

# **PERFORMANCE IMPROVEMENTS IN MLOPS PIPELINE**

Ratnasingam Kasthuriraajan

219352M

MSc in Computer Science

Department of Computer Science and Engineering  
Faculty of Engineering

University of Moratuwa  
Sri Lanka

April 2023

# **PERFORMANCE IMPROVEMENTS IN MLOPS PIPELINE**

Ratnasingam Kasthuriraajan

219352M

Thesis submitted in partial fulfillment of the requirements for the degree  
MSc in Computer Science

Department of Computer Science and Engineering  
Faculty of Engineering

University of Moratuwa  
Sri Lanka

April 2023

## **DECLARATION**

I declare that this is my own work and this Thesis does not incorporate without acknowledgement any material previously submitted for a Degree or Diploma in any other University or Institute of higher learning and to the best of my knowledge and belief it does not contain any material previously published or written by another person except where the acknowledgement is made in the text. I retain the right to use this content in whole or part in future works (such as articles or books).

Signature:

Date: 27. 06. 2023

The supervisor should certify the Thesis with the following declaration.

The above candidate has carried out research for the MSc in Computer Science Thesis under my supervision. I confirm that the declaration made above by the student is true and correct.

Name of Supervisor: Prof. Indika Perera

Signature of the Supervisor:

Date: 30/06/2023

## **ACKNOWLEDGEMENT**

I would like to express my sincere thanks and gratefulness to my MSc Research Project supervisor, Prof. Indika Perera who guiding me through all semesters and unconditionally support me in acquiring all needed resources to achieve my MSc Research Project Thesis.

I am particularly thankful for his major help in the research effort, which included giving the required skills, resources, guidance, supervision, and beneficial suggestions. With his expertise and constant help, I was able to finish my study program properly on time. I would like to convey my thanks to all other lecturers who taught throughout the course. I would like to convey my sincere thanks to all the participants of the demonstration of our solution and survey followed by that which is an immense help to complete this study program. I would also like to thank all my friends from this degree program who motivated me throughout the course period and supported me in discovering relevant study material. I am extremely thankful to my parents, brother, colleagues and close friends for their support. Finally, I would like to convey my sincere thanks to all who support me in this entire journey.

## ABSTRACT

In the modern world, most of the enterprises willing to leverage the use of machine learning models in their applications. Due to the high demand usage of the machine learning models in production, need to bring the machine learning models from research to production with minimal time duration, MLOps emerge an unavoidable practice. Big scope of the MLOps opens many doors for research. MLOps is one of the emerging topic among researchers. There are many people involved in the entire machine learning life cycle with various roles. Similar to DevOps, MLOps is also a culture that should be practiced by all the parties with different roles who involved in the entire process to get a better outcome. MLOps adopts many practices from DevOps and it has some own set of practices as well. Even though there are many tools and technologies developed to build MLOps pipeline, there are still rooms for further studies to improve the performance of the MLOps pipelines.

There are many phases in the entire machine learning process such as data handling, model training, model evaluation, hyperparameter tuning, model deployment, model versioning, and model monitoring etc. For a successful performance of an MLOps pipeline, all of these phases should be automated as much as possible. Performance improvements in the MLOps pipeline can be achieved in terms of easiness of usage, time and cost.

In this study we have taken a simple machine learning problem called "Stock price prediction for Google stock prices using LSTM". We have analysed many tools that can be used in MLOps pipeline. Finally we have implemented an end-to-end MLOps pipeline with open source tools and technologies for the selected machine learning problem. Our final solution is implemented using DVC, MLflow, Evidently and GitHub Actions.

We compared our final solution along with other solutions available in the market and analysed the pros and cons. Our solution is very flexible to use. It has no vendor locking. If any modifications or extensions of tools needed, it can be plugged easily into the proposed architecture. We have automated almost all the phases in the MLOps pipeline. It reduce the time taken to bring the machine learning models from research to production. Since we have used free and open source tools mostly, it is very cost effective. We have found that our final solution improves the performance of the MLOps pipeline in terms of easiness of usage, time and cost.

**Keywords:** MLOps, Machine Learning, Pipeline, DevOps, Data Version Control, Continuous Integration(CI), Continuous Deployment(CD), Continuous Training (CT), Workflow

## TABLE OF CONTENTS

Declaration of the Candidate & Supervisor	i
Acknowledgement	ii
Abstract	iii
Table of Contents	iv
List of Figures	vii
List of Tables	viii
List of Abbreviations	viii
List of Appendices	x
1 Introduction	1
1.1 Machine Learning in Real Life	1
1.2 Challenges in Bringing Machine Learning Models from Research to Production	2
1.3 How DevOps Overcome Similar Challenges in SDLC?	4
1.4 MLOps Concept	5
1.5 How MLOps Overcome the Challenges in Bringing ML to Production	10
1.6 Existing Approaches in MLOps	11
1.7 Challenges in Existing Approach	12
1.7.1 Project management	13
1.7.2 Communication and collaboration	13
1.7.3 Everything is code	13
1.7.4 CI/CD	13
1.7.5 Monitoring and logging	14
1.8 Our Solution	15
2 Literature Review	16
2.1 Introduction of MLOps	16
2.2 Challenges	17
2.3 Related works	17

