technology enterprises. Additionally, we present the results of a questionnaire answered by over 110 Iranian Machine Learning experts and Software Developers, shedding light on MLOps tools and the primary obstacles faced. The findings reveal that data quality problems, a lack of resources, and difficulties in model deployment are among the primary challenges faced by practitioners. Collaboration between ML, DevOps, Ops, and Science teams is seen as a pivotal challenge in implementing MLOps effectively.

Keywords— Machine Learning Operations, MLOps, MLOps Tools, MLOps Challenges, MLOps Solutions

I. INTRODUCTION

Over the past few years, there has been a significant and rapid growth in acronyms with the "Ops" suffix, which initially started by the merging of development and IT operations. This pairing together of disciplines helped enterprises better define their processes, improve the quality of their output, and operate at much faster speed. With the emergence of artificial intelligence, machine learning, and big data, various enterprises have gained a heightened consciousness of the significance of ModelOps, MLOps, DataOps, and AIOps.

MLOps stands for Machine Learning Operations, is a discipline that focuses on the continuous delivery cycle of machine learning models through automated pipelines. ModelOps on the other hand, is a paradigm used to manage model development from conception to deployment, DataOps provides tools for developing efficient data processing pipelines, while AIOps is an Artificial Intelligence-Driven operations platform that helps automate IT processes such as incident resolution. The intersection of Machine Learning, Model Management and Data Infrastructure in MLOps is an essential element for any organization looking to leverage the power of artificial intelligence. MLOps involves the intersection of machine learning, model management, and data infrastructure to build, test, and deploy machine learning models more efficiently and effectively. By understanding how these three components work together, organizations can better manage their models from conception to deployment. Machine learning is the process of using algorithms and statistical models to automatically improve the performance of a system based on data. It is a key component of MLOps, as it involves building and training machine learning models that can be deployed in production. With MLOps, data engineers can build automated pipelines that facilitate model development and deployment while also allowing for easy monitoring and maintenance.

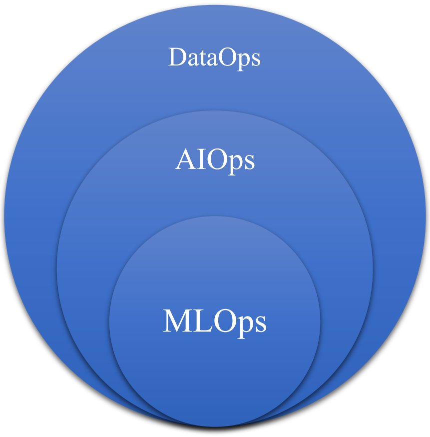

Figure 1 - Intersection of DataOps, AIOps and MLOps [1]

MLOps presents itself as a valuable methodology for the establishment and enhancement of machine learning and artificial intelligence solutions. Through the adoption of an MLOps approach, data scientist and ML engineers can effectively cooperate and expedite the progression of model development and production by implementing the practices of continuous integration and deployment (CI/CD).

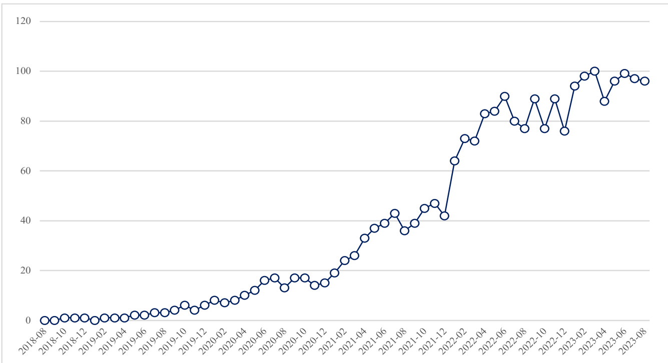

Fig 2 - MLOps Topic Growth on Google Tends from 2018 to 2023 [2]

