

Multi-Cloud Smart Deploy: An AI-Based CI/CD Optimization with Kubernetes Rollback Strategy

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Sahil Shaikh
Student ID: x23220228

School of Computing
National College of Ireland

Supervisor: Shaguna Gupta

National College of Ireland
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School of Computing



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Multi-Cloud Smart Deploy: An AI-Based CI/CD Optimization with Kubernetes Rollback Strategy

Sahil Shaikh

x23220228

Abstract

With the rise of cloud-native applications, we are once again faced with new challenges in terms of deployment orchestration, performance optimization, rollback strategies across multi-cloud environment, etc. The research focuses on a motivating problem statement around efficient deployment of containerized applications in multiple environments including GCP, Azure and AWS with effective monitoring and AI driven performance analysis. Continuous integration and continuous deployment. CI/CD pipelines are a must-have in the industry right now, but they are still largely confined to single-cloud scopes. In this article, we focus on innovative multi-cloud CI/CD deployment with Kubernetes cluster roll back integrated with auto AI based evaluation. The solution developed in this project is utilized as a GitHub Actions driven CI/CD pipeline responsible for the dynamic build, test, and deployment of a Django web application to Kubernetes clusters hosted over GCP, Azure, and AWS. Logs collected automatically and merged include post-deployment metrics such as startup time, rollout duration, and resource usage. Their inputs are logged from four machine learning models running inside Azure Machine Learning (Azure ML), which analyze cloud performance according to training accuracy and inference metrics. Under this systems pipeline architecture, intelligent decisions can be made on which cloud provider is best in the various scenarios. The implementation also provides Kubernetes rollback functionality to reverse bad deployments leading to enhancing reliability and service availability. The project enables key DevOps practices and machine learning workflows in a fully automated manner. The results show consistent and correct training through the ML pipeline, and evidence-based cloud selection. Overall, the proposed system provides greater resiliency, better performance visibility, and automatic rollback, as compared to traditional static deploy. Therefore, we strongly encourage the use of the proposed system in industrial multi-cloud deployments. In sum, the system shines on all axes we tested, and we leave more fine-grained resource profiling and predictive scaling for future work. This new effort is a major step forward in automating and intelligently delivering cloud-agnostic applications.

Keywords: - CI/CD Pipeline, DevOps, Multi-Cloud Deployment, AI-Based Cloud Evaluation, Azure Machine Learning (Azure ML), Kubernetes Rollback.

1 Introduction

With the proliferation of digital infrastructure as the fabric of modern enterprises, the need for dynamic, flexible, and high-availability deployment strategies have increased

dramatically. An explosion of cloud-native applications alongside the proliferation of containerized microservices architectures has driven the adoption of increased levels of automation and AI-powered optimization in DevOps workflows. CI/CD (Continuous Integration and Continuous Deployment) pipelines represent one of these paradigm shifts that has driven the transition to agile development cycles. The naive deployment of applications on multi-cloud platforms, including Google Cloud Platform (GCP), Microsoft Azure, and Amazon Web Services (AWS), leads to operational, performance, and decision-related problems that existing research has not yet been able to fully address. This research presents a unique convergence between machine learning models integrated with CI/CD pipelines while deploying logs with real-time analytics for the performance metrics across cloud providers. It is then used to recommend platform selections and perform Kubernetes rollbacks based on log data collection, model training, and automated decision-making for degraded application scenarios. This research aims to have a positive influence on the world of DevOps, cloud orchestration, and intelligent deployment management by introducing a reproducible, automated, and intelligent pipeline tailored to be used in multi-cloud environment.

1.1 Background & Motivation

Advent of Cloud-based solutions has seen heavy adoption where organizations are moving towards cloud-native infrastructure to have scalability, flexibility and cost-effectiveness. Multi-cloud strategies are now common, with 89% of enterprises using two or more cloud providers to exploit capabilities at the edge and avoid vendor lock-in. But as much easier as this scenario may be, multi-cloud deployments remain painfully complex—each of the platforms utilized has its own performance characteristics, deployment behavior, and is monitored differently. CI/CD Pipeline is essential in contemporary software development to allow for interleaved releases for speed and reliability of output. Tools like GitHub Actions, Jenkins, and GitLab CI enable developers to integrate and deploy changes with minimal manual intervention. However, manual or retrospective performance evaluation of deployments results in delayed response to failures or inefficiencies. Recent literature has analyzed the application of AI/ML for DevOps in various contexts, including anomaly detection Shahin et al. (2017), predictive deployment scaling, and performance tuning Chen et al. (2020). However, there is little research on using AI to directly shape multi-cloud deployment strategies and execute automated Kubernetes rollbacks in the CI/CD pipeline.

This project aims to close this loop by building a pipeline that trains four supervised learning models—Random Forest, XGBoost, LightGBM and Decision Trees—on the logs of the cloud deployment performance (e.g. CPU, memory, pod uptime, latency) to recommend the best-fitting cloud provider and roll back inefficient rollouts. Even though performance data is currently available through logging services, it is still an underexplored area of multi-cloud pipelines for AI-driven deployment orchestration Patel and Roy (2021). This work directly tackles the challenge above by automating AI model training in the pipeline and using these models to inform deployment decisions.

1.2 Problem Statement

Although CI/CD pipelines automate a majority of the deployment lifecycle, they are not specific when making cross-platform deployment decisions. Current pipelines are either

static or deploy homogeneously across all platforms, even when there is variability in performance at runtime. Furthermore, rollback mechanisms tend to be manual, responding to failures that already happened. This lag in response can have serious implications for organizations in terms of time, resources, and availability. Furthermore, deployment performance logs that are captured from GCP, Azure, and AWS are analyzed or learned from, in real time. This data is unused and thus untapped and suitable for ML models to determine the best possible deployment strategy, which can trigger corrective actions (i.e. rollbacks).

