University of Amsterdam

Master Thesis

KPMG - Digital Enablement

Implementing AIOps for Enhanced Performance Anomaly Diagnosis in Distributed Cloud Applications.

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GitHub Repository: `https://github.com/jojoJochem/CloudSentinel`

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Abstract

The increasing complexity and dynamic nature of distributed cloud applications necessitate advanced approaches to performance monitoring and anomaly detection. Traditional monitoring systems, which rely on static thresholds and predefined rules, often fail to effectively address the intricacies of modern cloud environments, resulting in delayed diagnostics and inefficient resource utilization. This thesis explores the implementation of Artificial Intelligence for IT Operations (AIOps) as a solution to these challenges, with a focus on enhancing performance anomaly diagnosis in distributed cloud applications.

This research develops and evaluates an AIOps framework tailored for distributed cloud environments, addressing key challenges such as scalability, integration with existing infrastructures, and user interface design.[1] The proposed framework integrates sophisticated machine learning algorithms, including CGNN-MHSA-AR and CausalRCA, to improve the accuracy and efficiency of anomaly detection and root cause analysis. The framework's modular architecture ensures adaptability across diverse cloud infrastructures, and its implementation demonstrates significant improvements in performance diagnostics.

Through real-world experimentation and a proof-of-concept deployment, this study validates the effectiveness of the AIOps framework in providing real-time, actionable insights, automating responses to performance anomalies, and ultimately contributing to more reliable and resilient cloud operations. The findings offer a contribution to the field by bridging the gap between theoretical AI advancements and their practical application in IT operations.

[1] https://github.com/jojoJochem/CloudSentinel

Chapter 1

Introduction

The increasing demand for high availability and reliability in distributed cloud applications presents significant challenges in performance monitoring and anomaly detection. Traditional monitoring systems, often reliant on static thresholds and predefined rules, struggle to capture the complexities of modern cloud environments, leading to delayed or inaccurate diagnostics, which prolongs downtimes and results in inefficient resource utilization Brondolin and Santambrogio 2020 & Shan et al. 2019. The need for more intelligent, adaptable systems has become evident, particularly as cloud infrastructures grow in scale and complexity Taherizadeh et al. 2016.

Current approaches to performance monitoring in distributed cloud applications reveal notable gaps. Many existing tools lack the flexibility to adapt to dynamic cloud environments and often fail to integrate seamlessly into CI/CD workflows Vemuri, Thaneeru, and Tatikonda 2024 & Zampetti et al. 2021. Additionally, user interfaces of these tools can be cumbersome, hindering their usability and adoption Hrusto, Engström, and Runeson 2022 & Ergasheva et al. 2020. Scalability remains a critical concern, especially when faced with the vast amounts of data generated by distributed applicationsTaherizadeh et al. 2016 & Xin 2023.

To address these challenges, AIOps (Artificial Intelligence for IT Operations) has emerged as a promising solution. AIOps combines big data, machine learning, and other AI technologies to enhance IT operations processes, including event correlation, anomaly detection, and root cause analysis Rijal, Colomo-Palacios, and Sánchez-Gordón 2022 & Sabharwal and Bhardwaj 2022. AIOps frameworks are designed to handle the data complexity inherent in distributed cloud applications, providing real-time, actionable insights and automating responses to performance anomalies Du, Xie, and He 2018 & Xin 2023

This research aims to bridge the identified gaps by developing an AIOps framework tailored for distributed cloud environments. The framework will focus on enhancing scalability, ensuring seamless integration with existing infrastructures, and providing a user-friendly interface that supports flexible configuration Giamattei et al. 2023 & Abduldaem and Gravell 2019. By addressing

these key areas, the proposed solution aims to improve the accuracy and efficiency of performance diagnostics, ultimately contributing to more reliable and resilient cloud operations.

1.1 Research Questions

To address the complexities and challenges associated with performance monitoring and anomaly response in distributed cloud applications, we focus our research on the implementation and enhancement of an AIOps framework. Our research questions are designed to explore the feasibility, design principles, and effectiveness of such frameworks. These questions aim to provide an understanding of how AIOps can be utilized to improve performance diagnosis in cloud environments.

1.1.1 Main Research Question

RQ How can an AIOps framework be effectively implemented and validated within a cloud environment to ensure reliable and scalable anomaly detection and root cause analysis?

This primary question seeks to uncover the overall feasibility and effectiveness of integrating AIOps frameworks within distributed cloud environments. We aim to explore the fundamental aspects of framework design and implementation that enable accurate performance diagnosis and responses to anomalies.

1.1.2 Sub-Questions

SQ1 How can the AIOps framework be designed for seamless integration with existing cloud infrastructures while ensuring a user-friendly interface that supports flexibility and configurability for diverse operational needs?

This sub-question explores the design considerations necessary for integrating the AIOps framework with existing cloud infrastructures while maintaining a user-friendly interface. It is accountable for ensuring that the framework is both technically compatible and accessible to users, allowing for easy configuration and adaptability across different operational settings.

SQ2 What are the components and technologies necessary for developing and validating an AIOps framework in a cloud environment, and how do they interact to achieve effective anomaly detection?

This sub-question focuses on identifying the key components, technologies, and interactions needed for the successful development of an AIOps framework. It aims to establish how these elements contribute to the overall effectiveness of anomaly detection and root cause analysis within the framework, ensuring that the system operates as intended when deployed in a cloud environment.

SQ3 How does the AIOps framework perform under varying workloads, and what strategies can be employed to ensure its scalability and responsiveness in a dynamic cloud environment?

This sub-question addresses the framework's ability to maintain high performance under varying workloads. It seeks to understand the challenges and strategies associated with scaling the AIOps framework, ensuring that it remains responsive and efficient in dynamic cloud environments, which is critical for its practical deployment and real-world application.

