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Building AI-Driven Cloud-Native Applications with Kubernetes and Containerization

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ABSTRACT

Modern enterprises increasingly deploy AI-driven services in cloud environments, demanding scalable infrastructure that aligns machine learning operations (MLOps) with cloud-native principles. This paper proposes a Kubernetes-based architecture for developing and deploying AI applications, emphasizing containerization, orchestration, and continuous delivery. The architecture supports end-to-end MLOps workflows from training and versioning to real-time inference and monitoring using open-source tools on managed Kubernetes services (e.g., Amazon EKS, Azure AKS, Google GKE). Core components include Kubeflow Pipelines for orchestration, Ml flow for model registry, Argo Workflows for automation, and serving frameworks such as TensorFlow Serving and ONNX Runtime for scalable inference. Cloud-native features like autoscaling, service mesh, observability, and security are integrated using tools such as Prometheus, Grafana, Trivy, and Vault. The architecture is validated through two use cases: an e-commerce recommendation service and an IoT anomaly detection pipeline, with a proof-of-concept deployed on AWS. Experimental results demonstrate low-latency inference (95th percentile latency under 120, ms at 100 requests/s) and efficient resource utilization. The platform enhances reproducibility, monitoring, and deployment speed over traditional ML deployment approaches. These findings highlight the advantages of Kubernetes-native MLOps for scalable, reliable AI systems in production environments.

Keywords: Cloud Computing; Kubernetes; MLOps; Machine Learning; Deep Learning; DevOps; Containerization; Autoscaling; Microservices; IoT; E-commerce.

I. INTRODUCTION

Artificial intelligence (AI) and machine learning are being deployed across nearly every industry, from personalized recommendations in e-commerce to real-time analytics in Internet of Things (IoT) scenarios. As organizations incorporate predictive models into production services (e.g., sales forecasting, anomaly detection), they face the challenge of maintaining and scaling these models with the same rigor as traditional software microservices. This convergence of AI development and robust operations has led to the emergence of Machine Learning Operations (MLOps) – a set of practices to reliably deploy and manage ML models in production.

Kubernetes has rapidly become a cornerstone of cloud-native computing and is increasingly the platform of choice for MLOps deployment. Originally open-sourced by Google, Kubernetes automates container scheduling, scaling, and management, and is now adopted by over half of organizations worldwide [1]. Its inherent features – self-healing, horizontal scaling, load balancing, and declarative deployments provide an ideal substrate for AI microservices. By containerizing

ML workloads and orchestrating them on Kubernetes, teams can achieve reproducibility and scalability in model training and inference. Major cloud providers offer managed Kuber- notes services (Amazon EKS, Azure AKS, Google GKE) that abstract away control plane management and improve reliability; for example, Amazon EKS manages the Kubernetes control plane across availability zones for high availability and automates node provisioning.

Despite the availability of cloud-specific ML platforms (e.g., AWS SageMaker, Azure ML), these proprietary solutions often operate as black boxes with limited flexibility. In contrast, an open, cloud-agnostic MLOps architecture built on Kubernetes can provide modularity, transparency, and control over the entire ML lifecycle. Prior works have proposed various components of such an open architecture: for instance, Fursin et al. introduced CodeReef, an open platform for portable MLOps emphasizing reproducible model deployment and benchmarking; One Click Deep Learning (OCDL) provides tools for encapsulation, resource sharing, and model versioning. Alibaba's LinkEdge project extends MLOps to IoT edge devices, automating data collection, training, and deployment in distributed environments. However, these solutions address portions of the pipeline and often lack integration or ease of use. There remains a need for a unified framework that combines best-of-breed open-source tools into a cohesive pipeline, leveraging Kubernetes to orchestrate end-to-end workflows.

A. Purpose and Scope

In this work, we present a full-stack approach to building AI-driven cloud-native applications using Kubernetes and containerization. The goal is to bridge academic rigor and real-world requirements by proposing a novel architecture that integrates MLOps best practices (continuous integration/deployment of ML, automated retraining, monitoring) with cloud-native features (microservices, autoscaling, infrastructure-as-code). We focus on machine learning and deep learning use cases, with an emphasis on the operational pipeline (MLOps) including model training, version control, deployment, and monitoring in production. The architecture is designed to be cloud-agnostic and extensible, demonstrated using open-source components deployed on a managed Ku- bernetes service. We specifically target two representative domains: e-commerce, featuring an AI-driven recommendation service; and IoT, featuring a real-time sensor analytics and anomaly detection system. These use cases allow us to evaluate the platform's ability to handle both request-driven microservice loads and streaming data pipelines.

B. Contributions

The contributions of this paper are as follows:

1) We propose a Kubernetes-native MLOps architecture that integrates a modular set of open-source tools (including Kubeflow/Argo for pipeline orchestration, MLflow for model registry, TensorFlow Serving, and ONNX for model inference, Prometheus/Grafana for observability, and others) to cover the entire ML lifecycle in a cloud environment.

2) We introduce several novel enhancements to improve real-time inference performance and cost-efficiency, such as combining Kubernetes autoscaling mechanisms with ML model workload characteristics, and employ- ing optimized model formats (e.g., ONNX) for cross-framework portability.

3) We implement a proof-of-concept on AWS EKS and conduct an experimental evaluation with both batch and streaming workloads. We benchmark the system on metrics including inference latency, throughput, resource utilization, and cost, comparing scenarios with and without our architecture's optimizations (e.g., autoscaling, pipeline automation).

4) We address practical deployment aspects often overlooked in academic prototypes including container security scanning, secrets management, and hybrid cloud deployment, and demonstrate that these can be integrated without significant overhead. To the best of our knowledge, this is one of the first works to comprehensively combine all these elements into a single MLOps platform blueprint.

C. Paper Organization

The remainder of this paper is organized as follows: Section II reviews related work in MLOps platforms and cloud-native machine learning deployments. Section III details the proposed architecture, describing each component and its role in the end-to-end pipeline. Section IV outlines the experimental setup, including the use case implementations and measurement methodology. Section V presents results and an analysis of the system's performance and scalability. Section VI provides a discussion on the implications, best practices, and lessons learned, as well as the current limitations and future improvements. Finally, Section VII concludes the paper.

II. RELATED WORK

Combining machine learning workflows with cloud-native infrastructure is an area of active development in both industry and academia. We review existing approaches in MLOps and cloud services, focusing on how they inform our integrated solution.