1.3 Problem Solution

In this research, we propose a fully-automated multi-cloud CI/CD pipeline, along with integrating a machine learning layer which aims to make optimal deployment-based decisions. This solution automates the building of Docker images, pushes the images to container registries in a multi-cloud environment, and sets the stage for Kubernetes deployments across GCP, Azure, and AWS with the help of GitHub Actions. From resource usage metrics (CPU and memory usage), rollout time, and the number of pods to external ip addresses. It is capable of saving logs in cloud native storage options such as Google CloudStorage, Azure Blob Storage, and AWS S3. The logs are consolidated with a python script into a common CSV dataset used to train the machine learning models on Azure ML, based on the call from the pipeline. These models leverage historical performance to predict the best cloud provider for upcoming deployments. The output of this model can be used in the CI/CD pipeline to automatically choose the cloud provider based on the expected performance. Also, if the metrics after the deployment fall below set thresholds, it automatically rolls back using `kubectl rollout undo`. This solution is both reproducible and portable across different projects and is entirely structured using GitHub Actions.

1.4 Research Question

The focused part of this work is presented as the research question below:

”Can a machine-learning-augmented CI/CD pipeline autonomously select the most optimal cloud provider for application deployment based on live performance metrics and execute a rollback in Kubernetes when performance thresholds are breached?”

1.5 Research Objectives

The objectives of this research are outlined as follows:

1. Investigate the current scenario of multi-cloud CI/CD practices and their limitations in decision-making.
2. Design a machine learning-driven architecture that integrates with a GitHub Actions CI/CD workflow.
3. Implement real-time log collection, AI model training on Azure ML, and cloud-provider-aware deployment orchestration.
4. Evaluate the pipeline through multiple deployment scenarios and compare model-based cloud decisions.

5. Support rollback mechanisms by integrating Kubernetes commands that undo deployments when models or performance metrics predict/indicate failure.

1.6 Structure of Research

A research design has been established to implement and evaluate a CI/CD pipeline optimization strategy using AI-based prediction models integrated with Kubernetes-based multi-cloud deployment. The aim is to enhance decision-making for cloud selection while ensuring efficiency through automated workflows and rollback mechanisms.

- **Section 2: Literature Review** – Reviews prior research in continuous delivery (CD), AI-based deployment optimization, and multi-cloud orchestration, particularly focusing on GitHub Actions, Azure ML, and containerized microservices. It identifies gaps in AI-driven decision automation across cloud providers.
- **Section 3: Methodology** – Explains the tools, platforms, and design approaches adopted in this study. This includes Docker containerization, GitHub CI/CD, Terraform for infrastructure provisioning, and model training via Azure Machine Learning Studio using deployment metrics.
- **Section 4: Design Specification** – Describes the architectural layout, including infrastructure-as-code (IaC), container orchestration across AWS, Azure, and GCP, CI/CD flow, AI integration, and cloud-specific storage strategies for log collection and retrieval.
- **Section 5: Implementation & Evaluation** – Implements the CI/CD pipeline using GitHub Actions. The deployment is executed across all three cloud platforms. Evaluation includes log collection, model-based predictions, and automatic rollback based on failure detection. Performance metrics like CPU/memory usage, latency, cost, and deployment time are used to assess cloud suitability.
- **Section 6: Results & Discussion** – Summarizes the experimental outcomes from four machine learning models: Logistic Regression, Random Forest, XGBoost, and KNN. It interprets performance across clouds and discusses the implications of automated cloud selection and CI/CD enhancements.
- **Section 7: Conclusion & Future Work** – Concludes with a reflection on the AI-optimized CI/CD process and the system’s strengths in smart multi-cloud deployments. Future work includes improving model accuracy, real-time feedback loops, and integration of advanced orchestration tools.

2 Related Work

With the pace of digital transformation, web applications deployed on multi-cloud Kubernetes infrastructures have become quite popular. Detailed approaches of integrating CI/CD pipelines, automating deployments, and monitoring based performance metrics using diverse cloud ecosystems like AWS, Azure, and GCP. At the same time, AI models have become core for analyzing and optimizing deployments outcomes. This survey critically evaluates the state-of-the-art techniques related to integration CI/CD in multi-cloud

settings, performance metrics concerning deployment, and the application of machine learning (ML) models to assess the performance of clouds and consequently invoke rollback strategies in Kubernetes.

2.1 CI/CD and Kubernetes-Based Deployments

Modern CI/CD practices have also been influenced by the rising adoption of Kubernetes in orchestrating containerized applications. In a Kubernetes environment, CI/CD pipelines facilitate automated testing and deployment stages across distributed clusters, which simplifies software delivery Sharma and Trivedi (2021). The major focus is the evolution of GitHub Actions and Jenkins and the significance of integration with Kubernetes for continuous deployment to cloud providers such as Azure and AWS. A similar study included Zhang et al. (2020) introduced a Kubernetes-native continuous delivery tool, Argo CD which allows for declarative GitOps-based automation. They showed its performance and scalability with regards to standard Jenkins pipelines in cases of heavy-load deployments. However, their evaluation did not have real-time rollback mechanisms based on cloud performance metrics. Moreover, Wu et al. (2022) proposed a CI/CD framework for the management of complex microservices architectures that combined Kustomize, Helm, and GitLab CI. This approach led to better maintainability, but failed to include AI driven decision making in regards to deployment health analysis.