By addressing these research questions, we aim to develop an understanding of the design, implementation, and effectiveness of AIOps frameworks in distributed cloud applications. The insights gained from this research will contribute to the development of more robust, adaptable, and intelligent performance monitoring and anomaly response systems.

1.2 Contribution

In this thesis, we make a significant contribution by translating theoretical AI algorithms into practical, real-time applications specifically designed for AIOps in distributed cloud environments. Our primary focus is on bridging the gap between advanced AI capabilities and their effective deployment in dynamic, real-world cloud settings.

To this end, we developed an AIOps framework that integrates sophisticated machine learning algorithms with the operational requirements of distributed cloud applications. By implementing and refining two novel algorithms, CGNN-MHSA-AR and CausalRCA, we demonstrated how these theoretical models can be successfully applied in real-time scenarios, achieving both accuracy and efficiency in detecting anomalies and diagnosing their underlying causes.

A key aspect of our work involved addressing the challenges of scalability and flexibility, ensuring that our AI-driven solutions could function effectively across diverse cloud environments. We carefully designed our framework with a modular architecture, allowing the AI algorithms to maintain their performance when deployed in different cloud infrastructures, thereby ensuring their practical utility in a variety of operational settings.

Beyond the technical achievements, we conducted a real-world implementation and evaluation of our AIOps framework. In a proof-of-concept environment, we tested the practical application of the algorithms under varying conditions, demonstrating that our framework meets practical concerns such as usability and seamless integration with existing cloud infrastructures.

Our research makes a contribution to the field by showing how theoretical AI advancements can be translated into practical, scalable tools ready for deployment in modern cloud environments. Through this work, we advance the practical use of AI in IT operations, turning theoretical concepts into actionable, real-time solutions for performance monitoring and anomaly detection in distributed cloud applications.

1.3 Structure of the Thesis

In **Chapter 2**, we outline the related works for our research. We begin by exploring the historical context and evolution of AIOps, tracing its origins and its progression into cloud computing. This is followed by a review of AIOps frameworks, comparing their features, and discussing their strengths and limitations. Additionally, we examine performance monitoring techniques and tools used in distributed systems, explore their integration with CI/CD pipelines, and assess their effectiveness and efficiency. The role of machine learning in AIOps is scrutinized, focusing on the algorithms employed, notable successes and failures, and the challenges faced in their application. The chapter concludes by identifying research gaps and opportunities, and discussing the theoretical and practical implications of our study.

Chapter 3 outlines the key requirements for our proposed AIOps framework. We discuss the functional requirements, which include data collection and management, real-time data processing, anomaly detection, and automated response and resolution. We also address the non-functional requirements such as scalability, reliability, robustness, portability, and integration. Usability requirements are considered, emphasizing the importance of user interface and experience, as well as configuration and customization. Performance requirements are specified, focusing on system performance, monitoring, and reporting. Finally, we cover continuous improvement and learning mechanisms, including adaptability and feedback mechanisms, as well as security and compliance requirements related to data security and regulatory compliance.

In **Chapter 4**, we present the system design and architecture of our AIOps framework. We begin by discussing the design methodology, including the principles and process we followed. We then describe the high-level architecture of the system and detail the design of its components. Data management aspects such as data collection, storage, processing, and anomaly data sets for AI training. We outline the selection, training, and deployment of machine learning models, and discuss system integration and interfaces, including user interfaces and data interoperability, as well as examining Scalability strategies and data flow within the system are also examined.

Chapter 5 focuses on the implementation of the proof of concept. We describe the development environment, including hardware, operating systems, development tools, frameworks, libraries, and programming languages used. We provide detailed descriptions of the implementation of various modules, such as data collection, data processing, anomaly detection, learning and adaptation, and the user interface. Finally, we discuss the challenges encountered during implementation.

In **Chapter 6**, we present the results and evaluation of our implemented system. We provide an overview of the system, describing its main components and the deployment environment and configuration. The data used for evaluation is detailed, and we discuss the evaluation metrics and performance indicators employed. We present the results of experiments conducted, including the performance of specific algorithms, CGNN-MHSA-AR and CausalRCA,

and assess the system's flexibility and portability. The chapter concludes with the theoretical and practical implications of the results.

Chapter 7 offers a discussion of our findings. We revisit the research questions and discuss how our study addresses them. We acknowledge the limitations of the study and propose future directions for research. The Chapter provides a reflective analysis of the research process and its outcomes.

Finally, **Chapter 8** concludes the thesis by summarizing the key findings and contributions of our research. We reflect on the significance of our study in the context of AIOps for distributed cloud applications and propose potential avenues for future work.

Chapter 2

Related Works

In this chapter, we explore the development and evolution of Artificial Intelligence for IT Operations (AIOps), starting from its roots in traditional IT operations management. We discuss how the rapid expansion of cloud computing showed the limitations of manual IT service management, leading to the introduction of the term AIOps. This term signifies the shift towards using machine learning and data analytics to automate IT operations.

We then examine how the growth of cloud services and microservices architectures has increased the complexity of IT operations management. This section reviews literature that addresses the need for efficient performance monitoring and specialized engineering approaches adapted to the dynamic nature of microservices.

The chapter continues with a review of current AIOps frameworks. We compare their functionalities, architectures, and use cases. We show the strengths and limitations of these frameworks, showing the need for scalable solutions that can handle real-time operations and integrate with various IT tools.

We also cover performance monitoring in distributed systems, discussing innovative techniques that manage the complexities of these systems and the importance of non-intrusive monitoring solutions that provide detailed operational insights.

Furthermore, we discuss the integration of AIOps with CI/CD pipelines. We show how this enhances software development by enabling automated anomaly detection and proactive problem resolution. This integration improves system reliability and operational agility, supporting continuous improvement in DevOps practices.