II. RELATED WORKS

Both AIOps and MLOps are novel fields, and naturally, they have not yet accumulated a substantial amount of pertinent research and literature. The MLOps inception can be traced back to 2015 by Sculley et al. [3] where they explored several machine leaning specific risk factors to account for in system design, and since then, its development has been notably robust. Sasu Makineth et al. [4] explain the significance of MLOps in data science from a study that engaged 331 industry experts from 63 different countries. Testi et al. [5] review the current scientific researches and propose a taxonomy for clustering scientific reports and studies on MLOps. Symeonidis et al. [6] made an overview of MLOps field by operation and elements definition with focus on challenges, trends and related tools. Renggli et al. [7] explain the importance of data quality for MLOps system while describe how different features of data quality propagate through diverse phase of machine learning development. Cheng et al. [8] review the vision of AIOps, trends challenges and opportunities, particularly with focus on the underlying AI techniques and propose a comprehensive taxonomy of techniques to solve related problems. Lones [9] provides a brief overview of typical errors that arise when working with machine learning and suggests strategies to prevent them. Paleyes et al. [10] reviews published studies of implementing machine learning solutions across diverse use cases, industries, and applications. Their study demonstrates that professionals encounter obstacles throughout the entire deployment procedure. Hewage and Meedeniya [11] studies on examining existing technical challenges associated with software development and deployment within organizations engaged in machine learning projects. Their study describes the availability of MLOps tools for helping software development. Tabassam [12] presents a comprehensive review of MLOps, advantages, challenges progresses and techniques such as frameworks, Docker, Kubernetes and GitHub actions. Ahmed's [13] studies on recognizing trends and valuable understandings to improve the MLOps workflow. His study involves a general MLOps workflow, covering crucial stages such as business problem definition, data ingestion, data preparation, model development, model deployment, monitoring, management, scalability, and governance. Zhengxin et al. [14] made a comprehensive detailed review of the modern MLOps technologies. Calefato et al. [15] investigated on MLOps activities implanted on GithHub with focus on GitHub ACTIONS and Continuous Machine Learning (CML), two workflow's development automation solutions. By identification of related issues, their study results demonstrate integration of MLOps practices in GitHub projects is relatively limited.

III. MLOps

MLOps represents a new concept and emphasizes how to optimally coordinate data scientists and operations staff for the efficient development, deployment, and monitoring of models since machine learning productization is difficult. In this regard, machine learning, data engineering and software engineering are involved in MLOps paradigm discipline.

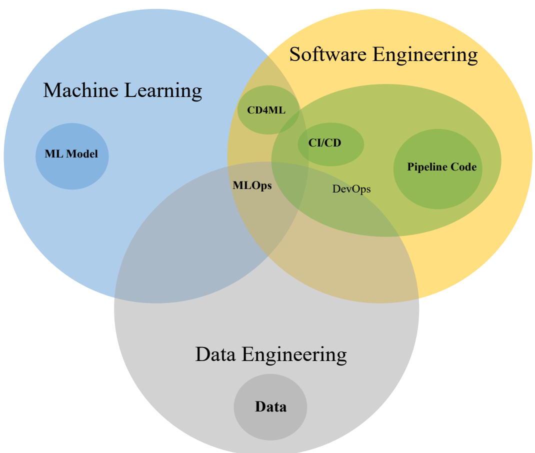

Figure 4 - Disciplines Intersection of MLOps Paradigm[16]

It also necessitates teamwork and transitions between groups, ranging from data engineering to data science and ml engineering. The most important roles in MLOps paradigm are ml engineer, MLOps engineer, DevOps engineer, data engineer, backend engineer and software engineer. MLOps culture includes the following practices:

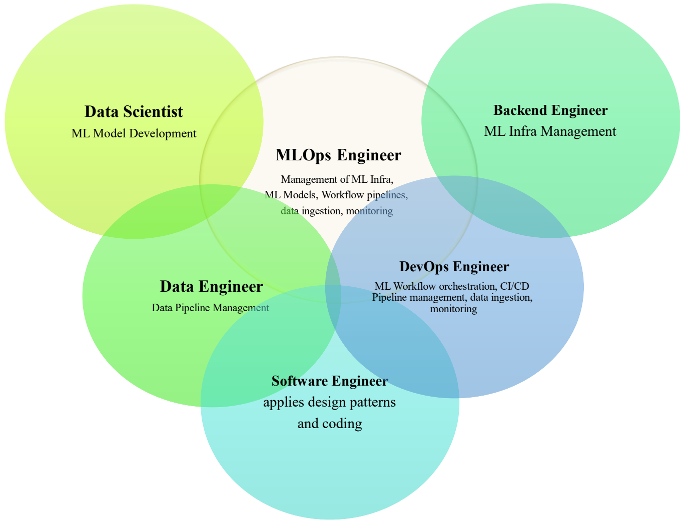

Figure 5 –MLOps Roles and Responsibilities Intersections [16]

The key advantages of MLOps include Efficiency, Scalability and Risk reduction.

1) Efficiency: MLOps facilitates faster model development by data teams, resulting in higher-quality machine learning models and expedited deployment and production processes.

2) Scalability: It allows for the extensive scalability and management of numerous models. MLOps supports continuous integration, delivery, and deployment, ensuring smooth operation and oversight.

3) Risk reduction: MLOps facilitates increased transparency and rapid response to regulatory examinations and drift evaluations of machine learning models. This approach ensures better conformity with industry's policies and standards. The image shows the steps of the machine learning process in detail [14].