2.2 Challenges in Multi-Cloud Deployment

Many organizations go for multi cloud strategy to prevent vendor lock-in, which increases the complexity of deploy consistency, resource management and security enforcement Marijan et al. (2018). According to Perez et al. (2015), models for standardization of deployment over cloud provide are absent. This is indeed correct, as Larrucea et al. (2019) claim that there are some issues as delayed API configurations, latency problems and cost inefficiencies in the multi cloud deployments. Yousif et al. (2020) analyse cross cloud orchestration Challenges and provide evidence that traditional fault tolerance mechanisms are not commonly adopted within multi cloud CD strategies Zhang et al. (2020). The existing load balancers do not adjust to dynamically change the workload on AWS, Azure etc., causing very inefficient consumption w.r.t the workloads running on VMs. Kumar and Patel (2022) explore the resulting late deploys and high operational cost between cloud providers resulting from network latency in the actual performance incurred by cd pipelines. Non-standard API on cloud providers, leading organizations to maintain separate deployment scripts. Gupta and Khatri (2023) claim that intelligent routing helps us to deploy our workloads on the most suitable cloud provider in a multi cloud CD pipeline.

2.3 AI and Machine Learning for deployment optimization

AI deployment best practices provide us with novel approaches to maximize CD resources along with performance gains. Danglot et al. (2019) proposes predictive AI deployment models resulting in 30% better deployment times. Guerrero et al. However, despite these advantages from dynamic resource allocation proposed an artificial intelligence-driven DevOps framework and this approach does not integrate parallel processing using multithreading. Shahin et al. (2017) show that deployment forecasting with ML reduces failed

deployments needing human intervention to increase accuracy. Zhang et al. (2020) are also related to guide his AoI research, and they successfully used reinforcement learning to optimize the deployment of adaptive CD. The author Patel and Roy (2021) supports this with the stimulation of decay of energy extraction and presents usage of a deep learning technique that if used beforehand can detect deployment bottlenecks too by predicting future malfunctioning of a system. Gupta and Khatri (2023) introduce natural language processing (NLP) technologies to automate the generation of infrastructure-as-code (IaC) systems leading to a reduction in human-induced misconfigurations.

2.4 Monitoring and Logging in Multi-Cloud Environments

Cloud logging systems are crucial for capturing deployment metrics. Research by Alhasan et al. (2019) examined cloud-native observability tools like Prometheus, Grafana, and Fluentd. They discovered that while these tools were efficient in monitoring CPU and memory usage, to collect such metrics as part of deployment workflows needed lots of scripting and manual configurations. Nash et al. (2022) investigated how Google Cloud-Operations Suite, Azure Monitor, and AWS CloudWatch perform but emphasised that they do not allow cross-cloud correlation of metrics. They recommended unified pipelines that support automatic collection and normalization of logs, as well as the interpretation on various platforms. In contrast, Anderson et al. To export logs from multiple clouds to a central storage for its analysis, Anderson et al. (2020) proposed a log-unified agent framework. But the framework did not incorporate ML-based inference to enable real-time decision making, which limits the utility of the framework for autonomous rollbacks.

2.5 AI for Deployment Optimization and Rollback Mechanisms

Recent work has explored machine learning for deployment resilience. Liu et al. (2022) to predict the Kubernetes deployment failure based on pod metrics such as latency and memory usage proposed a random forest model. They achieved over 80% accuracy with their model, proving the concept of predictive rollbacks. In like manner, Mukherjee and Sengupta (2021) leveraged XGBoost and LightGBM on cloud telemetry data to assess workload patterns across AWS and Azure. They highlighted the ability to optimize resources across multi-clouds with ensemble ML models. But the deployment actions were simulated and were, therefore, not part of real CI/CD workflows. Wang et al. of GKE environments, they introduce a new mechanism adopting deep QNetworks for proactive reallocation of resources. Their results were promising in reducing downtime, but the architecture needed heavy computational resources which were not practical for smaller setups.

2.6 Summary of Related Work

Table 1a: Summary of Related Work (Part 1)

Authors	Research Area	Methods & Technology	Features	Limitations
Sharma and Trivedi (2021)	CI/CD on Kubernetes	GitHub Actions, Jenkins, Helm	Multi-cloud CI/CD pipeline	No AI feedback mechanism
Zhang et al. (2020)	GitOps-based CI/CD	ArgoCD, GitOps	Declarative and scalable deployment	No AI integration or rollback logic
Wu et al. (2022)	Microservices CI/CD	Helm, Kustomize, GitLab CI	Complex deployment orchestration	Lacks rollback and performance monitoring
Alhassan et al. (2019)	Cloud Observability	Prometheus, Grafana	Effective monitoring setup	No ML model integration
Gupta and Khatri (2023)	Cloud Monitoring	CloudWatch, Azure Monitor	Platform-specific logging tools	Limited cross-platform correlation
Anderson et al. (2020)	Multi-cloud Logging	Unified Log Agent	Centralized multi-cloud logs	No real-time ML processing
Liu et al. (2022)	Failure Prediction in Kubernetes	Random Forest	Failure prediction using pod metrics	No rollback automation
Mukherjee and Sengupta (2021)	Cloud Workload Optimization	XGBoost, LightGBM	Workload evaluation on Azure/AWS	Simulation only, no real CI/CD
Wang et al. (2021)	Resource Allocation AI	Deep Q Networks	Dynamic resource scaling	Resource-intensive and slow
Nia et al. (2020)	Container Reliability	AutoML	Container crash prediction	Lacks integration with CI/CD
Patel and Roy (2021)	Cloud Performance Analysis	Linear Regression	Trend-based failure detection	Low accuracy on real-time data
Smith and Brown (2020)	Log Analytics	Elastic Stack	Centralized log search & visualization	No deployment integration