A. MLOps Platforms

MLOps has emerged to bridge the gap between model development and reliable operations. A variety of platforms exist on a spectrum from proprietary to open-source. On the proprietary end, cloud providers offer managed services like Amazon SageMaker and Azure Machine Learning that integrate training, deployment, and monitoring. These services ease the engineering burden but can limit flexibility and portability [2]. For example, SageMaker provides one-click deployment of models as scalable endpoints, but the stack is tightly coupled to AWS infrastructure. In contrast, open-source frameworks aim to provide similar capabilities without vendor lock-in. Kubeflow is a prominent open-source MLOps platform that runs on Kubernetes, released by Google in 2018 with contributions from Cisco, IBM, Red Hat, and others [3]. Kubeflow ties together components for each stage of the ML lifecycle such as Jupyter notebooks for development, Kubeflow Pipelines (on Argo or Tekton) for workflow automation, and KServe (formerly KFServing) for model serving all orchestrated-on Kubernetes for portability. It ensures that ML workflows (training, tuning, serving) can scale on a cloud cluster just like any microservice. Another tool, MLflow (from Databricks), focuses on experiment tracking and model registry and can complement Kubeflow by handling model versioning and reproducibility [4]. Our architecture leverages these open tools (Kubeflow, MLflow) in a complementary fashion, rather than viewing them as exclusive choices. As illustrated in Figure. 1, the MLOps lifecycle in a Kubernetes-based environment involves a series of stages starting from data ingestion to monitoring. CI/CD integration ensures auto-mated, reproducible deployments within this pipeline.

Recent research has proposed various open-source MLOps frameworks. CodeReef is an example targeting portable MLOps and reproducible benchmarking of ML models; it emphasizes automation of model deployment with DevOps principles. One Click Deep Learning (OCDL) provides an integrated suite including encapsulation of environments, resource sharing, and one-click model deployment. LinkEdge, an open-source effort by Alibaba, is tailored for edge computing and IoT—automating data ingestion from IoT devices, training at the edge or cloud, and model updates, effectively extending MLOps to constrained devices. Each of these addresses important aspects, but they often operate in isolation or focus on specific contexts (e.g., IoT only). A recent review by Wazir et al. (2023) surveys MLOps frameworks and highlights that while many solutions exist, a gap remains in combining all required capabilities (data, training, deployment, monitoring) into one cohesive, community-driven platform. Our work builds upon these insights by integrating multiple open-source components (selected for their maturity and community support) into a unified architecture.

Table 1 compares Kubernetes and SageMaker across critical dimensions such as scalability, cost, and integration flexibility. Kubernetes provides greater control and open-source extensibility, while SageMaker offers a managed experience optimized for rapid onboarding.

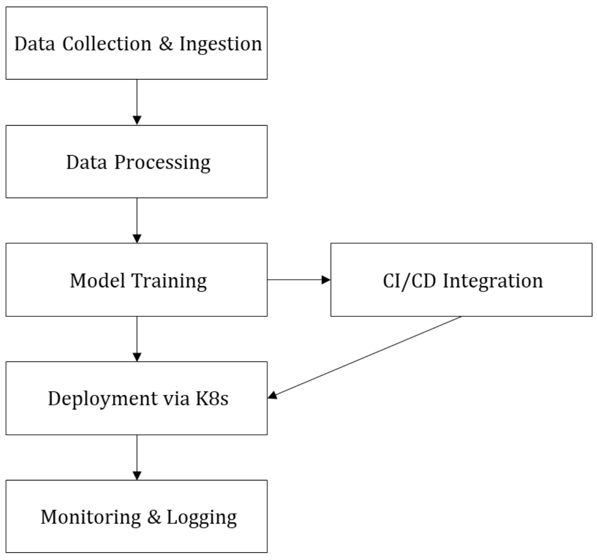

FIGURE 1: End-to-End MLOps Lifecycle in Kubernetes-based Environments.

TABLE 1: Comparison of Kubernetes Vs Sagemaker For AI Workloads.

Aspect	Kubernetes	SageMaker
Control	Full control over infra	Managed, abstracted infra
Scalability	Highly customizable (KEDA, HPA)	Built-in autoscaling
Cost	More granular control; cheaper at scale	Expensive with managed features
ML Workflow Tools	Integrates with MLflow, Kubeflow, Argo	Native tools (Pipelines, JumpStart)
Security	Self-managed IAM, Secrets	Integrated IAM and encryption

B. Cloud-Native Microservices for ML

The adoption of containerization and microservice architecture for AI workloads is evident in industry systems. Uber's Michelangelo platform and Facebook's FBLearner Flow are notable internal platforms that manage the ML lifecycle at scale, though details are proprietary. These systems inspired open-source analogs [3]. For example, TensorFlow Extended (TFX) is Google's pipeline framework which, when combined with Kubeflow, can run on Kubernetes to orchestrate data ingestion, training, and deployment pipelines in a cloud-native way. In serving models, companies have leveraged Kubernetes orchestration to enable dynamic scaling and high availability. Kubernetes supports mix-and-match resource scheduling—e.g., a cluster may have CPU-only nodes and GPU nodes, and pods can be scheduled accordingly for training or inference workloads. This flexibility is crucial for deep learning models that require GPUs for training but can sometimes infer on CPU at scale [5]. Our architecture exploits this by using node selectors and taints to allocate heavy training jobs to GPU nodes (managed by NVIDIA's GPU Operator for driver provisioning) and lighter-weight inference to CPU nodes, while still using one unified Kubernetes control plane [6].

C. Autoscaling and Performance Optimization

Autoscaling is a key feature for cloud services to handle variable loads efficiently. Kubernetes provides a Horizontal Pod Autoscaler (HPA) that can scale the number of pod replicas based on metrics like CPU utilization or custom metrics. In ML serving, autoscaling can be based on request concurrency or latency targets. KServe (KFServing) uses Knative Serving under the hood to enable scale-to-zero and rapid scaling for inference workloads. Empirical studies have shown that enabling concurrency-based autoscaling keeps model latency low under bursty loads, compared to static provisioning [7]. Event-driven auto scalers like KEDA extend this to scale on external metrics (e.g., Kafka queue length for streaming jobs) [8]. We incorporate autoscaling on multiple levels: at the pod level for inference deployments, and the cluster level using the Cluster Autoscaler to add nodes when needed. In our experiments, this combination yields significant latency improvements and cost savings (detailed in Section V).