3	Methodology	23
3.1	Research Gap	23
3.1.1	Identified Research Problems	23
3.2	Research Objective	23
3.2.1	Build a complete MLOps Pipeline	24
3.2.2	Increase Automation Capabilities in Data Handling Phases	24
3.2.3	Use Open Source Platforms as Much as Possible	24
3.3	Important Steps in MLOps	24
3.4	Tools to Use in Each Steps	26
3.4.1	DVC	28
3.4.2	MLflow	28
3.4.3	Neptune	29
3.4.4	Pachyderm	30
3.4.5	Optuna	30
3.4.6	SigOpt	31
3.4.7	Kubeflow	33
3.4.8	Polyaxon	33
3.4.9	Airflow	34
3.4.10	BentoML	35
3.4.11	Cortex	36
3.4.12	Seldon	36
3.4.13	Fiddler	37
3.4.14	Hydrosphere	37
3.4.15	Evidently	38
3.4.16	GitHubAction	38
3.5	Commercial Vendors	39
3.5.1	AWS SageMaker	39
3.5.2	Vertex AI	39
3.5.3	Azure Machine Learning	40
3.6	Proposed Solution	40

4	Experiment	42
4.1	Experimental setup	42
4.1.1	Dataset Identification	42
4.1.2	Data Versioning	43
4.1.3	Implementation of Initial Model	44
4.1.4	Performance Metrics Identification	45
4.1.5	Hyper Parameter Tuning	45
4.1.6	Pipeline for CI/CD	46
4.1.7	Model Registry and Model Deployment	47
4.1.8	Model Versioning	48
4.1.9	Prediction API Development	48
4.1.10	Model Monitoring	49
4.1.11	Pipeline for Continuous Training	50
4.2	Final solution	51
5	Result	53
5.1	Fulfillment of Research Objective	53
5.1.1	End-to-End MLOps pipeline	54
5.1.2	Data handling automation	57
5.1.3	Usage of Open source tools	57
5.2	Comparison with Commercial Tools	57
5.3	Closing Remarks	63
6	Conclusion	64
6.1	Discussion	64
6.2	Conclusion	64
6.3	Future Work	65
	References	66
	Appendix A Getting Concern to Conduct Demonstration and Survey	72
	Appendix B Suggestion Survey	79
	Appendix C Comparison Survey	83



## LIST OF FIGURES

<b>Figure</b>	<b>Description</b>	<b>Page</b>
Figure 1.1	Three Types of Machine Learning	1
Figure 1.2	DevOps Loop	5
Figure 1.3	MLOps Life-cycle	6
Figure 1.4	MLOps combination	7
Figure 1.5	Machine Learning steps to manually serve the model for a prediction service.	7
Figure 1.6	ML pipeline automation for CT.	8
Figure 1.7	CI/CD and automated ML pipeline.	9
Figure 1.8	Stages of the CI/CD automated ML pipeline.	9
Figure 1.9	High-level process view of MLOps	11
Figure 1.10	An MLOps architecture	12
Figure 4.1	The Proposed MLOps Pipeline - Architecture Diagram	43
Figure 4.2	Final solution for MLOps Pipeline - Architecture Diagram	52
Figure 5.1	MLflow Dashboard	54
Figure 5.2	MLflow Dashboard - Experiment Details View	55
Figure 5.3	Model Registry & Model Versioning	55
Figure 5.4	GitHub Action workflow diagram	56
Figure 5.5	GitHub Action workflow diagram of pipeline	56
Figure 5.6	Comparison with Commercial Tools Survey Result-Flexibility	58
Figure 5.7	Comparison with Commercial Tools Survey Result-Community Support	59
Figure 5.8	Comparison with Commercial Tools Survey Result-Ease of Use	59
Figure 5.9	Comparison with Commercial Tools Survey Result - Cost-effectiveness	59
Figure 5.10	Comparison with Commercial Tools Survey Result-Vendor Locking	60
Figure 5.11	Comparison with Commercial Tools Survey Result-Steep learning curve	60
Figure 5.12	Comparison with Commercial Tools Survey Result-Customization	60
Figure 5.13	Comparison with Commercial Tools Survey Result-Scalability	61
Figure 5.14	Comparison with Commercial Tools Survey Result-Stability	61
Figure 5.15	Comparison with Commercial Tools Survey Result-Time taken	61
Figure 5.16	Prediction Result Graph of Our Sample ML Problem	62

## LIST OF TABLES

<b>Table</b>	<b>Description</b>	<b>Page</b>
Table 3.1	Open source tools and licences	27
Table 4.1	Tools and technology selection for final solution	51
Table 5.1	Details of survey participants	58
Table 5.2	Comparison of Our Solution with Commercial Vendors	62

## LIST OF ABBREVIATIONS

<b>Abbreviation</b>	<b>Description</b>
AI	Artificial Intelligence
AWS	Amazon Web Services
CD	Continuous Delivery
CI	Continuous Integration
CT	Continues Training
DVC	Data Version Control
ML	Machine Learning
MLDC	Machine Learning Development Cycle
SaaS	Software as a Service
SDLC	Software Development Life Cycle

## LIST OF APPENDICES

<b>Appendix</b>	<b>Description</b>	<b>Page</b>
Appendix -A	Getting Concern to Conduct Demonstration and Survey	72
Appendix -B	Suggestion Survey	79
Appendix -C	Comparison Survey	83