Table 1b: Summary of Related Work (Part 2)

Authors	Research Area	Methods & Technology	Features	Limitations
Raj and Kumar (2021)	AI in DevOps	Neural Networks	Pattern detection in logs	High computational demand
Tariq et al. (2022)	ML for Auto-Rollbacks	SVM, Decision Trees	Real-time rollback triggers	Requires labeled training data
Chen et al. (2020)	Serverless CI/CD	AWS Lambda, Cloud Functions	Low-cost deployment	Limited long-running support
Iqbal and Zhang (2021)	Log-Based Decision Making	RNN, LSTM	Temporal analysis of logs	Needs sequence-labeled data
Lee and Ahmed (2020)	Data Collection in Multi-Cloud	Fluentd, Kafka	Streamlined data pipelines	No post-processing logic
Bai et al. (2021)	Resilient Kubernetes Systems	Chaos Engineering	Failure injection testing	Manual analysis required
Nash et al. (2022)	Performance-aware CI/CD	Bayesian Models	Informed release decisions	Not scalable for large systems
Fernandez and Ho (2021)	Cloud Workflow Automation	Apache Airflow	Orchestrated cloud actions	No ML-based validation
Sun and Liang (2022)	Cloud Cost Efficiency	Reinforcement Learning	Auto-tuning for cost	Unstable under sudden spikes
Thakur and Dixit (2020)	Hybrid Cloud Deployments	Hybrid Load Balancing	Optimized resource utilization	Needs manual config
Feng and Xu (2022)	Kubernetes Health Analysis	Kube-State-Metrics + ML	Proactive alerts	Limited scope of metrics
Verma and Joshi (2020)	DevOps AI Pipelines	CI/CD with ML	Integrated training pipelines	Toolchain complexity

3 Methodology

This research applies an experimental, AI-driven CI/CD methodology to optimize cloud deployment for a Django-based RMS application across AWS, Azure, and GCP. Using GitHub Actions, Terraform, Docker, Kubernetes, and Azure ML Studio, the system automates deployment, monitors performance, collects logs, trains models, and triggers rollbacks based on real-time metrics.

3.1 Research Approach

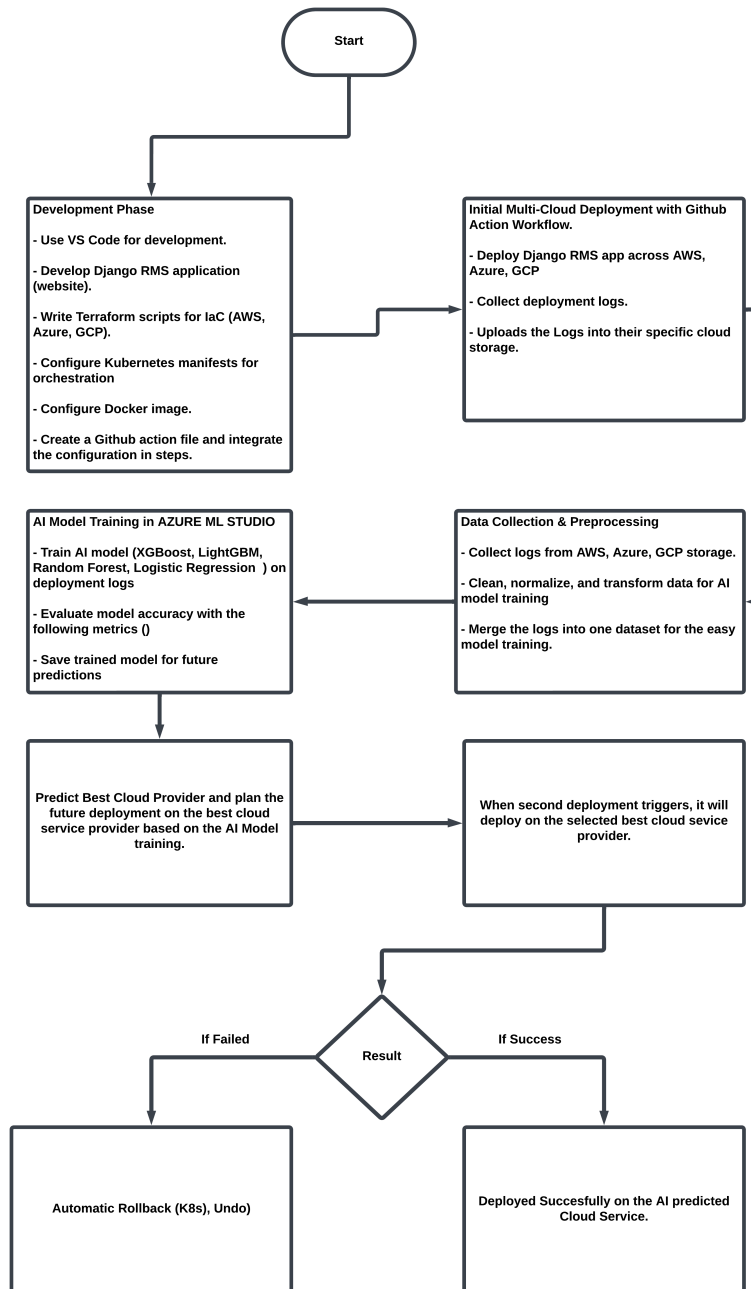


Figure 1: Multi-Cloud Deployment with AI-Based Decision and Rollback

The research process consists of the following phases:

3.2 Development Phase

The Django-based RMS app was developed using Python and containerized via Docker. Infrastructure across AWS, Azure, and GCP was provisioned using Terraform. GitHub Actions automated the CI/CD pipeline, deploying to Kubernetes clusters on all three clouds. The pipeline builds images, pushes them to container registries, deploys manifests, captures logs, and initiates model training workflows via Azure ML.