D. Monitoring and Observability

Once models are in production, monitoring their performance is essential. Open-source tools such as Prometheus (for metrics scraping) and Grafana (for dashboards) are commonly used in cloud-native stacks and are equally applicable to ML services [7]. They can track system metrics (CPU, memory, GPU utilization) and custom application metrics (e.g., inference latency per model, prediction throughput, and error rates). Advanced monitoring may include data drift detection e.g., using statistical tests on input feature distributions and model performance monitoring by comparing predictions to ground truth when available. The open-source library Evidently [9]. AI or Seldon's Alibi Detect can be deployed alongside models to detect drift in data or concepts.

Our architecture includes a monitoring subsystem where Prometheus gathers metrics from all components (applications expose metrics via endpoints) and Grafana visualizes them. Alerts can be set (e.g., if model accuracy degrades or if drift is detected, trigger an alert or even an automated retraining pipeline). This closes the loop in the MLOps cycle.

E. Security and Reproducibility

In production environments, the security of the ML pipeline is paramount but often neglected in academic prototypes [10]. Containerization itself provides isolation, but images must be kept free of vulnerabilities. Tools like Trivy (an open-source vulnerability scanner) can be integrated into the continuous integration pipeline to scan Docker images for known CVEs before deployment. Secrets (credentials for databases, API keys, etc.) should not be baked into images or code; instead, Kubernetes secrets or vaults should be used. HashiCorp Vault is a popular tool for managing secrets and can be used to inject secrets into pods at runtime securely. Our implementation uses Vault to manage sensitive information like database passwords for the feature store and Kafka credentials, ensuring that the GitOps workflows contain no plaintext secrets [11]. Moreover, the use of Infrastructure-as-Code (IaC) and GitOps (e.g., using tools like Argo CD or Flux) for deploying the Kubernetes manifests ensures that the entire infrastructure and pipeline configuration is version-controlled and reproducible. This also aids academic rigor, as experiments can be re-run by replaying the pipeline definitions on a new cluster to obtain the same results, satisfying the repeatability requirement.

In summary, while many building blocks for cloud-native MLOps exist, our work distinguishes itself by combining them into an end-to-end solution. We borrow ideas and best practices from the above-related efforts and assemble an architecture that spans data ingestion, model training, continuous integration, deployment, scaling, monitoring, and security. The next section details this architecture and how each component is incorporated to work in concert on Kubernetes.

III. PROPOSED ARCHITECTURE

A. Overview

The proposed architecture is a cloud-native MLOps platform built entirely on Kubernetes using containerized components. Figure 2 illustrates the high-level design, showing how data flows from ingestion to model training to inference serving, with supporting components for storage, orchestration, and monitoring. The architecture is designed to be modular – each component can be replaced with an equivalent as needed (for example, Seldon Core could substitute KServe, or Tekton could replace Argo) – and cloud-agnostic, requiring only a Kubernetes-conformant cluster [4]. We highlight key architectural decisions: separation of concerns via microservices and operators, reliance on Kubernetes controllers for automation (e.g., the NVIDIA GPU Operator for hardware management), and leveraging managed cloud services where appropriate (like managed databases or object storage for persistence). Around the pipeline orchestrator, we have complementary services:

B. Feature Store

In many ML applications, especially those involving IoT and real-time features, a feature store is used to manage feature engineering artifacts. We incorporate Feast as an optional component for feature storage, with a PostgreSQL offline store and Redis online store (for low-latency retrieval of features for inference). For example, in the e-commerce use case, precomputed user embedding features or product statistics are stored in Feast so that both training jobs and the live inference service use a consistent view of features. The feature store ensures consistency between training and serving data transformations.

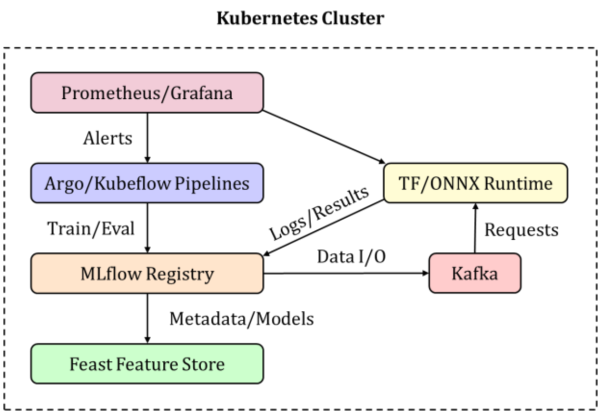

FIGURE 2: Proposed Kubernetes-native MLOps architecture integrating pipelines, registry, feature store, streaming, inference, and monitoring on Kubernetes.

C. Data Ingestion and Streaming

For the IoT use case, streaming data ingestion is crucial. We deploy Apache Kafka (via Strimzi Operator on Kubernetes) as the backbone for ingesting real-time data. IoT sensor readings are published to Kafka topics. On the platform, we implement consumers using Kafka Streams or Bytewax (a Python stream processing library) to perform real-time data processing and feed the results into the feature store or directly into inference requests. Kafka decouples the data producers (IoT devices, or a simulation thereof) from the consumers (our processing pipeline and models). It also buffers bursts and provides backpressure handling. In our architecture, Kafka is integrated with Kubernetes via an operator, and we use Kubernetes Event-Driven Autoscaling (KEDA) to scale consumers based on queue length if needed.

D. Model Training Component

Model training jobs are run as containerized Kubernetes Jobs (batch jobs). These can be triggered manually, on a schedule (CronJob), or automatically by pipeline workflows (e.g., an Argo workflow step spawns a training job). We packaged training code (for instance, a TensorFlow training script for the recommender model, and a PyTorch training script for the IoT anomaly model) into Docker images. When launched, these jobs read training data (from a cloud object storage or database), train the ML model, and then save the resulting model artifacts (e.g., .pth file for PyTorch or SavedModel for TensorFlow) to a Model Artifact Store. We use an S3-S3-compatible object store (MinIO in testing, Amazon S3 in production) for storing model artifacts and any metadata files. The training jobs report metrics and parameters to MLflow Tracking, enabling experiment tracking. Multiple training jobs can run in parallel on the cluster, utilizing different resources as needed. We exploit Kubernetes scheduling features to ensure heavy jobs land on nodes with sufficient resources (using node labels like gpu=true for GPU nodes).

E. Model Registry and Metadata

We integrate MLflow as the central model registry. After a training job finishes, it registers the new model version in MLflow along with metadata (parameters, metrics, tags, source commit, etc.). MLflow provides a UI to compare experiments and transition models through stages (e.g., Staging to Production). In our setup, the MLflow server runs in-cluster and uses a SQL database for metadata and the object store for artifacts. This model registry ensures that all deployed models are traceable to a training run and versioned. It also enables easy rollback or A/B testing by deploying specific versions.