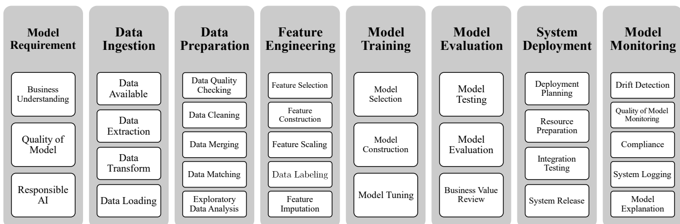

Figure 6 – Machine Learning Process Step by Step [14]

IV. MLOps Tools

The MLOps landscape featured a wide variety of tools and platforms aimed to help organizations and individuals efficiently handle parts or the entire machine learning lifecycle. The field is rapidly evolving, offering practitioners a multitude of options to effectively implement machine learning. In this part, we introduce the most important MLOps tools and platform utilized by leading technology companies in the world and mention some of their exclusive MLOps infrastructure.

A. End to End MLOps Platforms

End-to-end MLOps platforms offer a cohesive environment as a unified ecosystem that optimizes the entirety of the machine learning workflow, from data preparation and model development to deployment and monitoring [17].

Table 1 - End to End MLOps Platforms

Name	Type	Release Date
Google Cloud Platform	Public	2008
Microsoft Azure	Public	2010
H2O.ai	Open Source	2012
Iguazio	Private	2014
AzureML	Open Source	2015
Databricks	Private	2015
Valohai	Public	2016
Amazon SageMaker	Public	2017
MLflow	Open Source	2018
Kubeflow	Open Source	2018
AliBaba Cloud ML	Public	2018
DataRobot	Private	2019
MetaFlow	Open Source	2019
Cloudera	Public	2020
Vertex AI	Public	2021

B. Experiment tracking, metadata storage, and management

Experiment tracking and model metadata management tools enable the user to track experiment parameters, and visualizations, ensuring the ability to reproduce them and facilitating collaboration opportunities.

Table 2 - MLOps Experiment tracking, model storage, and management.

Name	Type	Release Date
Neptune.ai	Private	2017
Comet ML	Private	2017
TensorBoard	Open Source	2017
Weights and Biases	Private	2018
CML	Open Source	2018
MLflow	Open Source	2018
ModelDB	Open Source	2020
AimStack	Open Source	2021

C. Dataset labeling and annotation

Dataset labeling and annotation tools form a critical component of ML systems, enabling you to prepare high-quality training data for their models. These tools offer an efficient process for data annotation, guaranteeing accurate and consistent labeling that fuels model training and evaluation.

Table 3 - Dataset labeling and annotation.

Name	Type	Release Date
Scale AI	Non-free	2016
Labelbox	Private	2017
Amazon Ground Truth	Public	2018
Kili	Non-free	2018
Superb AI	Non-free	2018
Snorkel Flow	Private	2019
SuperAnnotate	Non-free	2020
Encord Annotate	Non-free	2020

D. Data storage and versioning

Data storage and versioning tools enables to maintain data integrity, collaboration, facilitate the reproducibility of experiments and ensure accurate ML model development and deployment. Data versioning enable to trace and compare different iterations of datasets.

Table 4 - Data storage, preprocessing and versioning.

Name	Type	Release Date
iMerit	Private	2012
Pachyderm	Private	2014
Labelbox	Private	2017
Prodigy	Private	2017
Comet	Private	2017
Data Version Control	Open Source	2017
Qri	Open Source	2018
Weights and Biases	Private	2018
Delta Lake	Open Source	2019
Doccano	Open Source	2019
Snorkel	Private	2020
Supervisely	Private	2020
Segments.ai	Private	2020
Dolt	Open Source	2020
LakeFS	Open Source	2020

E. Feature stores

Feature stores provide a unified framework for the storage, management, and provision of ML features. They facilitate the discovery and sharing of feature values, essential for both training and deploying machine learning models.

Table 5 – Feature Stores and Feature Engineering

Name	Type	Year
Iguazio Data Platform	Private	2014
TsFresh	Private	2016
Hopsworks Feature	Open Source	2016
Featuretools	Private	2017
dotData	Private	2018
AutoFet	Open Source	2019
Feast	Open Source	2019
Tecton	Non-free	2019
Featureform	Open Source	2019
Rasgo	Private	2020
HopsWork	Private	2021
Databricks Feature	Private	2021
Vertex AI Feature Store	Public	2021

F. Hyperparameter optimization

As of 2023, the landscape of hyperparameter optimization tooling has remained largely unchanged, with the familiar and established tools continuing to dominate the field.

Table 6 - Hyperparameter optimization

Name	Type	Release Date
Hyperopt	Open Source	2013
SigOpt	Public	2014
Google Vizier	Public	2017
Scikit-Optimize	Open Source	2017
Optuna	Open Source	2018
Talos	Open Source	2018
Optuna	Open Source	2019

G. Workflow orchestration and pipelining tools

Workflow orchestration and pipelining tools are essential components for streamlining and automating complex ML workflows.

Table 7 - Workflow orchestration and pipelining tools

Name	Type
ZenML	Open Source
Kedro Pipelines	Open Source
Flyte	Open Source
Prefect	Open Source
Mage AI	Open Source

H. Model deployment and serving

Model deployment and serving tools enable you to deploy trained models into production environments and serve predictions to end-users or downstream systems.