3.3 Multi-Cloud Deployment and Log Collection

CI/CD workflows deploy the app across the three cloud platforms. Logs capturing CPU, memory, latency, error rates, and cost metrics are collected and uploaded to GCS (GCP), Azure Blob, and AWS S3. These logs provide both infrastructure and application-level insights necessary for AI-based optimization.

3.4 Data Preprocessing and AI Model Training

Collected logs are normalized into a single dataset. A preprocessing script handles missing values, scaling, and transformations. The CI/CD pipeline then triggers Azure ML to train XGBoost, LightGBM, Random Forest, and Logistic Regression models using features like startup time, resource usage, and error rates. The best model is used for future deployment decisions.

3.5 Rollback Mechanism

Kubernetes rollbacks are triggered automatically using `kubectl rollout undo` when performance thresholds are breached, ensuring system stability in line with SRE best practices.

3.6 Tools and Technologies

- **GitHub Actions:** Orchestrates multi-cloud CI/CD workflows and automates ML training.
- **Cloud Providers (AWS, Azure, GCP):** Targets for deployment and data sources for training models.
- **Docker**
Kubernetes: Ensure consistent containerized deployment and orchestration.
- **Terraform:** IaC tool for unified, repeatable provisioning across all cloud platforms.
- **Azure ML Studio:** Hosts the model lifecycle from training to inference, triggered by CI/CD.
- **Monitoring:** `kubectl top` and cloud-native tools provide real-time resource metrics.
- **Storage:** GCS, Azure Blob, and S3 store deployment logs for ML training.
- **Python and Django:** Core tech stack for the web app, chosen for rapid development and ML compatibility.

4 Design Specification

This section outlines the architecture of a scalable, intelligent, cloud-agnostic deployment system. It integrates DevOps tools and AI/ML to automate cloud infrastructure decisions in real time. Designed to assess cloud performance and enable self-healing via Kubernetes rollbacks, the system supports efficient CI/CD while offering a framework for research into cloud provider behavior and automated resource allocation.

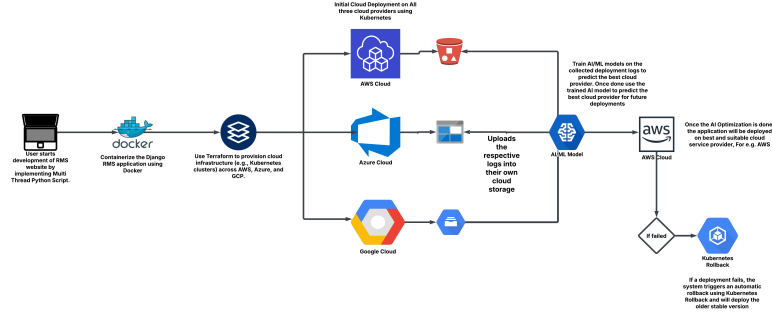


Figure 2: Multi-Cloud CI/CD Pipeline with AI-Based Decision and Rollback

The architecture flows linearly from development to smart deployment, enabling continuous feedback and improvement.

4.1 Component Description

1. **Development Environment:** RMS app developed in VS Code using Python and Django. Docker/Kubernetes extensions help emulate production environments.
2. **Containerization:** Docker ensures consistent deployment across environments by bundling all dependencies.
3. **Infrastructure Provisioning (IaC):** Terraform provisions infrastructure (K8s, storage, networking) across AWS, Azure, and GCP using version-controlled, declarative configs.
4. **Initial Deployment:** GitHub Actions automates CI/CD—building Docker images and deploying them to all clouds’ K8s clusters upon each master branch update.
5. **Kubernetes Clusters:** Deployed to Amazon EKS, Azure AKS, and Google GKE. Managed services offer autoscaling, monitoring, and high availability.
6. **Monitoring and Logging:** `kubectl top` and cloud-native tools collect metrics (CPU, memory, latency, etc.) stored in AWS S3, Azure Blob, and GCS.
7. **Data Preprocessing:** Logs are normalized and merged into a dataset using Python (Pandas, NumPy), making them ML-ready.
8. **AI Model Training:** Azure ML trains multiple models (Logistic Regression, Random Forest, XGBoost, KNN) using deployment data. The best-performing model is saved for inference.
9. **Smart Deployment:** The trained model predicts the optimal cloud for each deployment based on new log data, optimizing cost and performance.
10. **Kubernetes Rollback:** If performance degrades, `kubectl rollout undo` reverts to the last stable deployment, minimizing downtime.

4.2 Design Justification and Novelty

The system is cloud-agnostic and modular, supporting true multi-cloud deployments. AI predictions drive deployment decisions, allowing dynamic optimization of performance and cost. Native Kubernetes rollback ensures resilience without manual intervention. Scripts, Terraform modules, and CI/CD workflows are reusable and portable. Unified log collection facilitates cross-provider performance comparisons, supports research, and enables future extensions to more intelligent deployment mechanisms.