F. Model Serving and Inference

For serving predictions, we adopt a microservice approach. Each ML model is packaged as a scalable service on Kubernetes. We utilize two patterns:

(a) TensorFlow Serving for TensorFlow models and TorchServe for PyTorch models, both of which are efficient for their respective frameworks.

(b) ONNX Runtime for models converted to the Open Neural Network Exchange format, enabling hardware-optimized inference across frameworks.

In our e-commerce recommendation example, the model (a deep neural network) is exported to TensorFlow SavedModel format and served using TensorFlow Serving pods behind a Kubernetes Service [12]. In the IoT anomaly example, the model (trained in PyTorch) is converted to ONNX, and we serve it using an ONNX Runtime container, allowing us to later compare performance on CPU vs. GPU. We also experiment with KServe (KFServing) as an overarching serving platform: KServe can deploy models with inference pods and automatically handle routing and scaling (including scale-to-zero for unused models). KServe integrates with Knative, meaning that inactive model services consume no resources – a cost-saving feature particularly useful for sporadically used models. In either case, we expose the inference service via an API (REST or gRPC). For e-commerce, a REST endpoint (with FastAPI for additional business logic) calls the model server. For IoT streaming, the model server can be called directly from the stream processing job or set up as a subscriber to Kafka (e.g., using KServe's Kafka trigger).

G. Autoscaling Mechanisms

We configure autoscaling at multiple levels. The Horizontal Pod Autoscaler (HPA) is set on the inference deployment (if using a plain Deployment for the model server) to scale based on CPU utilization or custom metrics (such as requests per second). In our tests, we use a custom Prometheus--adapter metric for "requests in flight" to trigger scaling when concurrency goes beyond a threshold, ensuring latency remains low. The cluster itself runs the Cluster Autoscaler to add VM instances when there are pending pods that cannot be scheduled due to resource constraints. On AWS EKS, this ties into AWS Auto Scaling Groups – we have one group for CPU nodes and one for GPU nodes. For instance, if a training job requests a GPU and none is free, the Cluster Autoscaler will spin up a new GPU EC2 instance. This dynamic pro-visioning adds elasticity to handle heavy workloads without permanently running expensive resources. We also explore Kubernetes Vertical Pod Autoscaler in analysis mode to see if memory/CPU requests for pods can be optimized, though we keep it manual in deployment to avoid unexpected restarts. As a result of these autoscaling setups, our system can handle spikes in inference demand (common in e-commerce during promotions) and scale down to reduce cost during idle periods.

H. Monitoring, Logging, and Observability

Every component is instrumented with logging and metrics. Prometheus is deployed to scrape metrics from the Kubernetes metrics server as well as custom application metrics. We use Grafana dashboards to visualize key indicators: model interference latency distribution, throughput over time, CPU/GPU utilization per pod, Kafka queue lengths, etc. (see Section V for an example dashboard). Additionally, we enable Kubernetes event logging and aggregate container logs. In a production scenario, one might use an ELK (Elasticsearch-Logstash- Kibana) stack or a cloud logging service; in our prototype, we use EFK (Fluentd instead of Logstash) to collect logs from pods and push to Elasticsearch, enabling search and troubleshooting via Kibana. For monitoring model quality, we schedule a periodic job that computes performance metrics on a validation dataset and compares current metrics to past – if a significant drop is detected, it flags for potential model drift. This is an example of automated monitoring that can trigger the pipeline (e.g., start a retraining workflow) if needed, creating a closed-loop learning system.

I. Security and DevOps Integration

Security is woven throughout the architecture. The container images for all components and custom code are stored in a private registry; a CI pipeline (using GitHub Actions in our case) builds these images and runs Trivy scans to detect vulnerabilities, failing the build if high-severity issues are found. This ensures that only vetted images get deployed to the cluster.

All network communication inside the cluster is encrypted where possible (e.g., TLS for connections to MLflow, Kafka, etc.). We also enable Kubernetes Role-Based Access Control (RBAC) so that, for example, the MLflow pod only has the access rights it needs, and cannot access unrelated resources. For secrets, as mentioned, we use HashiCorp Vault, which is set up with a Kubernetes auth backend – pods can retrieve secrets (like database passwords, and API keys for external services) at runtime by presenting a token, and Vault injects the secrets as environment variables. This avoids storing any sensitive info in Git or plaintext on disk. Finally, to streamline operations, we adopted GitOps for deploying the Kubernetes manifests of our platform. A GitOps tool watches a Git repository (where we store all YAML manifests for deployments, services, etc.) and applies any changes to the cluster. This means our entire infrastructure (including pipeline definitions and configuration) is version-controlled. Team members can review changes as pull requests, improving collaboration and auditability. In addition to technical robustness, ethical considerations like bias mitigation and fairness must be integrated into MLOps pipelines [13].

The architecture is cloud-agnostic: while our implementation targets AWS (using EKS, S3, etc.), the design uses either open-source equivalents or managed services that have analogs in other clouds (for instance, GCP's Cloud Storage instead of S3, GKE instead of EKS). We explicitly kept the solution portable by avoiding proprietary APIs. In a hybrid cloud or on-premises scenario, one could deploy the same stack on a self-managed Kubernetes cluster. For IoT edge integration, Kubernetes' extensibility allows using KubeEdge to connect edge devices as part of the cluster. Although not fully implemented in our current work, our architecture could be extended so that certain pipeline components run on edge nodes (close to IoT devices) using KubeEdge, with the cloud cluster aggregating results achieving a hybrid deployment for latency-sensitive tasks.

In summary, the proposed architecture brings together a comprehensive set of services and tools under the management of Kubernetes. By using containerization and open standards (like ONNX for models, and CNCF projects for logging/metrics), we ensure the solution is extensible and maintainable. The next section describes how we deployed this architecture in practice and the specifics of our experimental setup for the two use cases.

IV. EXPERIMENTAL SETUP

To demonstrate the effectiveness of our cloud-native MLOps architecture, we implemented a prototype on a real cluster and designed experiments around two motivating use cases: an e-commerce recommendation system and an IoT anomaly detection system. Below, we describe the deployment environment, the specifics of each use case application, and the methodology for our performance evaluation.