Table 8 - Model deployment and serving.

Name	Type	Release Date
Algorithmia	Private	2014
TensorFlow Serving	Open Source	2016
KubeFlow	Open Source	2018
OpenVino	Open Source	2018
Triton Inference Server	Open Source	2018
BentoML	Open Source	2019
OctoML	Open Source	2019
Seldon Core	Private	2020
Torch Serve	Open Source	2020
KFServing	Open Source	2020
Syndicai	Private	2020
BodyWork	Open Source	2021
Cortex	Private	2021
Sagify	Open Source	2021

I. Model observability

Model observability tools can allow you to gain insights into the behavior, performance, and health of your deployed ML models.

Table 9 - Model observability

Name	Type	Release Date
Unravel Data	Private	2013
Fiddler AI	Private	2018
Losswise	Private	2018
Superwise	Private	2019
MLrun	Open Source	2019
WhyLabs	Open Source	2020
Arize AI	Private	2020
Evidently AI	Open Source	2020
Aporia	Open Source	2021
Deep Checks	Private	2021

J. The Massive Industrial Companies Cases

In the recent years, some of the most leading technology companies have launched their own dedicated MLOps platforms while they have faced two fundamental challenges: First, the time needed on design, build, and deploy the ML model in the operational environment. The main goal is to reduce the time from several months to several weeks. Also, the stability of models in terms of predictions and reproduction of these models in various and complex conditions are the most important goals of leading companies such as Netflix [18][19], Uber [20][21][22], Databricks [23][24], Google [25], Airbnb [26], and other companies such as Walgreens Boots Alliance [27], DoorDash [28] and Spotify [29][30].

V. Experts Experiences

In this study, over 110 experts participated in an online questionnaire and answered 14 questions. After weeks of collecting feedback from experts, we started to analyze the answers. The design of the questions has been done in consultation with several experts in the field. Targeted professionals are MLOps Engineers, ML Engineers, Data Scientists, Software Engineers, Data Engineers, DevOps Engineers, Backend Engineers, and AI Engineers.

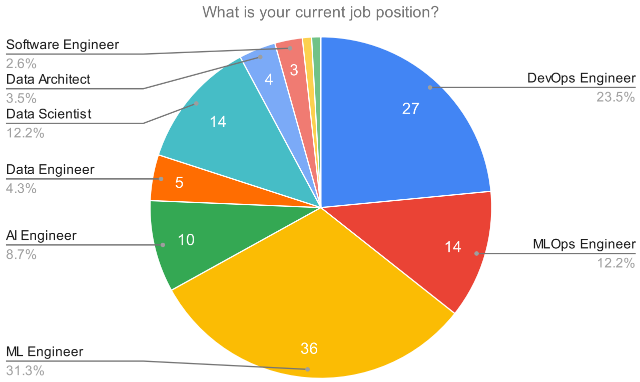

Figure 3 – Experts Current Job Positions

Figure 3 shows the current job position of our respondents. The results show that, 36 (31.3%) are Machine Learning Engineer, 27 (23.5%) are DevOps Engineer, 14 (12.2%) are MLOps Engineer, 14 (12.2%) are Data Scientist,10 (8.7%) is Artificial Intelligence Engineer, 5 (4.3%) are Data Engineer, and 3 (2.6%) are Software Engineer.

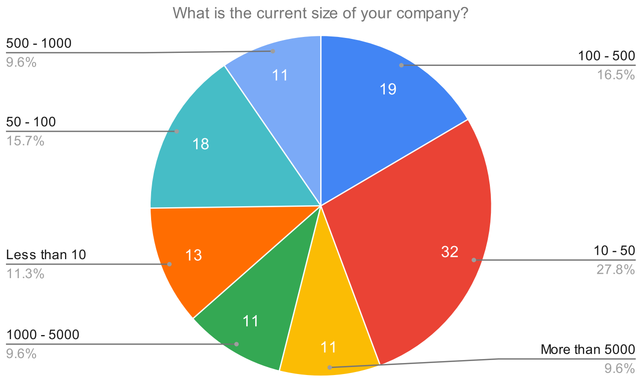

Figure 4 –Size of Companies

Figure 4 shows the size of our respondent's company. The results show that, approximately 32 individuals (27.8%), are employed in organizations ranging in size from 10 to 50 employees, 19 individuals (16.5%), are employed in organizations ranging in size from 100 to 500 employees, 18 individuals (15.7%), are employed in organizations ranging in size from 50 to 100 employees, 13 individuals (11.3%), are employed in organizations ranging in size less than 10 employees, 11 individuals (9.6%), are employed in organizations ranging in size from 1000 to 50000 employees, 11 individuals (9.6%), are employed in organizations ranging in size more than 5000 employees, and 11 individuals (9.6%), are employed in organizations ranging in size more from 500 to 1000 employees,