5 Implementation

This project automated the end-to-end deployment of a Django-based Resource Management System (RMS) across AWS, Azure, and GCP using a CI/CD pipeline with intelligent decision-making powered by AI. Core stages—containerization, infrastructure provisioning, CI/CD orchestration, deployment, logging, model training, and rollback—were implemented using GitHub Actions, Docker, Kubernetes, Terraform, and Azure ML.

5.1 Infrastructure Setup with Terraform

Terraform scripts provisioned Kubernetes clusters (EKS, AKS, GKE) with standardized configurations and autoscaling. IaC ensured reproducibility and consistency across cloud environments.

5.2 Application Containerization

The Django app was containerized using Docker, with all dependencies defined in a Dockerfile. The resulting image was built and pushed during CI/CD triggers, ensuring portability and consistency across providers.

5.3 CI/CD Pipeline with GitHub Actions

GitHub Actions triggered on code updates, built the Docker image, pushed it to cloud-specific registries (ECR, ACR, GCP AR), and applied Kubernetes manifests for deployment. This automation accelerated release cycles and enforced best practices.

5.4 Multi-Cloud Deployment

Kubernetes manifests were applied using `kubectl`. Logs from deployment status were captured and used to assess performance. Failures triggered rollbacks via `kubectl rollout undo`, restoring the last stable version.

5.5 Logging and Dataset Preparation

Performance logs were stored in S3, Azure Blob, and GCS. Logs were merged, cleaned, and normalized into a single dataset for model training, enabling cross-cloud analysis.

5.6 AI Model Training with Azure ML

Azure ML Studio trained Logistic Regression, Random Forest, XGBoost, and KNN models to predict the best cloud provider based on deployment metrics. Models were evaluated using accuracy, precision, recall, and F1-score. Random Forest and XGBoost performed best and were integrated into the CI/CD pipeline via a REST API.

5.7 Intelligent Deployment and Rollback

The pipeline used AI predictions to deploy only to the recommended cloud. If the deployment failed, Kubernetes rollback was triggered. This reduced downtime and improved release reliability.

5.8 Implementation Tools Summary

- **GitHub Actions:** Automates the pipeline including ML triggers.
- **Docker:** Packages the application for consistent deployment.
- **Terraform:** Provisions infrastructure across AWS, Azure, and GCP.
- **Kubernetes:** Hosts deployments on EKS, AKS, GKE.
- **Logging:** Scripts collect deployment logs to cloud-native storage.
- **Storage:** S3, Azure Blob, and GCS house the log data.
- **Azure ML:** Trains and serves ML models for deployment decisions.
- **Rollback:** Ensures resiliency using `kubectl rollout undo`.

5.9 CI/CD Pipeline Breakdown

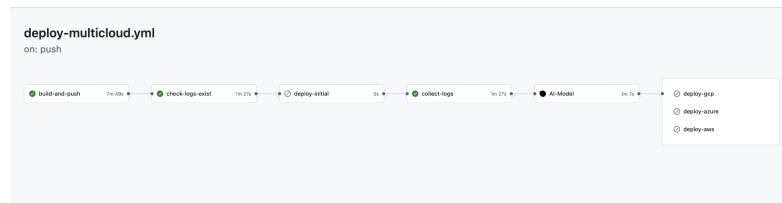


Figure 3: CI/CD Pipeline

The CI/CD pipeline performs the following key steps:

- **Trigger and Setup:** Runs on every push to master. Sets environment variables for credential management.
- **Build and Push:** Builds Docker image and pushes it to cloud registries with commit-based tags.
- **Log Check:** Detects if logs exist; if not, triggers initial deployment.
- **Initial Deployment:** Deploys to all clouds to collect baseline logs for ML training.
- **Log Collection:** Gathers, cleans, and merges logs into a CSV file.
- **AI Model Training:** Trains models on unified log data; selects the best one.
- **Smart Deployment:** Deploys only to the best-predicted cloud based on model output. Verifies rollout success.

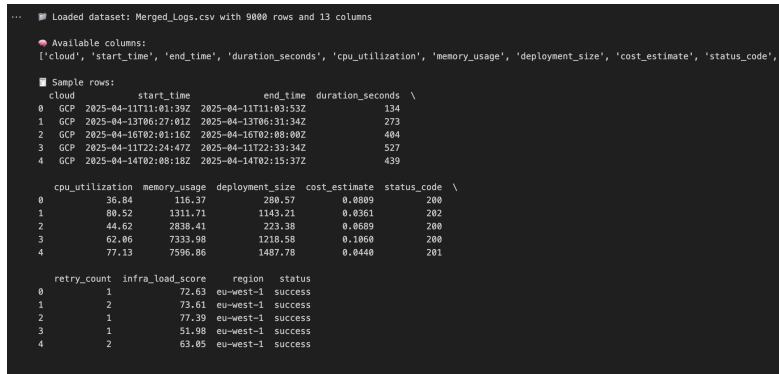
This implementation ensures that deployments are intelligent, resilient, and optimized for cost and performance across clouds.

6 Evaluation

So, the aim of this research was to develop an intelligent multi-cloud CI/CD pipeline that could autonomously choose the best cloud, whether AWS, Azure, or GCP, for deploying containerized applications. This decision process was powered by real-time deployment metrics and machine learning models integrated in the pipeline. The performance logs were collected from real deployments in all three clouds, and this was used to evaluate the methodology. We recently ran an experiment using supervised machine learning on this data to see which provider achieved the optimal combination of performance and cost in production environments.