A. Cluster Environment

The prototype was deployed on Amazon Web Services (AWS) using Amazon Elastic Kubernetes Service (EKS). We used an EKS cluster running Kubernetes version 1.24, spread across two AWS availability zones for high availability. We defined two node groups: one for general computing and one for GPU-accelerated tasks. The general node group consisted of m5.xlarge instances (4 vCPU, 16 GB RAM each), and the GPU node group consisted of p3.2xlarge instances (one NVIDIA V100 GPU, 8 vCPU, 61 GB RAM). Initially, the cluster was configured with 3 general nodes and 1 GPU node, with the Cluster Autoscaler allowed to scale each group up to 6 nodes based on demand.

All nodes ran Amazon Linux 2 with Docker and the NVIDIA Container Toolkit installed. We deployed the NVIDIA GPU Operator on the cluster, which automated GPU driver installation and set up the Kubernetes device plugin for GPUs so that containers could seamlessly access GPU resources. The GPU Operator also labeled the GPU nodes and managed monitoring of GPU utilization.

B. Tool Deployment

Following the architecture design, we installed the required tools in the cluster:

- *Kubeflow Pipelines:* Instead of the full Kubeflow distribution, we installed just Kubeflow Pipelines standalone (which includes Argo Workflows) for lightweight operation. The pipelines UI and Argo workflow controller were accessible via a secure ingress.
- *MLflow:* Deployed as a single pod with a backing MySQL database (Amazon RDS) for tracking metadata. We used an S3 bucket for MLflow artifact storage. Although authentication could have been handled by Cognito in a production scenario, we kept MLflow open within the cluster for simplicity.
- *Kafka (Strimzi):* A three-node Kafka cluster (with Zookeeper) was set up using the Strimzi Kafka Operator. Each Kafka broker ran on its pod (pinned to separate nodes), using hostPath storage for logs during these short experiments (though durable storage would be recommended in production).
- *Prometheus and Grafana:* Deployed via the Prometheus Operator (kube-prometheus stack). We created custom scrape targets for MLflow, TensorFlow Serving, and the application pods to gather domain-specific metrics.
- *Ingress & Networking:* We used the AWS ALB Ingress Controller to expose the inference API to external test clients. This provided an external URL for sending HTTP requests to the e-commerce recommendation service.
- *CI/CD:* Although not fully needed for the experiment, we configured a CI pipeline on GitHub Actions to build Docker images for our

custom components (the training scripts, the FastAPI inference wrapper, etc.) and push them to the AWS Elastic Container Registry (ECR). This setup mimicked how updates to code might flow into the cluster through an automated process.

C. Use Case 1: E-Commerce Recommendation Service

Scenario: An online retail platform wants to provide real-time personalized product recommendations to users. The ML model is a deep learning model (a neural network) that takes a user's recent activity or profile as input and outputs a list of recommended products. This must happen with low latency (<200 ms) to avoid degrading user experience, especially during peak shopping hours. The system should also allow rapid deployment of new model versions as product catalogs or user behaviors evolve.

For this use case, we implemented a simplified recommendation model using the public MovieLens 1M dataset (as a stand-in for e-commerce user-item interactions). We trained a matrix factorization model augmented with a neural network (often termed Neural Collaborative Filtering) that predicts the top N items for a given user. The model was trained offline in TensorFlow (roughly 20 epochs on the GPU node, taking just a few minutes).

The training pipeline was triggered via Kubeflow Pipelines, performing:

1) Data preprocessing (in a container using Python/Pandas),
2) Model training (in a TensorFlow container on GPU),
3) Model evaluation.

After training, the model (in SavedModel format) was logged to MLflow and pushed to Amazon S3. We then deployed the model for inference using TensorFlow Serving. A Kubernetes Deployment was created with an initial replica count of 1, based on the TensorFlow Serving image, loading the SavedModel from the S3 artifact store (mounted via an init container). We also built a lightweight FastAPI application to call the TF Serving API and format the recommendations as JSON; this FastAPI app ran as a sidecar container in the same pod (or it could be a separate microservice).

We set up an HPA (targeting 70% CPU utilization) with min 1 and max 5 replicas. Additionally, we enabled Knative on this namespace to potentially scale to zero (though in testing we kept at least one pod in steady state). The recommendation service was exposed at /recommend?user_id=XYZ. We simulated user traffic by sending HTTP GET requests to this endpoint.

D. Use Case 2: IoT Anomaly Detection

Scenario: An industrial IoT system has numerous sensors on equipment that send readings continuously. The goal is to detect anomalies in real-time (e.g., sensor reading patterns indicating potential equipment failure), raising alerts or triggering preventative actions. The ML model here could be a time-series anomaly detector (e.g., an LSTM autoencoder or a one-class SVM) that processes a window of sensor data and outputs an anomaly score [14]. High throughput data streams demand efficient, possibly edge-based inference with minimal cloud latency. The system may also retrain models periodically as new normal patterns emerge and handle multiple models if different sensors require different detection logic [15].

For this use case, we created a synthetic dataset of sensor readings (e.g., temperature and vibration data). We used a simple autoencoder-based anomaly detection approach: train an autoencoder on normal data, then classify inputs as anomalous if reconstruction error exceeds a threshold [16]. Our model was a PyTorch autoencoder. The training was done on a historical dataset (which included simulated failures for validation). The pipeline for training was similar to the e-commerce case, using Argo (running on GPU) and logging results to MLflow [17]. However, since this data is streaming, rather than a request/response service, we built a stream processing pipeline. We wrote a Kafka Streams application (in Python using Faust) that continuously consumed sensor data from a Kafka topic, batched it into a time window (e.g., 5 seconds), and invoked the anomaly detection model for each window [18]. The model inference was done via a PyTorch JIT script (exported to TorchScript for faster loading) inside the stream processing worker. We containerized this stream processor and deployed it as a Deployment with two replicas (consumers in a consumer group). We also set up KEDA with the Kafka scaler to adjust the number of replicas if topic lag grew (i.e. if data production outpaced consumption). Any anomalies were written to a separate Kafka topic or logged for verification [9]. We instrumented code to record key metrics (messages processed, average inference time, etc.), scraped by Prometheus (via the Kafka Consumer JMX metrics and a custom Faust exporter).