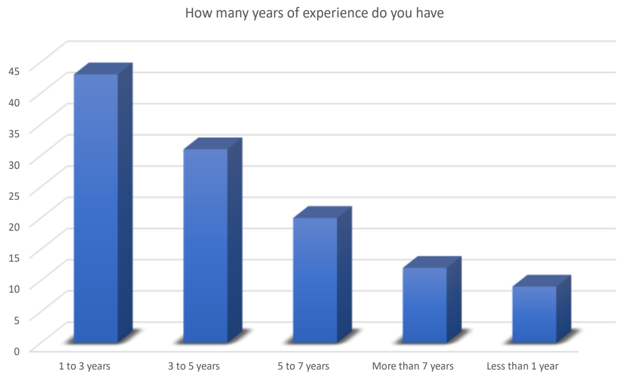

Figure 5 – Experts Experiences per Year

Figure 5 displays the quantity of individuals' years of experience. Based on the data analysis, our report indicates that 43 individuals (37.4%) possess a work experience ranging from 1 to 3 years, 31 individuals (27%) possess a work experience ranging from 3 to 5 years, 20 individuals (17.4%) possess a work experience ranging from 5 to 7 years, 11 individuals (9.6%) possess a work experience more than 7 years, 9 individuals (7.8%) possess a work experience less than a year and 1 individual (0.9%) possess a work experience more than 15 years.

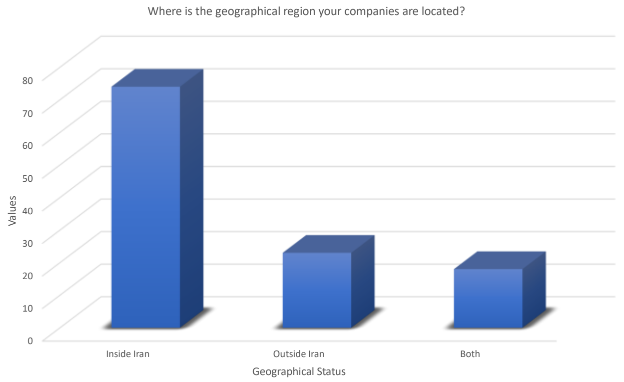

Figure 6 – Companies Geographical Location

Figure 6 shows the geographical distribution of companies to which individuals have affiliations. The results indicate that 74 individuals (64.3%) are employed by companies located within Iran, 23 individuals (20%) are affiliated with companies outside of Iran, and 18 people (15.7%) are engaged in collaborative work with both domestic and international companies.

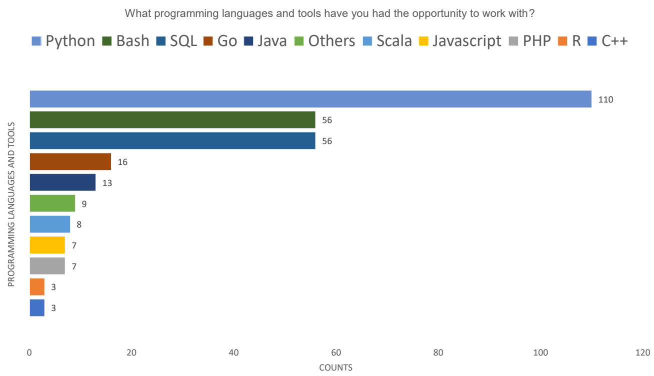

Figure 7 - Programming Languages

Figure 7 displays the programming languages in which individuals have the highest coding and software development experience. The results indicate that 110 programmers (95.7%) primarily utilize the Python programming language for their coding and software development, total of 56 individuals (48.7%) employ SQL for tasks related to database topics, 56 individuals (48.7%) seek assistance from the Bash command language within the Unix and Linux environments, 16 individuals (13.9%) find greater assistance from the statically typed, compiled high-level Go programming language, 13 individuals (11.3%) uses the Java programming language for software development efforts, 8 individuals (7%) use strong statically typed high-level general-purpose Scala programming language for coding, 7 individuals (6.1%) uses the JavaScript for web development tasks, 3 individuals utilize the R language for statistical data analysis, while another three people employ the C++ language for the development of system programs, and 9 individuals use other programming languages and tools for their specific software development tasks.

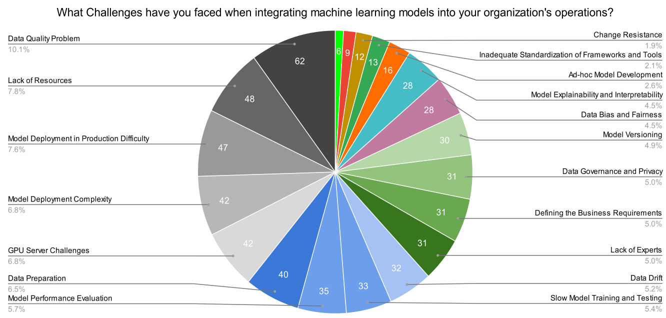

Figure 8 – MLOps Different Challenges

Figure 8 refers to the challenges and difficulties faced by developers in implementing the MLOps paradigm at Enterprise. The table 10 lists the challenges in descending order of importance, with the most significant challenges at the top and the less critical ones toward the bottom.