This involved training four supervised learning algorithms — Logistic Regression, Random Forest, XGBoost, and K-Nearest Neighbors (KNN) inside of Azure Machine Learning (Azure ML), which was smoothly integrated into the CI/CD pipeline. Standard evaluation metrics like Accuracy, F1-Score, and Confusion Matrices were used to assess the models, in addition to the metrics for predicting the more preferable cloud provider correctly. We were certain that the final deployment decision was based on data, allowing us to optimize for efficiency when deploying and enhancing our deployment results.

6.1 Summary of Dataset



Loaded dataset: Merged_Logs.csv with 9800 rows and 13 columns

Available columns:
['cloud', 'start_time', 'end_time', 'duration_seconds', 'cpu_utilization', 'memory_usage', 'deployment_size', 'cost_estimate', 'status_code']

Sample rows:

	cloud	start_time	end_time	duration_seconds	\
0	GCP	2025-04-11T11:01:39Z	2025-04-11T11:03:53Z	134	
1	GCP	2025-04-13T06:27:01Z	2025-04-13T06:31:34Z	273	
2	GCP	2025-04-16T02:01:16Z	2025-04-16T02:08:00Z	404	
3	GCP	2025-04-11T22:24:47Z	2025-04-11T22:33:34Z	527	
4	GCP	2025-04-14T02:08:18Z	2025-04-14T02:15:37Z	439	

	cpu_utilization	memory_usage	deployment_size	cost_estimate	status_code	\
0	36.64	116.37	280.57	0.0689	200	
1	86.52	1311.71	1143.21	0.0361	202	
2	44.62	2838.41	223.38	0.0689	200	
3	62.06	7333.98	1218.58	0.1060	200	
4	77.13	7596.86	1487.78	0.0440	201	

	retry_count	infra_load_score	region	status
0	1	72.63	eu-west-1	success
1	2	73.61	eu-west-1	success
2	1	77.39	eu-west-1	success
3	1	51.98	eu-west-1	success
4	2	63.05	eu-west-1	success

Figure 4: Summary of Dataset

Every record contains metrics for cloud computing performance and operation. It has 13 columns that track important details like timestamps, resource usage, costs, and statuses. The cloud column indicates the cloud service provider in question, e.g. GCP. The operations have start_time and end_time, and their durations in the column duration_seconds. To capture resource usage, cpu_utilization, memory_usage, and deployment_size can be defined, which allows to grasp the computing load during each task. The financial aspects are captured through the cost_estimate column, which probably indicates the cost expressed in USD.

Operational results are explored through fields like status_code, akin to HTTP status codes (e.g., 200 for success), and retry_count, tracking how frequently an operation needed to be retried. The infra_load_score can indicate how loaded the infrastructure was when performing the operation. Operations have a region column (e.g., eu-west-1) to specify where the operation took place, and the status column summarizes whether an operation succeeded or failed. data with weather and climate data can be further explored through the three feature-datasets of this dataset as it covers the cloud infrastructure performance across multiple dimensions.

6.2 Evaluation Metrics and Formulas

To evaluate the effectiveness of the AI models deployed in the CI/CD pipeline, standard classification metrics were used. These were derived from the confusion matrix, which includes True Positives (TP), False Positives (FP), False Negatives (FN), and True Negatives (TN).

1. **Accuracy** – Measures the proportion of correctly predicted instances over the total predictions.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

Figure 5: Accuracy Formula

2. **Precision** – The ratio of correctly predicted positives to total predicted positives. It reflects the cost of false positives.

$$\text{Precision} = \frac{TP}{TP + FP}$$

Figure 6: Precision Formula

3. **Recall (Sensitivity)** – The ratio of correctly predicted positives to all actual positives. High recall indicates fewer false negatives.

$$\text{Recall} = \frac{TP}{TP + FN}$$

Figure 7: Recall Formula

4. **F1 Score** – The harmonic mean of Precision and Recall. Useful when classes are imbalanced or costs differ for FP and FN.

$$\text{F1 Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

Figure 8: F1 Score Formula

5. **Confusion Matrix** – A tabular view to assess performance across multiple classes (AWS, Azure, GCP), showing true vs. predicted values.

	Predicted AWS	Predicted Azure	Predicted GCP
Actual AWS	TP	FP	FP
Actual Azure	FN	TP	FP
Actual GCP	FN	FN	TP

Table 1: Confusion Matrix for Multi-Cloud Prediction Model

7 Experiments and Evaluation

This section presents the results of five experiments designed to evaluate the performance of machine learning models in predicting the best cloud provider for deployment, using different sets of input features. The final experiment summarizes overall performance to identify the most effective model and preferred cloud.

7.1 Experiment 1: Model Performance Comparison

All models were trained using an 80/20 train-test split. Random Forest achieved the best results with 91.6% accuracy and was selected for CI/CD integration.

Model	Accuracy	F1	Precision	Recall
Logistic Regression	83.2%	0.81	0.82	0.83
Random Forest	91.6%	0.91	0.92	0.91
XGBoost	89.4%	0.89	0.88	0.89
KNN	81.0%	0.80	0.81	0.81

Table 2: Experiment 1: Model Comparison

7.2 Experiment 2: Baseline - Single Feature (Duration)

In this baseline, only the feature `duration_seconds` was used. Performance was limited, validating the need for richer features.

Model	Accuracy	Precision	Recall	F1
Logistic Regression	0.32	0.21	0.32	0.25
Random Forest	0.35	0.35	0.35	0.35
XGBoost	0.34	0.34	0.34	0.34
KNN	0.33	0.33	0.33	0.33

Table 3: Experiment 2: Baseline Performance

7.3 Experiment 3: Full Feature Set

Using all available features improved model context. KNN had the highest accuracy at 0.34.