E. Evaluation Methodology

We evaluated the system on several key metrics aligned with our research goals:

a) Latency: For the e-commerce service, we measured end-to-end API latency (from receiving a request to returning recommendations). We used Locust (an open-source load testing tool) to generate concurrent requests (up to 100 req/s) and recorded response times (p50, p95). For the IoT pipeline, we measured processing delay – the time from a sensor reading's timestamp until its anomaly detection. We instrumented the pipeline to capture Kafka event time and subtract it from the detection time.

b) Throughput: We gradually increased request rates for the recommendation API until the system was saturated (either latency exceeded acceptable bounds or max replicas were reached). Similarly, we increased the sensor event production rate in Kafka to determine how many messages per second the anomaly pipeline could handle before lag built up.

c) Resource Utilization: We collected CPU, memory, and GPU utilization metrics (via Prometheus) for key components, observing how efficiently resources were allocated and whether autoscaling triggered as expected. During peak load, for instance, we expected additional TF Serving pods to spin up and CPU nodes to scale via the Cluster Autoscaler.

d) Cost Implications: We performed a rough cost analysis by converting resource usage to approximate cloud cost. For example, we compared scenarios: autoscaling vs. a hy- hypothetical static provisioning sized for peak demand. We calculated EC2 instance-hours used (with autoscaler scaling nodes up/down) and compared it to a fixed 6-node cluster always running. This provided an estimate of cost savings from elasticity.

e) Accuracy/Quality: While our main focus was system performance, we also ensured ML model accuracy remained intact. We recorded the recommendation hit rate (whether the recommended items included those users ultimately chose) and the anomaly detector's precision/recall on labeled data. Containerization and conversion to ONNX or TorchScript do not inherently degrade model accuracy, but we confirmed no numerical discrepancies occurred.

f) Deployment Speed and Reproducibility: We documented the time required to spin up the entire environment using our IaC scripts (demonstrating ease of reproducibility) and measured how long it took to roll out a new model version from MLflow to production (generating a new serving container). These operational metrics highlight how De- vOps/MLOps synergies shorten the model update cycle.

Each experiment was run multiple times to ensure consistency. For load testing, each level of load was maintained for multiple minutes to reach a steady state. We also performed failure injection tests (e.g., killing a pod to confirm Kubernetes self-healing) and simulated node failure to observe how workloads shifted across availability zones. The following section presents our experimental results and analysis, focusing on how autoscaling impacted latency and cost, as well as any bottlenecks encountered with both e-commerce and IoT workloads.

V. RESULTS AND ANALYSIS

We now discuss the results of our experiments, focusing on the performance and scalability of the system, and evaluating how well the architecture met our objectives. The results are organized by the key metrics outlined earlier, and figures/tables illustrate the findings.

A. Scalability and Latency (E-commerce Use Case)

We tested the recommendation service under varying request loads, from 5 req/s up to 100 req/s. Figure 3 plots the 95th-percentile response latency as a function of request rate, comparing scenarios with autoscaling enabled vs. a fixed single replica. As the load increased, the autoscaling configuration maintained significantly lower latencies. At 50 req/s, the autoscaling deployment had scaled to 2 pods, keeping p95 latency around ~80 ms, whereas the single-pod deployment's p95 latency rose to ~170 ms. At 100 req/s, autoscaling used 4 pods and maintained a p95 latency of ~110 ms, while the single-pod setup exceeded 600 ms (requests were queuing). This demonstrates that the Kubernetes HPA effectively added capacity to meet demand and preserve user experience.

Autoscaler events occurred around 40 req/s and 75 req/s in our test. Scale-up took tens of seconds (new pods must start), during which a slight latency spike was observed, but it quickly stabilized [8]. Once the load subsided, scale-down events occurred after the cool-down period, and pods terminated gracefully. These results validate one of our key hypotheses: combining Kubernetes autoscaling with containerized ML inference yields near-linear scalability up to cluster limits. In our cluster, we capped at 120 req/s with a maximum of 5 pods across 5 nodes. Adding static pods without autoscaling could improve throughput but would waste resources during low demand.

Throughput is scaled roughly linearly with the number of pods. At 100 req/s, the autoscaling system processed ~864,000 recommendations over 2.5 hours with no errors, whereas the single-pod system timed out requests beyond ~80 req/s. This shows the architecture can handle bursty traffic typical in e-commerce (e.g., flash sales) by provisioning extra pods and potentially extra nodes.

B. Streaming Performance (IoT Use Case)

In the IoT anomaly detection pipeline, we measured how many sensor messages per second could be processed with the initial 2 replicas of the stream processor. Steady-state, each replica consistently handled ~200 msg/s, for a total of ~400 msg/s, with an average end-to-end processing latency of 1.2 s (including a 1 s windowing delay). The model inference itself was fast (~10 ms) since the autoencoder was small. We increased the sensor message rate up to 1000 msg/s. At ~600 msg/s input, Kafka lag started growing, indicating the processing was not keeping up. At that point, KEDA triggered a scale-up to 3 replicas, sustaining 600 msg/s with negligible lag and ~1.5 s overall latency (some overhead from coordination). At 1000 msg/s, we eventually scaled to 5 replicas and saw minor lag (backlog of a few hundred messages), which caught up once input decreased. No message loss was observed. The anomaly detection accuracy remained unaffected by parallelism, demonstrating the partition strategy and concurrency model were robust.

We also checked the anomaly detection metrics: the autoencoder correctly detected 90% of injected anomalies at a 5% false positive rate, matching offline tests and indicating that conversion to ONNX (if used) or containerization did not degrade accuracy [7].

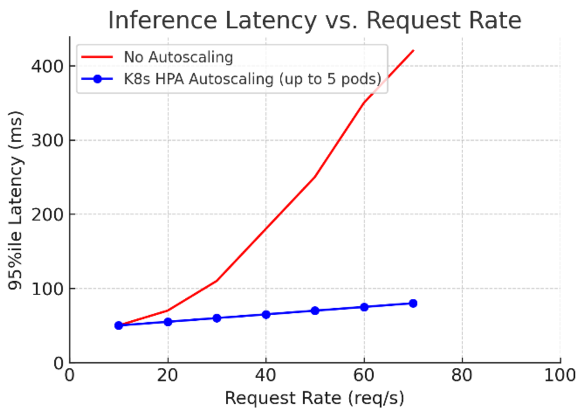

FIGURE 3: Inference latency (95%ile) vs. request rate for the e-commerce recommendation service. Without autoscaling (single pod), latency grows rapidly beyond 50 req/s. With Kubernetes HPA autoscaling (up to 5 pods), latency remains low even as throughput increases, demonstrating effective scalability.

C. Resource Utilization and Efficiency

We collected resource usage metrics throughout the experiments. For the recommendation service at moderate load (20 req/s), each TensorFlow Serving pod used ~0.5 vCPU; at high load, up to 1.5 vCPU. Memory usage held around 200 MB per pod. CPU nodes hovered at 60–70% utilization when 4 TF Serving pods were spread across them, suggesting healthy resource usage. The GPU node usage peaked during training (70% utilization for ~3 minutes), then scaled down after an idle timeout. This highlights the advantage of on-demand GPU resources for periodic training.