We address the role of machine learning in AIOps, focusing on how algorithms like clustering, decision trees, and neural networks are used for anomaly detection and performance prediction. We explore the implementation challenges and opportunities for innovation that could advance AIOps frameworks.

Lastly, we discuss several areas where current research and practical implementations of AIOps fall short. These gaps include the need for more scalable and adaptable monitoring tools capable of handling massively distributed archi-

tectures, the challenge of maintaining high data quality for model training, and the importance of developing intuitive, user-friendly dashboards that enhance human-machine collaboration. Addressing these gaps presents opportunities for advancing the field of AIOps.

This chapter helps understand the diverse aspects of AIOps and provides a backdrop for the discussions in the subsequent chapters. We outline the current research gaps and potential areas for future advancements in the field.

2.1 Historical Context and Evolution of AIOps

2.1.1 Origins of AIOps

The development of AIOps can be traced back to IT operations management, shaped by technological advancements and growing IT complexity. Initially challenged by the scale and speed of cloud and data center growth, traditional IT service management often fell short due to its manual and reactive nature. (Rijal, Colomo-Palacios, and Sánchez-Gordón 2022)

Coined by Gartner in 2016 n.d., the term AIOps evolved from "Algorithmic IT Operations" to signify the application of machine learning and data analytics to automate IT operations. This shift aimed to improve operational responsiveness, predict system outages, and optimize IT management.

Driving factors for AIOps adoption include:

- **Complex IT Environments**: The demand for advanced management tools is driven by the complexity of multi-cloud and microservices architectures. Modern IT environments are increasingly adopting cloud-based solutions, software-centric and microservices architectures, and virtualization and containers. These new architectures and technologies pose significant challenges, necessitating advanced management tools to handle the intricacies of such environments (Sabharwal and Bhardwaj 2022).

- **Efficiency and Speed**: There is a need for rapid, proactive management in dynamic IT settings. AIOps enhances the efficiency and speed of IT operations by providing real-time data analysis, reducing noise, and focusing on critical alerts. This proactive management is essential for maintaining stability and reliability across complex systems, allowing businesses to adapt quickly to changing market needs by updating functionalities based on feedback (Sabharwal and Bhardwaj 2022).

- **Enhanced Decision Making**: The use of deep analytics for better operational decisions and aligning IT with business objectives is another key factor. AIOps leverages machine learning and deep analytics to understand environments and make probabilistic conclusions, aiding in root-cause analysis and decision-making. This ensures that IT operations are closely aligned with business objectives, optimizing overall performance (Sabharwal and Bhardwaj 2022).

AIOps continues to evolve, focusing on accuracy in anomaly detection, resource utilization efficiency, and operational responsiveness. It aims to transform IT operations into more predictive and strategic functions, aligning closely with business outcomes. This integration supports modern IT demands, ensuring automation, efficiency, and continuous adaptation in operations management.

2.1.2 Evolution into Cloud Computing

The rise of cloud computing and microservices architectures introduced greater complexity in IT operations management. Distributed systems, characterized by decentralized components communicating over networks, present unique challenges for traditional monitoring and troubleshooting practices. Papers like Brondolin and Santambrogio 2020 address this, highlighting the importance of efficient performance monitoring that minimizes overhead while providing detailed performance insights. Heinrich et al. 2017 further discuss the need for specialized performance engineering approaches tailored to microservices due to their dynamic nature.

2.2 Review of Current AIOps Frameworks

2.2.1 Overview of Leading Frameworks

The evolution AIOps has led to the development of various frameworks designed to enhance incident management processes. Based on the work of Remil et al. 2024 an overview is provided of leading AIOps frameworks, focusing on their functionality, architecture, and typical use cases.

Functionality of AIOps Frameworks

AIOps frameworks are designed to support comprehensive incident management tasks, including detection, prediction, prioritization, classification, duplication, root cause analysis, correlation, and mitigation. These frameworks leverage advanced machine learning and big data analytics to provide key functionalities. Frameworks utilize a combination of statistical models, conventional machine learning classifiers, and deep learning techniques to identify anomalies and deviations from normal operations. Predictive models, such as Long Short-Term Memory networks and Random Forests, forecast potential incidents before they occur, enabling proactive measures. Algorithms rank incidents based on severity and business impact, ensuring critical issues are addressed promptly. Classification algorithms group incidents based on their characteristics, while duplication methods identify and merge duplicate reports. Causality and correlation studies within a unified topology help pinpoint the underlying causes of incidents, reducing redundancy and highlighting dependencies. moreover, correlation algorithms analyze relationships between incidents to automate mitigation strategies and minimize impact.

Architecture of AIOps Frameworks

The architecture of AIOps frameworks typically involves multiple layers to ensure scalability, flexibility, and efficient data management:

- **Data Collection and Ingestion** Dynamic infrastructures generate vast amounts of data, including logs, performance metrics, and network traffic. Collection agents, such as Telegraf and Fluentd, gather this data from diverse sources.
- **Data Storage and Organization** Data is categorized into structured, semi-structured, and unstructured types. A hybrid data lakehouse architecture, combining the features of data lakes and warehouses, is often employed to store and organize data.
- **Data Processing and Analysis** Machine learning models analyze the ingested data to detect patterns and predict incidents. Distributed computing frameworks, such as Apache Kafka and Apache NiFi, handle large-scale data processing.
- **Visualization and Monitoring** Tools like Grafana and Kibana provide user-friendly interfaces for real-time monitoring and data visualization, enabling IT professionals to diagnose issues and identify anomalies quickly.
- **Intelligent Incident Management** The core of the architecture includes intelligent algorithms that guide incidents through a structured workflow from detection to resolution, ensuring a consistent and well-coordinated response.