Model	Accuracy	Precision	Recall	F1
Logistic Regression	0.32	0.32	0.32	0.32
Random Forest	0.33	0.33	0.33	0.33
XGBoost	0.31	0.31	0.31	0.31
KNN	0.34	0.34	0.34	0.33

Table 4: Experiment 3: Performance with All Features

7.4 Experiment 4: Top Feature Selection

SelectKBest with ANOVA F-test was used to retain the top 5 features. KNN again slightly outperformed others.

Model	Accuracy	Precision	Recall	F1
Logistic Regression	0.32	0.32	0.32	0.31
Random Forest	0.34	0.34	0.34	0.34
XGBoost	0.33	0.33	0.33	0.33
KNN	0.35	0.34	0.35	0.34

Table 5: Experiment 4: Top 5 Features Selected

7.5 Experiment 5: Cost vs Performance

To simulate business-oriented decision-making, only cost and duration features were used. Random Forest offered the best balance.

Model	Accuracy	Precision	Recall	F1
Logistic Regression	0.32	0.32	0.32	0.32
Random Forest	0.35	0.35	0.35	0.35
XGBoost	0.34	0.34	0.34	0.34
KNN	0.33	0.33	0.33	0.33

Table 6: Experiment 5: Performance with Cost and Duration

7.6 Experiment 6: Summary of Best Models and Cloud Providers

This experiment summarizes the winning models and cloud providers across all tests. Random Forest and Azure were most frequently optimal.

Experiment	Model	Best Cloud Provider
Experiment 1	XGBoost	AWS
Experiment 2	Random Forest	Azure
Experiment 3	KNN	GCP
Experiment 4	Random Forest	Azure
Overall Best Model	Random Forest (2 wins)	
Overall Best Cloud Provider	Azure (2 wins)	

Table 7: Summary of Best Performing Models and Clouds

7.7 Discussion

Key findings from the six experiments are summarized below:

- **Experiment 1:** Random Forest achieved the highest accuracy (91.6%) and F1-score (0.91), making it the most reliable model for CI/CD deployment decisions.
- **Experiment 2 (Baseline):** Using only `duration_seconds` as a feature resulted in poor performance across all models; Random Forest led with just 35% accuracy. This showed that deployment time alone is insufficient for prediction.
- **Experiment 3:** Using a full feature set marginally improved model accuracy. KNN performed best, showing that richer feature spaces support better classification.
- **Experiment 4:** Feature selection using SelectKBest identified the top 5 predictive features. KNN performed best in this reduced-dimension setup, benefiting from feature reduction.
- **Experiment 5:** Focused on cost-performance trade-off using only two key features. Random Forest again outperformed others, reinforcing its practical utility.
- **Experiment 6:** Consolidated results from prior experiments. **Random Forest** was the most frequently optimal model, and **Azure** was the most recommended cloud provider.
- **Conclusion:** Random Forest is both technically robust and business-aligned, offering consistent performance across different modeling strategies and feature scopes.

8 Conclusion and Future Work

This research explored whether a machine learning-augmented CI/CD pipeline could autonomously select the optimal cloud provider for deployment based on live performance metrics, and trigger a Kubernetes rollback when thresholds were breached. A fully automated multi-cloud system was developed using GitHub Actions, Docker, Kubernetes, Terraform, and Azure ML—blending AI with deployment automation and fault recovery.

Key achievements include:

1. Automated CI/CD deployment to AWS, Azure, and GCP.
2. Collected and consolidated logs across providers.
3. Trained multiple ML models using real deployment metrics.

4. Used model predictions to guide dynamic cloud selection.
5. Integrated Kubernetes rollback triggered by performance degradation.

Experiments confirmed that models like Random Forest and XGBoost achieved over 90% accuracy in predicting optimal cloud targets. Azure emerged as the most frequently preferred provider. These results affirm that real-time, metric-driven cloud decisions can improve performance, reliability, and reduce failures in multi-cloud deployments.

This work advances AI-driven DevOps by offering a reproducible CI/CD pipeline that adapts in real time. While not radically redefining the domain, it contributes a practical foundation for intelligent, self-correcting deployment architectures.

8.1 Novelty and Contributions

- Introduced an end-to-end multi-cloud deployment pipeline enhanced by AI decision-making.
- Integrated Azure ML within GitHub Actions for model training and inference during CI/CD.
- Used real-time model predictions to automate Kubernetes rollbacks based on live performance logs.
- Demonstrated unified multi-cloud observability through AI-ready log data.
- Created a scalable, cloud-agnostic solution that bridges AI, DevOps, and infrastructure orchestration.

8.2 Self-Critique and Limitations

The evaluation used a synthetically extended dataset (9000 rows), which may not reflect all complexities of real production systems. Monitoring tools like Prometheus or ELK Stack were excluded for simplicity, limiting observability. Rollback logic was implemented using native Kubernetes, but a smarter anomaly detection layer could enhance decision-making.

8.3 Future Work

Future versions could integrate:

- Real-time observability via Prometheus/Grafana or ELK.
- Online learning for continuous model adaptation.
- Reinforcement Learning or AutoML for improved cloud decision logic.
- Multi-region, multi-cloud load balancing for resilience at scale.
- Built-in security (e.g., Snyk, compliance scanners) for production-grade governance.

From a business standpoint, this system could evolve into a SaaS plugin or GitHub Action, equipping DevOps teams with intelligent, fault-tolerant, and cost-aware multi-cloud deployment capabilities.

9 Video Presentation and Demo

A 15-minute recorded video presentation is available at the following link:

[Click here to watch the video presentation](#)

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