Table 10 - MLOps Challenges in order of Importance at Enterprise

Challenges	Votes
Data Quality Problem	62
Lack of Resources	48
Model Deployment in Production Difficulty	47
GPU Server Challenges	42
Model Deployment Complexity	42
Data Preparation	40
Model Performance Evaluation	35
Slow Model Training and Testing	33
Data Drift	32
Data Governance and Privacy	31
Defining the Business Requirements	31
Lack of Experts	31
Model Versioning	30
Model Explainability and Interpretability	28
Data Bias and Fairness	28
Ad-hoc Model Development	16
Inadequate Standardization of Frameworks and Tools	13
Change Resistance	12
Others	9
Data Silos and Fragmentation	6

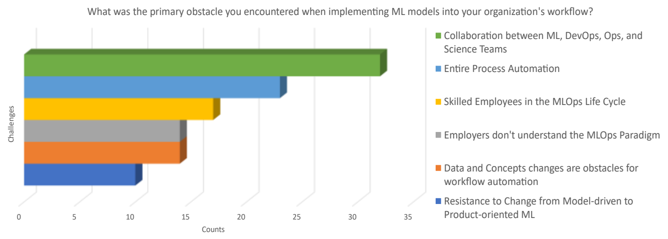

Figure 9 - MLOps Primarily Obstacles

Figure 9 shows the primary and pivotal challenge of MLOps within the organization as determined by experts' viewpoints while in the table 11 Primary Challenge are listed by expert's viewpoints.

Table 11 - Primary Challenge of MLOps at Enterprise

Challenges	**Votes**
Collaboration between ML, DevOps, Ops, and Science Teams	32
Entire Process Automation	23
Skilled Employees in the MLOps Life Cycle	17
Data and Concepts changes are obstacles for workflow automation	14
Employers don't understand the MLOps Paradigm	14
Resistance to Change from Model-driven to Product-oriented ML	10

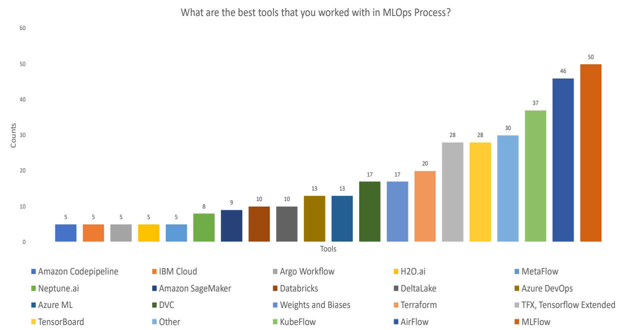

Figure 10 - Most frequently utilized MLOps Tools at Enterprise

Figure 10 refers to the Most frequently utilized MLOps Tools at Enterprise, while in the table 12, tools are listed by popularity order.

Table 12 - Most frequently utilized MLOps Tools at Enterprise

Tools	**Counts**
MLFlow	50
AirFlow	46
KubeFlow	37
Apache Kafka	31
TFX, Tensorflow Extended	28
TensorBoard	28
Ansbile	22
Terraform	20
DVC	17
Weights and Biases	17
Azure DevOps	13
Azure ML	13
Databricks	10
DeltaLake	10
Microsoft PowerShell	10
Amazon SageMaker	9
Neptune.ai	8
Amazon Codepipeline	5
IBM Cloud	5
Argo Workflow	5
H2O.ai	5
MetaFlow	5

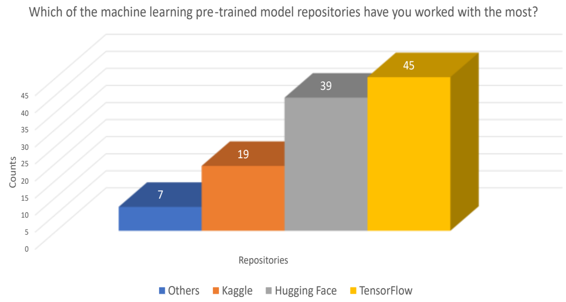

Figure 11 - Pre-trained Machine Learning Repositories

The findings indicate that among the 110 respondents, 45 individuals primarily relied on the TensorFlow repository for pre-trained machine learning models, 39 people engaged with the Hugging Face repository, 19 respondents predominantly utilized the Kaggle repository, and 7 individuals used other repositories.