Typical Use Cases of AIOps Frameworks

AIOps frameworks are employed across various industries to enhance the efficiency and reliability of IT operations. Frameworks are used to monitor and manage large-scale cloud environments, such as Microsoft Azure, to detect failures and optimize resource allocation. Banks and financial services use AIOps to predict and prevent system downtimes, ensuring high availability and minimizing financial losses due to outages. E-commerce companies leverage AIOps to maintain smooth operations during peak traffic periods, such as sales events, by detecting and mitigating performance bottlenecks. Telecom providers utilize AIOps frameworks to monitor network health, predict potential service disruptions, and automate corrective actions to maintain service quality. Healthcare organizations implement AIOps to ensure the reliability of critical IT systems, such as electronic health records platforms, by predicting and addressing potential failures.

2.2.2 Comparison of Features

A critical comparison of AIOps platforms would consider key aspects like scalability, real-time capabilities, the types of machine learning algorithms employed,

and their integration with other IT tools. The systematic grey literature review by Giamattei et al. 2023 provides a helpful basis for such a comparison, as it catalogs a large number of monitoring tools specifically tailored to DevOps and microservice environments. As shown in Table 2.1, the review summarizes various types of tools and their integration with other IT tools.

Table 2.1: Tool Types and Their Integration with IT Tools

Tool Type	**Purpose**	**Integration with IT Tools**
Monitoring	Monitoring microservices, systems performance	Integrated with visualization tools (e.g., Grafana, Graphite) for real-time data display. Many tools also integrate with alerting/event management technologies like Kafka.
Data Collection	Collecting data during system execution	Require integration with databases for persistence and often work alongside other monitoring tools to capture data in real-time from various sources.
Visualization	Visualizing monitoring outcomes	Integrated into monitoring tools, providing dashboards and charts (e.g., Prometheus with Grafana) for decision support and system analysis.
Event Management	Real-time event capture and alerting	Often combined with monitoring tools to trigger alerts based on specific thresholds or events within the system.

2.2.3 Strengths and Limitations

While existing frameworks offer various features, they can still face limitations. For instance, Brondolin and Santambrogio 2020 point out potential scalability concerns in large-scale deployments and some monitoring approaches' dependency on specific operating systems. This underscores the need for continuous innovation in AIOps solutions.

2.3 Performance Monitoring in Distributed Systems

2.3.1 Techniques and Tools

Performance monitoring in distributed systems often relies on specialized techniques and tools capable of collecting and analyzing metrics from various components across a complex infrastructure. Brondolin and Santambrogio 2020 introduce an innovative approach using a black-box monitoring strategy and eBPF (extended Berkeley Packet Filter) technology. This method offers several

advantages, including low overhead and precision in metric gathering. BPF allows for the execution of sandboxed programs directly within the Linux kernel, enabling detailed observations and modifications at various points within the software stack without compromising system stability or security.

Additionally, Taherizadeh et al. 2016 propose a network-level monitoring framework that dynamically adapts application configurations to optimize performance based on real-time network conditions. This shows the importance of network awareness in distributed system optimization. Both papers mention the need for lightweight, non-intrusive monitoring solutions that can provide detailed insights in the complex environment of cloud infrastructures.

The importance of flexible and adaptable monitoring solutions is further reinforced by real-time topology mapping approaches investigated in Shiraishi et al. 2020. The authors explore dynamic sensor deployment to address changing microservices topologies, how monitoring tools must evolve in tandem with the systems they monitor. Additionally, the integration of technologies like eBPF demonstrates the increasing sophistication of monitoring techniques within these complex environments.

The challenges associated with traditional performance monitoring techniques in the context of large-scale microservice systems are highlighted by Shan et al. 2019. These systems face significant issues due to the high volume and complexity of data, the dynamic nature of microservices, and the computational cost of existing machine learning approaches. Shan et al. 2019 offer an innovative unsupervised approach, ϵ-Diagnosis, to address small-window long-tail latency, characterized by sharp variability and heavy-tailed distribution within short statistical windows. This method efficiently identifies root causes in real-time, demonstrating the need for specialized techniques to handle specific types of performance anomalies within the complex environment of distributed systems.

2.3.2 Effectiveness and Efficiency

Recent studies, such as Giamattei et al. 2023, provide valuable insights into the effectiveness and efficiency of monitoring tools designed for microservices and DevOps environments. Their findings show the diversity of tools available and the challenges in selecting the most appropriate ones according to an organization's specific needs. While multiple tools and techniques offer performance monitoring solutions, the effectiveness and efficiency in real-world operational settings, particularly the scalability and precision of diagnosis within large microservice systems, remains a concern. Studies like Seifermann 2017 and Xin et al. 2022 provide valuable insights into these complex issues. Seifermann's industrial case study shows the importance of tool integration and business-aligned strategies, while Xin demonstrates the potential of AI techniques, including machine learning and causal inference, in improving the trustworthiness of performance diagnosis.

2.4 Integration with CI/CD Pipelines

Integrating AIOps into CI/CD pipelines has the potential to enhance software development by embedding advanced analytics and machine learning capabilities. Research demonstrates that AIOps, or Artificial Intelligence for IT Operations, can automate anomaly detection and proactive problem resolution, leading to improved identification and management of performance issues before they impact production systems Vemuri, Thaneeru, and Tatikonda 2024. This integration allows development and operations teams to identify and address performance issues in real time, which reduces the mean time to resolution and minimizes the impact of potential failures on end-users.