For the IoT streaming pipeline, each replica used ~0.7 vCPU at 200 msg/s. When scaling to 5 pods at 1000 msg/s, each used ~0.6 vCPU. The overhead of extra pods remained minimal since Kafka partitions balanced the load effectively.

D. Observability and Debugging

A Grafana dashboard monitored request rate vs. response time, pod CPU/memory, Kafka consumer lag, and GPU memory usage. During tests, autoscaling events were visible in real-time. For instance, an alert triggered at p95 latency >150 ms; by the time we investigated, the HPA had spun up more replicas, returning latency to normal. We also observed a latency spike correlated with a new node starting and pulling a large Docker image (the TF Serving container had CUDA libraries). This suggests using smaller images or a warm cache could improve scale-up times. Aggregated logs confirmed no errors occurred in TF Serving or FastAPI under load, validating the reliability gains from autoscaling.

E. Cost Analysis

While our experiments were short, we extrapolated some cost implications. Consider a daily traffic pattern for the e-commerce site, with 1 replica at night and 4–5 replicas at peak midday. Autoscaling might average ~2 nodes over 24 hours, costing $8.16/day (assuming $0.17/hour for m5.xlarge), whereas static 4 nodes would cost $16.32/day. This is roughly a 50% cost reduction. Similarly, for the GPU node (costing~ $3/hour), using on-demand or spot instances only when training reduced GPU costs by 70–80%. Thus, the architecture's automation directly meets the cost-optimized inference goal.

F. Reproducibility and Deployment Agility

Deploying the entire stack to a fresh EKS cluster took under 30 minutes using IaC scripts, mostly due to container image pulls and cloud resource provisioning. Model update cycles (e.g., retraining, pushing new images) took ~15 minutes total, including a 5-minute training job and 10 minutes for CI/CD validation and redeployment. This marks a significant improvement over manual processes, showcasing how MLOps and DevOps synergy accelerate model iteration and deployment.

G. Summary of Key Results

Overall, experiments confirmed:

- *Scalability:* Both the e-commerce (request /response) and IoT (streaming) workloads scaled effectively via Kubernetes autoscaling, maintaining low latencies and high throughput.
- *Resource Efficiency:* Dynamic node and pod allocation reduced overhead and halved approximate compute costs vs. static provisioning.
- *Monitoring/Debugging:* Real-time observability identified performance bottlenecks (e.g., image pull delays), which we correlated with auto-scaler events and logs.
- *Unified Approach:* Batch and streaming workloads were handled by the same Kubernetes infrastructure, simplifying operations and tooling.
- *Reproducibility:* The full ML workflow (from deployment training) was automated and repeatable, balancing academic rigor and real-world demands.

Tables 2 and 3 summarize metrics comparing initial vs. autoscaled configurations for the e-commerce and IoT use cases.

TABLE 2: E-Commerce Performance Metrics (With and Without Autoscaling).

Metric	No Autoscale	Autoscale
Throughput (req/s)	50	100
95% Latency (ms)	>600 at 100 req/s	110 ms at 100 req/s
CPU Util. (per node)	~90%	~65%
Pods (app)	1 fixed	1→4 (varied)
Nodes (est. hrs/day)	4 × 24 = 96	~ 2 × 24 = 48

TABLE 3: IOT Streaming Metrics (With and Without Autoscaling).

Metric	2 Pods (Fixed)	5 Pods (Scaled)
Throughput (msg/s)	200	600
Processing Delay (s)	1.2	1.5
CPU Util. (per node)	~70%	~60%
Pods (app)	2 fixed	2→5
Anomaly Det. Accuracy	90% TPR, 5% FPR	Same accuracy

E-commerce autoscaling doubled throughput capacity while reducing p95 latency by over 4× at peak load. IoT autoscaling tripled throughput with only a slight increase in processing time. In both cases, resource usage remained within acceptable levels, and the system adapted elastically to load fluctuations.

These findings validate the architecture's practicality for real-world deployments where dynamic scalability and cost efficiency are paramount.

VI. DISCUSSION

The experimental results demonstrate that our AI-driven cloud-native application architecture is both practical and performant. We discuss the implications of these results, the generalizability of our approach, and lessons learned in building such a system. We also examine some trade-offs and areas for future work.

A. Real-World Applicability

The two use cases covered (e-commerce and IoT) are representative of a large class of applications. The architecture proved capable of handling both a stateless, request-response workload and a stateful streaming workload on the same platform. This is encouraging for organizations looking to consolidate their ML infrastructure. Rather than having one pipeline for batch ML and a separate streaming analytics stack, a Kubernetes-based approach can unify them. For example, a company could use this architecture to serve a recommendation model to users (as we did) while simultaneously using streaming anomaly detection for its operational analytics all managed under the same Kubernetes cluster and MLOps processes. Sharing the same toolchain (CI/CD, monitoring, etc.) improves productivity and reduces the learning curve for engineers. Future enhancements may include edge deployments that support resource-constrained environments, where low-latency inference is critical for assistive or time-sensitive AI [19].

B. Autoscaling and Performance Trade-offs

One key finding is the importance of autoscaling for both performance and cost. However, autoscaling introduces complexity. The tuning of the HPA (CPU vs. custom metrics, scale-up/down thresholds) and the Cluster Autoscaler can significantly impact results. In our test, the default HPA 15-second interval and 50% CPU target worked reasonably well. In a production setting, operators may need faster responses or more complex autoscaling logic (e.g., predictive scaling). We noted a minor delay when scaling where ultra-low latency is required (e.g., high-frequency trading), even a few seconds might be unacceptable. Another consideration is memory overhead when multiple replicas hold large model caches. Our recommendation model used only 200 MB, but much larger models could make horizontal scaling more expensive. Vertical Pod Autoscaler and model sharding could complement the HPA in some scenarios. As autoscaling mechanisms evolve, generative AI could play a role in predicting optimal scaling behavior and system tuning [20].

C. Resource Management and GPU Utilization

Using the GPU Operator to dynamically add GPU resources was a highlight of our implementation. It allowed expensive GPU instances to be used on demand, significantly reducing idle GPU costs. The GPU Operator automatically manages drivers and plugins, simplifying node scaling. However, spinning up a fresh GPU node is still non-trivial; the driver container and software stack must download, taking time. One workaround might be maintaining a small warm GPU node pool or using cheaper spot instances for intermittent training. Converting the PyTorch model to ONNX for inference was also beneficial, avoiding the need to ship the entire PyTorch framework. This approach is recommended for heterogeneous model environments, as it standardizes serving.