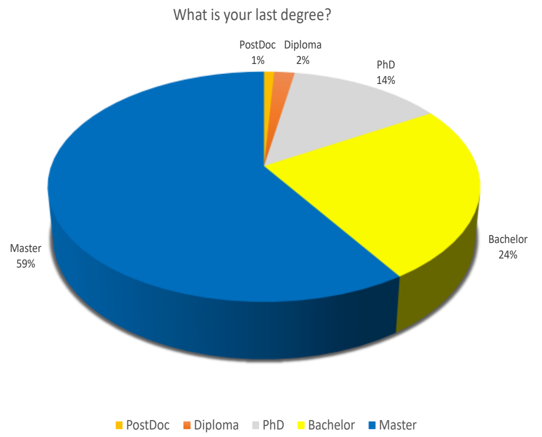

Figure 12 - Experts Educational Levels

The results show that out of 110 respondents, 65 (59%) have a master's degree, 27 (24%) have a bachelor's degree, 15 (14%) have a PhD, 2 (2%) have a diploma and 1 (1%) is a Postdoctoral researcher.

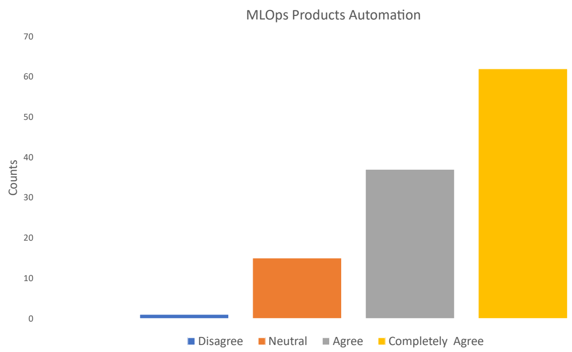

Figure 13 - MLOps Automation

Figure 14 shows the opinions of experts regarding the following phrase: "MLOps is closely associated with the collaboration between ML engineers and developers to automate the development of ML products". The results show that out of 110 respondents, 60 (53.9%) agree with the statement, 35 (32.2%) completely agree, 14 (13%) are neutral, and 1 (0.9%) disagree with the statement.

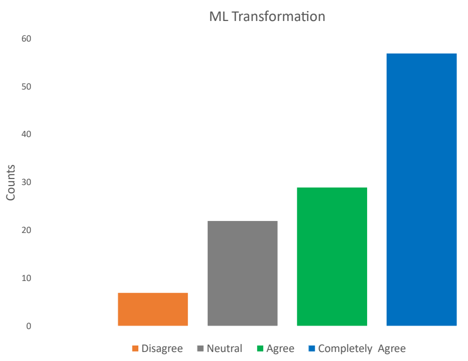

Figure 14 – Machine Learning Transformation

Figure 14 shows the experts opinions regarding the following phrase: "MLOps is currently undergoing a significant transformation in ML Engineering and revolutionizing the way in which these processes are conducted". The results indicates out of 110 respondents, 55 (49.6%) agree with the statement, 22 (19.1%) completely agree, 27 (25.2%) are neutral, and 6 (6.1%) disagree with the statement.

VI. Conclusion

This study has presented a brief overview of the evolving landscape of MLOps and its significance in addressing the challenges faced by enterprises in managing machine learning models effectively. We presented an extensive list of MLOps tools and platforms utilized by leading technology companies, offering readers a valuable resource for navigating the MLOps landscape. Furthermore, the research has incorporated insights from over 110 Iranian Software experts, providing a glimpse into their experiences, challenges, and preferences. The findings reveal that data quality problems, a lack of resources, and difficulties in model deployment are among the primary challenges faced by practitioners. Collaboration between ML, DevOps, Ops, and Science teams is seen as a pivotal challenge in implementing MLOps effectively.

Acknowledgment

The authors, express their endless gratitude to all Iranian machine learning activists and software developers for sharing their valuable experiences towards conducting this research.

Refrences

[1] U. Data, "THE GUIDE TO DATAOPS, AIOPS, AND MLOPS in 2022." https://www.unraveldata.com/resources/dataops-aiops-and-mlops/.

[2] "Data Source: Google Trends," 2023. https://www.google.com/trends.

[3] D. Sculley *et al.*, "Hidden technical debt in machine learning systems," *Adv. Neural Inf. Process. Syst.*, vol. 2015-Janua, pp. 2503–2511, 2015.

[4] S. Makinen, H. Skogstrom, E. Laaksonen, and T. Mikkonen, "Who needs MLOps: What data scientists seek to accomplish and how can MLOps help?," *Proc. - 2021 IEEE/ACM 1st Work. AI Eng. - Softw. Eng. AI, WAIN 2021*, no. Ml, pp. 109–112, 2021, doi: 10.1109/WAIN52551.2021.00024.

[5] M. Testi *et al.*, "MLOps: A Taxonomy and a Methodology," *IEEE Access*, vol. 10, pp. 63606–63618, 2022, doi: 10.1109/ACCESS.2022.3181730.

[6] G. Symeonidis, E. Nerantzis, A. Kazakis, and G. A. Papakostas, "MLOps - Definitions, Tools and Challenges," *2022 IEEE 12th Annu. Comput. Commun. Work. Conf. CCWC 2022*, no. Cd, pp. 453–460, 2022, doi: 10.1109/CCWC54503.2022.9720902.