Studies have shown that CI/CD pipelines, when properly maintained and evolved, are highly effective in improving software quality and productivity by enabling early defect discovery and faster release cycles. AIOps integration further enhances these benefits by offering predictive analytics that enable preemptive actions, ensuring smoother deployments and reducing downtime. This approach fosters continuous improvement and operational efficiency by providing automated insights and recommendations, allowing teams to focus on more strategic initiatives Zampetti et al. 2021.

Key benefits include:

- **Automated Monitoring:** Research highlights that continuous monitoring of deployments to detect anomalies automatically helps maintaining high system reliability Vemuri, Thaneeru, and Tatikonda 2024.
- **Proactive Interventions:** By utilizing historical and real-time data, AIOps can predict and address potential issues before they escalate, supporting continuous delivery processes Vemuri, Thaneeru, and Tatikonda 2024.
- **Improved Decision-Making:** Immediate feedback on changes enhances decision-making for developers and operations teams, contributing to higher software quality and faster delivery times Zampetti et al. 2021.

These studies emphasize that integrating AIOps within CI/CD is beneficial for modern development practices, which prioritize automation, efficiency, and continuous learning. Maintaining and restructuring CI/CD pipelines becomes increasingly important to maximize the benefits of AIOps, ensuring that the pipelines can adapt to technological changes and continue to support high-quality software delivery Zampetti et al. 2021.

2.5 Role of Machine Learning in AIOps

2.5.1 Machine Learning Algorithms Used in AIOps

Machine learning is becoming central to AIOps solutions, with algorithms like clustering, decision trees, and neural networks commonly used for tasks such as

anomaly detection, root cause analysis, and performance prediction. Papers like Du, Xie, and He 2018 and Xin 2023 demonstrate how machine learning can analyze vast amounts of performance data to pinpoint anomalies and their sources in complex microservices architectures. Xin especially shows the benefits of ensemble learning and weakly-supervised techniques to improve the robustness of detection systems when labeled data is scarce.

2.5.2 Success Stories and Failures

While machine learning shows significant promise in AIOps, challenges remain. Data quality, model interpretability, and the need for continuous learning in dynamic environments are important for successful implementation. Moreover, Wang et al. 2020 demonstrate how machine learning-driven fault diagnosis can be integrated with workflow analysis for enhanced effectiveness, which is particularly important in distributed systems where interactions between components are crucial.

2.5.3 Challenges in ML Application

Despite progress, certain challenges persist. Scalability to very large cloud environments remains an issue, as seen in both Taherizadeh et al. 2016Xin 2023. Additionally, while Du, Xie, and He 2018 focus on hardware faults, the detection of complex, software-level anomalies in large, evolving microservices architectures requires further attention.

The potential of machine learning techniques to enhance performance monitoring and anomaly detection is further demonstrated by Shan et al. 2019. Their use of time-series similarity metrics within the ϵ-Diagnosis tool illustrates how algorithms can be tailored to specific anomaly types. Moreover, Xin 2023 explores AI-based frameworks, combining techniques like ensemble learning and causal inference to enhance performance diagnosis in complex distributed systems, underscoring the potential of such techniques in improving reliability and user trust.

Additionally, Hrusto, Engström, and Runeson 2022 introduce the concept of integrating continuous feedback from development teams to refine anomaly detection models within DevOps environments. This shows the importance of a collaborative approach between development and operations in real-world AIOps implementations.

2.6 Gaps and Opportunities

2.6.1 Identification of Research Gaps

The reviewed literature notes several gaps and challenges that the research could address:

- **Scalability and Adaptability:** Developing scalable monitoring and machine learning-driven diagnostic tools capable of handling massively distributed architectures, while minimizing performance overheads, and robustly handling rapidly changing microservices architectures, frequent updates, and evolving anomaly patterns (Taherizadeh et al. 2016, Xin 2023, Shiraishi et al. 2020, Hrusto, Engström, and Runeson 2022, Waseem et al. 2021).
- **Data Quality and Model Training:** Innovating methods to reduce dependency on labeled data while maintaining or improving the accuracy of detection mechanisms using techniques like semi-supervised learning (Xin 2023).
- **Network Awareness:** Integrating real-time network monitoring and proactive adjustments to optimize performance in highly dynamic distributed systems (Taherizadeh et al. 2016).
- **Usability and Human-Machine Collaboration:** Designing intuitive dashboards and tools that empower both operators and developers, promoting collaboration and actionable insights (Ivanov et al. 2019, Hrusto, Engström, and Runeson 2022, Ergasheva et al. 2020).
- **Strategic Implementation and Dashboards** Effective integration of AI-driven diagnostic tools with customized dashboards in a way that maximizes their impact on decision-making processes and aligns with the domain context remains an area for improvement (Abduldaem and Gravell 2019, Ergasheva et al. 2020).

2.7 Conclusion

In conclusion, in this chapter we reviewed the development and current state of Artificial Intelligence for IT Operations (AIOps). We traced its evolution from traditional IT operations management to its current use of machine learning and data analytics for automating IT operations. We examined how cloud computing and microservices architectures have increased the complexity of IT operations, requiring efficient performance monitoring and specialized engineering approaches.

The chapter also reviewed existing AIOps frameworks, comparing their functionalities, architectures, and use cases. We highlighted the need for scalable solutions that can handle real-time operations and integrate with various IT tools. We discussed techniques for performance monitoring in distributed systems, emphasizing non-intrusive monitoring solutions.

Additionally, we explored the integration of AIOps with CI/CD pipelines, showing how this improves software development through automated anomaly detection and proactive problem resolution. This integration supports continuous improvement in DevOps practices by enhancing system reliability and operational agility.

We also covered the role of machine learning in AIOps, detailing how algorithms are used for anomaly detection and performance prediction. Despite the advancements, challenges and opportunities for further innovation remain. We identified several research gaps and areas for future advancements, including improving scalability, data quality, real-time network awareness, and usability.