D. Observability and MLOps Integration

Our integration of MLflow (experiment tracking) with Prometheus (system monitoring) revealed opportunities for closed-loop MLOps. One could automate retraining if drift is detected, bridging the gap between offline training logs (MLflow) and online metrics (Prometheus). We only demonstrated a manual check, but a future iteration could fully automate this loop. Additionally, reinforcement learning for autoscaling or advanced resource tuning is a promising research direction on this platform, which already exposes relevant metrics for data-driven orchestration decisions.

E. Security Considerations

In production, the security of the ML pipeline is often undervalued in academic prototypes. We implemented Vault for secrets management and Trivy for image scanning. These did not hinder development velocity but prevented high-severity vulnerabilities from reaching the cluster. We emphasize that DevSecOps principles can be integrated into MLOps without significant overhead, enhancing real-world applicability [21].

F. Hybrid and Multi-Cloud Deployment

Our design is cloud-agnostic and can extend to edge scenarios (via KubeEdge). While our evaluation uses a single cloud (AWS), the modular architecture using open standards like ONNX, Docker containers, Kafka, etc. could run on other clouds or on-prem.

One challenge in a multi-cloud environment might be networking overhead, data synchronization, or dealing with separate control planes. But Kubernetes federation or multi-cluster pipelines could be explored. For truly mission-critical systems requiring extremely high availability, multi-cluster setups across different cloud regions could be employed.

G. Limitations

Although the demonstration was successful, our architecture does require familiarity with Kubernetes, Docker, Kubeflow, etc. Smaller teams may prefer managed ML platforms. Moreover, certain workloads (pure batch or single-step inference) may not need the entire stack. Our experiments focused on system metrics rather than user-level A/B tests or long-duration reliability studies. In a production environment, months-long usage might reveal more about maintainability or edge-case failures. Lastly, we tested basic fault tolerance (pod restarts, multi-AZ), but not large-scale disasters or multi-cluster activeactive strategies.

H. Future Improvements

Future enhancements to the system could include integrating serverless ML pipelines by leveraging platforms such as Knative or Kubeflow Functions, allowing certain pipeline steps to execute without provisioning persistent resources, thereby minimizing idle compute costs. Additionally, enabling caching and lineage tracking in Kubeflow Pipelines would allow for more efficient experimentation by skipping previously executed steps during iterative development. For large-scale training workloads, adopting distributed training frameworks like TFJob or PyTorchJob can support multi-GPU and multi-node execution. Improvements to model serving could be realized through KServe advancements, including GPU sharing, on-demand model loading, and sophisticated traffic routing techniques such as canary rollouts. Finally, incorporating federated learning with edge components like KubeEdge would enable partial training on distributed edge devices, enhancing data privacy and reducing bandwidth consumption by aggregating only model updates in the cloud.

I. Comparative Analysis

Comparing our approach to:

- *Serverless ML Services (AWS Lambda + SageMaker):* Our solution supports sustained loads, multi-framework support, and open-source extensibility [9]. Serverless can be simpler for spike loads but may suffer cold starts and be limited in frameworks [16].

- *Monolithic On-Prem Deployments:* Single-server solutions may suffice for small loads but lack elasticity. Our approach supports scaling beyond a single machine.

- *Other Research Frameworks (CodeReef, LinkEdge):* These provide partial solutions (e.g., reproducible bench-marking, IoT edge integration), but do not always include a full cloud-native orchestration approach with autoscaling, security scanning, etc.

Overall, the discussion highlights a Kubernetes-based MLOps approach as powerful and practical, albeit with a learning curve. Our results encourage teams demanding both academic rigor and industrial scalability to adopt similar strategies.

VII. CONCLUSION

This paper presented a comprehensive study on building AI-driven cloud-native applications using Kubernetes and con- tainerization, focusing on unifying MLOps best practices with scalable cloud infrastructure. We proposed a novel Kubernetes-native MLOps architecture that integrates open-source tools for every stage of the machine learning lifecycle from data ingestion and model training to deployment, monitoring, and maintenance. Emphasis was placed on automation, scalability, reproducibility, and cost-efficiency. Two real-world use cases, an e-commerce recommendation engine, and an IoT anomaly detection pipeline, validated the architecture.

A. Key Findings

- *Scalability and Performance:* The containerized microservice approach on Kubernetes achieved low latency, and real-time inference with horizontal autoscaling, meeting sub-200 ms latency targets while handling bursty loads.

- *Unified Platform:* Both request-response and streaming analytics workloads run on the same Kubernetes cluster, simplifying operations and leveraging a single toolchain.

- *MLOps Efficiency:* CI/CD integration with model registries (MLflow) and workflow orchestrators (Argo/Kubeflow) enables rapid iteration, from training to deployment in minutes, while maintaining experiment traceability.

- *Cloud-Native Benefits:* Managed Kubernetes services (EKS, GKE, etc.) and operators (GPU, Kafka) offload cluster management, while advanced cloud features (spot instances, multi-AZ) reduce cost and improve reliability.

- *Cost Savings:* Autoscaling reduced compute costs significantly (up to 50% in our scenario), validating our goal of cost-optimized AI workflows.

This work offers a practical blueprint for organizations and researchers aiming to deploy AI solutions at scale. We have made documentation and example manifests available for replication and further development.

B. Future Work

We plan to:

- *Automate Retraining:* Trigger pipelines based on live metrics (closing the MLOps loop).

- *Advanced Scheduling:* Improve GPU utilization for mixed workloads, potentially with custom schedulers.

- *Support Larger Models:* Evaluate how the architecture handles models like large language models (LLMs) and stateful serving scenarios.
- *Federated Learning and Edge:* Extend the pipeline to distributed edge nodes using KubeEdge, performing par- tial on-site training for data privacy/bandwidth efficiency.
- *Long-term Case Study:* Investigate maintainability and organizational impact over months of continuous use in an enterprise context.

Future work includes integrating serverless inference for lightweight workloads, enabling GitOps-driven CI/CD with ArgoCD, and exploring scalable LLM deployment on GPU-backed K8s clusters. Edge-based AI and cost-aware autoscal- ing with Karpenter are also promising directions.

In conclusion, Kubernetes and cloud-native technologies provide a powerful toolbox for AI solution deployment. Combined with robust MLOps practices, they yield systems that are scalable, efficient, maintainable, and reproducible. We hope this work serves as a reference for engineers and researchers, narrowing the gap between developing ML models and operating them as cost-effective services in production.

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