[7] C. Renggli, L. Rimanic, N. M. Gürel, B. Karlaš, W. Wu, and C. Zhang, "A Data Quality-Driven View of MLOps," no. 1, pp. 1–12, 2021, [Online]. Available: http://arxiv.org/abs/2102.07750.

[8] Q. Cheng *et al.*, "AI for IT Operations (AIOps) on Cloud Platforms: Reviews, Opportunities and Challenges," pp. 1–34, 2023, [Online]. Available: http://arxiv.org/abs/2304.04661.

[9] M. A. Lones, "How to avoid machine learning pitfalls: a guide for academic researchers," pp. 1–25, 2021, [Online]. Available: http://arxiv.org/abs/2108.02497.

[10] A. Paleyes, R. G. Urma, and N. D. Lawrence, "Challenges in Deploying Machine Learning: A Survey of Case Studies," *ACM Comput. Surv.*, vol. 55, no. 6, pp. 1–29, 2022, doi: 10.1145/3533378.

[11] N. Hewage and D. Meedeniya, "Machine Learning Operations: A Survey on MLOps Tool Support," no. February, 2022, doi: 10.48550/arXiv.2202.10169.

[12] A. Ikram and U. Tabassam, "MLOps : A Step Forward to Enterprise Machine Learning," 2023.

[13] A. M. A. Ahmed, "Exploring MLOps Dynamics: An Experimental Analysis in a Real-World Machine Learning Project," 2023, [Online]. Available: http://arxiv.org/abs/2307.13473.

[14] F. Zhengxin *et al.*, "MLOps Spanning Whole Machine Learning Life Cycle: A Survey," 2023, [Online]. Available: https://arxiv.org/abs/2304.07296v1.

[15] F. Calefato, F. Lanubile, and L. Quaranta, *A Preliminary Investigation of MLOps Practices in GitHub*, vol. 1, no. 1. Association for Computing Machinery, 2022.

[16] D. Kreuzberger, N. Kuhl, and S. Hirschl, "Machine Learning Operations (MLOps): Overview, Definition, and Architecture," *IEEE Access*, vol. 11, pp. 31866–31879, 2023, doi: 10.1109/ACCESS.2023.3262138.

[17] S. Oladele, "MLOps Landscape in 2023: Top Tools and Platforms," 2023. https://neptune.ai/blog/mlops-tools-platforms-landscape.

[18] "Metaflow," *Online*. https://metaflow.org/.

[19] F. Rönnlund, "Machine Learning Infrastructure Lessons from Netflix," 2018. https://valohai.com/blog/machine-learning-infrastructure-lessons-from-netflix/.

[20] J. Wang, "Continuous Integration and Deployment for Machine Learning Online Serving and Models," 2021. https://www.uber.com/en-DE/blog/continuous-integration-deployment-ml/.

[21] F. Rönnlund, "Michelangelo – Machine Learning Infrastructure at Uber," *Online*, 2017. https://valohai.com/blog/an-interview-with-former-product-manager-for-ubers-michelangelo-mike-del-balso/.

[22] J. Hermann, "Meet Michelangelo: Uber's Machine Learning Platform," *Online*, 2017. https://www.uber.com/en-DE/blog/michelangelo-machine-learning-platform/.

[23] M. Zaharia *et al.*, "Accelerating the Machine Learning Lifecycle with MLflow," *Bull. IEEE Comput. Soc. Tech. Comm. Data Eng.*, pp. 39–45, 2018.

[24] "MLflow, A platform for the machine learning lifecycle," *Online*. https://mlflow.org/.

[25] "Google TFX: an end-to-end platform for deploying production ML pipelines," *Online*. https://www.tensorflow.org/tfx.

[26] E. Brumbaugh *et al.*, "Bighead: A framework-agnostic, end-to-end machine learning platform," *Proc. - 2019 IEEE Int. Conf. Data Sci. Adv. Anal. DSAA 2019*, pp. 551–560, 2019, doi: 10.1109/DSAA.2019.00070.

[27] Y. Zhang, "MLOps at Walgreens Boots Alliance With Databricks Lakehouse Platform," 2022. https://www.databricks.com/blog/2022/12/05/mlops-walgreens-boots-alliance-databricks-lakehouse-platform.html.

[28] P. Reddy, "DoorDash's ML Platform – The Beginning," *Online*. https://doordash.engineering/2020/04/23/doordash-ml-platform-the-beginning/.

[29] D. Vohra, "Unleashing ML Innovation at Spotify with Ray," *Online*, 2023. https://engineering.atspotify.com/2023/02/unleashing-ml-innovation-at-spotify-with-ray/.

[30] J. Jin, "Empowering Traceable and Auditable ML in Production at Spotify with Hendrix," *Online*, 2022. https://mlconf.com/sessions/empowering-traceable-and-auditable-ml-in-production-at-spotify-with-hendrix/.