In the next chapter we will we will cover the key requirements for developing an effective AIOps framework. It will outline the functional, non-functional, usability, performance, and security requirements necessary to address the challenges and opportunities discussed in this chapter. The specific research gaps we aim to address include enhancing the scalability and flexibility of AIOps frameworks, and advancing usability through intuitive dashboard design.

Chapter 3

Key Requirements

In this chapter, we outline the requirements for the design and implementation of a robust and scalable AIOps framework tailored for cloud environments. These requirements ensure the framework can effectively monitor, analyze, and optimize cloud application performance while maintaining high standards of reliability and user satisfaction. The key requirements are categorized into functional, non-functional, usability, performance, continuous improvement, and security and compliance requirements.

A survey was conducted to evaluate the importance of these requirements as rated by participants who have significant experience in the field of distributed cloud computing. The subsequent sections delve into these categories in detail, elaborating only the specific requirements considered most important and filtered from Table A.1, providing an understanding of what is necessary to build a successful AIOps framework for monitoring cloud environments. The resulting requirements are outlined in Table 3.1.

Table 3.1: Key Requirements

No.	Category	Description
1. Functional Requirements		
1.1	**Data Collection and Management**	Automated data collection for cloud applications monitoring. Collects metrics, logs, and event streams from various sources.
1.1.1	*Data Sources*	Integration with cloud infrastructure and monitoring tools for continuous data capture.
1.2	**Real-time Data Processing**	Timely insights and responses.
1.2.1	*Stream Processing*	Technologies for real-time data stream analysis and anomaly detection.
1.3	**Anomaly Detection**	Accurate performance issue identification.

Table 3.1: Key Requirements

No.	Category	Description
1.3.1	*High Precision and Recall*	Minimize false positives and maximizes true positive rates.
1.4	**Automated Response and Resolution**	Automates interventions for issue mitigation and resolution.
1.4.1	*Diverse Automated Responses*	Varied responses based on detected anomalies.
1.4.2	*Integration with Operational Tools*	Compatibility with existing management tools.
2. Non-functional Requirements		
2.1	**Scalability**	Scales with increased data and operational size without performance loss.
2.1.1	*Operational Scalability*	Adapts to service deployment and scaling without reconfiguration.
2.2	**Reliability and Robustness**	Maintains uptime and robust performance under varying conditions.
2.2.1	*Reliability*	Operations with automatic recovery from failures.
2.2.2	*Fault Tolerance and Failover Mechanisms*	Redundancy and error handling.
2.2.5	*Stress Testing*	Tests system behavior under extreme conditions.
2.3	**Portability and Integration**	Portable across cloud environments and integrates with existing tools.
2.3.1	*Integration*	Integrates with tools like CI/CD pipelines and Kubernetes.
2.4	**User Interface and Experience**	Intuitive UI for easy access to features and data.
2.4.1	*Intuitive Design*	User-friendly design with familiar UI patterns.
2.5	**Configuration and Customization**	Configuration options for varied operational needs.
2.5.1	*Configuration*	Allows user modification of settings and preferences.
2.6	**System Performance**	Meets benchmarks for response times, processing speeds, and resource utilization.
2.6.1	*Response Times*	Requires rapid responses.
2.6.2	*Processing Speeds*	High processing speeds for real-time data analysis.

Table 3.1: Key Requirements

No.	Category	Description
2.6.3	*Resource Utilization*	Efficient resource use to avoid bottlenecks.
2.7	**Adaptability**	Allows framework to learn and adjust.
2.7.1	*Dynamic Learning Capabilities*	Adjusts algorithms based on performance feedback.
2.7.2	*Self-Optimizing Systems*	Framework to self-optimize through learning.
2.8	**Data Security**	Protects data against unauthorized access and loss.
2.8.1	*Encryption*	Uses secure encryption for data in transit and for data at rest.
2.8.2	*Access Controls*	Implements access controls.
2.9	**Regulatory Compliance**	Complies with regulations like GDPR and CCPA.

3.1 Functional Requirements

3.1.1 Data Collection and Management

For the AIOps framework to effectively monitor and optimize cloud application performance, automated data collection mechanisms are important. The framework should be capable of collecting various types of data, including metrics, logs, and event streams, from a multitude of sources within the cloud infrastructure.

Data Sources

The framework must integrate seamlessly with existing cloud infrastructure components and monitoring tools to capture data continuously. This integration ensures no critical data is missed, thereby enhancing the diagnostic capabilities of the AIOps system. As pointed out by Brondolin and Santambrogio 2020, effective performance monitoring relies on the capability to gather detailed and comprehensive data across the system's architecture.

3.1.2 Real-time Data Processing

Real-time data processing is necessary for an AIOps framework to provide timely insights and facilitate immediate response to emerging issues. This capability enables the system to act swiftly, preventing minor anomalies from escalating into severe disruptions.

Stream Processing

The usage cutting-edge stream processing technologies allows the AIOps framework to analyze and respond to data in real-time. The framework can use algorithms capable of processing high-velocity data streams to detect anomalies as they occur. This aligns with findings from Shiraishi et al. 2020, who mention the need for real-time processing in maintaining system performance across distributed architectures.

3.1.3 Anomaly Detection

Anomaly detection stands is a main function of the AIOps framework. It requires high accuracy to effectively identify and diagnose performance issues. This function will be capable of discerning between normal fluctuations and genuine anomalies.

High Precision and Recall

The anomaly detection mechanisms should achieve high precision and recall, minimizing false positives and ensuring that true issues are promptly addressed. This precision is necessary for maintaining trust in the AIOps framework and for ensuring operational efficiency, as discussed in the work of Du, Xie, and He 2018, which focuses on the reliability of anomaly detection systems in complex IT environments.

3.1.4 Automated Response and Resolution

Once anomalies are detected, the AIOps framework should facilitate automated interventions to mitigate or resolve issues. This automation plays an important role in maintaining system stability and performance.

Diverse Automated Responses

The framework should be capable of executing a variety of automated responses, from resource reallocation to executing recovery scripts, based on the nature of the detected anomaly. This requirement is supported by the work of Wang et al. 2020, who demonstrate the effectiveness of automated responses in maintaining system reliability in distributed environments.

Integration with Operational Tools

Seamless integration with other operational management tools is important for implementing response strategies. This ensures that the AIOps framework acts together with existing workflows and enhances the operational agility, as emphasized by Zampetti et al. 2021 in their study on AIOps integration within CI/CD pipelines.

3.2 Non-functional Requirements

3.2.1 Scalability

The AIOps framework should be designed to efficiently scale in response to an increase in data volume and operational size without degrading performance. This requirement addresses the challenges posed by distributed cloud architectures, which often experience fluctuations in demand and data throughput.

Operational Scalability

As new microservices are deployed or existing services are scaled, the AIOps framework must be able adapt without requiring significant reconfiguration. This capability makes sure that performance monitoring and anomaly detection can continue seamlessly as the operational scope expands.

Achieving these scalability goals involves leveraging cloud-native technologies and architectural principles that support dynamic scaling, such as microservices and containerization. These technologies allow the AIOps framework to distribute its workload across multiple servers dynamically and manage computational resources effectively, aligning with the scalability needs identified in the literature by Waseem et al. 2021.

3.2.2 Reliability and Robustness

Reliability

The AIOps framework must maintain high system uptime and availability to support continuous operations in distributed cloud environments. It should also include mechanisms to automatically recover from common failures without human intervention, thereby minimizing downtime and ensuring operational continuity.

Fault Tolerance and Failover Mechanisms

The design must include fault tolerance mechanisms, such as redundancy, failover capabilities, and error handling procedures that ensure continuous system operation even when individual components fail. The implementation of these features should be tested under scenarios of simulated failures to validate their effectiveness.

Stress Testing

To assess the robustness of the framework, stress testing could be conducted to determine its behavior under rough conditions. This includes testing the system's response to peak data inputs and its ability to maintain functionality during network or power interruptions. Such testing can help identify potential points of failure and areas for improvement. This ensures the framework remains resilient under stress (Heinrich et al. 2017).

3.2.3 Portability and Integration

Integration

Integration capabilities are equally important. The AIOps framework should seamlessly integrate with existing tools and platforms commonly used in cloud environments. This includes compatibility with CI/CD pipelines, container orchestration systems like Kubernetes, and various DevOps tools, ensuring that the framework enhances rather than disrupts existing workflows.

Tool Compatibility To achieve effective integration, the framework could provide APIs and plugins that facilitate easy connection with IT management and monitoring tools. This compatibility helps in leveraging existing data inputs and operational controls without the need for modifications to current systems.

Data Exchange Standards The framework should adhere to common data exchange standards and protocols to ensure that it can easily share data with other systems. This interoperability helps in collaborative anomaly detection and performance optimization efforts across different tools and platforms.

By focusing on both portability and integration, the AIOps framework can be deployed in any cloud environment. Additionally it can work cooperatively with the array of tools that enterprises use to manage their IT infrastructure. This focus on portability and integration addresses the need for AIOps solutions to be both customizable and scalable across diverse cloud environments.

3.3 Usability Requirements

3.3.1 User Interface and Experience

To ensure the AIOps framework is effectively utilized across various organizational levels, it can feature a user interface (UI) that is intuitive and streamlined. The UI can facilitate quick access to the most necessary features and offer a display of monitoring data and analytics outputs. The design principles should be minimalistic and clear to avoid overwhelming the user, which aligns with the principles of effective tool use in complex system monitoring as highlighted by Ivanov et al. 2019.

Intuitive Design

The interface should be designed to ensure that users can navigate easily and find functionalities without extensive training. This could mean using familiar UI patterns and leveraging best practices in UX design to enhance the usability of the framework. Consistency in design elements such as buttons, colors, and layout can help in reducing the learning curve and improving user adoption rates.

3.3.2 Configuration and Customization

Given the varied nature of distributed cloud environments, the AIOps framework can offer robust configuration and customization options to adapt to different operational scenarios. This flexibility allows users to set the system according to specific needs, enhancing its effectiveness and user satisfaction.

Configuration

Users could be able to modify settings and preferences to suit their operational context. This can be features such as setting thresholds for anomaly detection or customizing dashboards to highlight relevant data. This level of customization supports the dynamic nature of cloud operations and helps users to fine-tune the system based on real-time requirements.

3.4 Performance Requirements

3.4.1 System Performance

For the AIOps framework to efficiently support distributed cloud applications, it should meet specific performance benchmarks that ensure timely and accurate responses to operational demands. These benchmarks can be response times, processing speeds, and resource utilization, which are important in maintaining the reliability and efficiency of cloud services.

Response Times

The system must deliver fast responses to performance anomalies and system requests, adhering to time constraints to prevent operational disruptions. The expected response times could be defined based on the criticality of the tasks, with more urgent processes prioritized to ensure system stability. This requirement helps in environments where delays can lead to significant operational losses, as mentioned by Heinrich et al. 2017.

Processing Speeds

High processing speeds are important for the real-time analysis of large volumes of data generated within cloud environments. The framework should process data swiftly by leveraging optimized algorithms and efficient computing resources, as this facilitates immediate insights and actions. This capability allows for maintaining high-throughput systems where performance bottlenecks can have cascading negative effects.

Resource Utilization

Efficient resource utilization ensures that the AIOps framework does not become a performance bottleneck itself. The system should be designed to use compu-

tational resources sparsely, optimizing for the best performance with minimal overhead. Techniques such as load balancing and resource scaling can be employed to manage resource demand dynamically, as per the scalability strategies discussed by Waseem et al. 2021.

3.5 Continuous Improvement and Learning

3.5.1 Adaptability

For an AIOps framework to remain effective in the evolving landscape of cloud computing, it can be be designed with adaptability at its core. This involves the framework's ability to learn from its operations and adapt its functions accordingly, thereby enhancing its performance and capabilities over time.

Dynamic Learning Capabilities

The AIOps framework can incorporate mechanisms that allow it to dynamically adjust its algorithms based on feedback from its performance monitoring. This could include automated tuning of parameters and thresholds in response to detected anomalies or changes in the cloud environment. This capability ensures that the framework remains effective as new patterns of performance issues emerge, addressing the adaptability needs identified by Taherizadeh et al. 2016).

Self-Optimizing Systems

Integrating features that enable the framework to optimize its own operations through continuous learning processes is an interesting implementation. This could include the use of machine learning models that evolve based on new data, improving their accuracy and efficiency in anomaly detection and system diagnostics. The benefits of such self-optimizing systems in enhancing the robustness and responsiveness of AIOps solutions have been mentioned by Xin 2023.

3.6 Security and Compliance Requirements

3.6.1 Data Security

Ensuring the confidentiality, integrity, and availability of data within the AIOps framework is a factor to be considered, given the sensitivity and critical nature of performance data in cloud environments. The security measures can protect against unauthorized access, data breaches, and accidental or intentional data loss.

Encryption

Data transmitted to and from the AIOps framework can be encrypted using industry-standard protocols such as TLS (Transport Layer Security) to protect data in transit. Similarly, data at rest couls be encrypted using algorithms that comply with security standards, ensuring that data stored within the system remains confidential and secure from unauthorized access.

Access Controls

Implement strict access controls based on the principle of least privilege, ensuring that users and systems have access only to the resources necessary for their specific roles and functions. This should be complemented by multi-factor authentication (MFA) to further secure access to the AIOps platform, particularly for administrative functions that could impact the overall security posture of the system.

3.6.2 Regulatory Compliance

The AIOps framework must adhere to a range of compliance requirements that vary depending on the geographical location and industry in which it operates. This includes regulations related to data protection, such as GDPR in Europe and CCPA in USA, which dictate how personal and sensitive information must be handled and protected.

3.7 Conclusion

In this chapter, we have outlined the requirements for developing a robust and scalable AIOps framework for cloud environments. By categorizing these requirements into functional, non-functional, usability, performance, continuous improvement, and security and compliance, we provide a structured approach to ensure the framework can monitor, analyze, and optimize cloud application performance.

In the next chapter, we will explore the architectural design of the AIOps framework. We will discuss the key components and their interactions, providing a detailed blueprint for implementing the requirements outlined in this chapter.

Chapter 4

System Design and Architecture

In this chapter we cover the necessary components for implementing an AIOps framework in cloud environments. We discuss the importance of a well-designed architecture that meets the functional and non-functional requirements, as well as including usability, performance, continuous improvement, and security.

We mention the need for modularity and scalability to make the framework integrates with existing cloud infrastructures and tools. Advanced technologies for real-time data processing, anomaly detection, and automated responses are important for maintaining performance and reliability.

Additionally, continuous improvement mechanisms are discussed to enable the framework to evolve and optimize over time. Security and compliance requirements are also mentioned to ensure data protection and adherence to regulatory standards.

The architectural considerations and design principles outlined provide a solid foundation for developing an AIOps framework that effectively monitors, analyzes, and optimizes cloud application performance. This framework is set to enhance the efficiency and reliability of cloud operations, serving as a guide for practical implementation and ongoing improvement.

4.1 Design Methodology

4.1.1 Design Principles

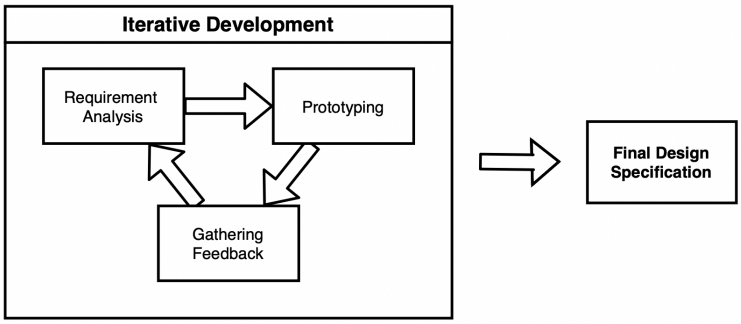
The AIOps framework is structured around principles that ensure its effectiveness and adaptability in diverse cloud environments: *Modularity, Scalability, Interoperability and Continuous Learning and Adaptation. Modularity* enables the system to be divided into independent modules that facilitate easier updates and maintenance. *Scalability* ensures the framework can handle varying loads and data sizes without performance degradation. *Interoperability* to operate

with existing systems, the framework is built with standard APIs and follows common data exchange protocols. This ensures that it can easily integrate with other tools and platforms.The design supports *Continuous Learning and Adaptation* to new challenges and operational conditions. This includes mechanisms for feedback, monitoring, and performance tuning.

4.1.2 Design Process

The design process adopted for the AIOps framework follows an iterative approach. This method supports revisions and refinements based on stakeholder feedback and updating requirements accordingly. The process began with a initial design phase where basic functionalities were outlined. Subsequent phases focused on enhancing these functionalities through iterative testing and feedback loops, ensuring alignment with the demands of cloud environments (figure A.4).

Figure 4.1: Schematic Drawing Design Process



1. Drafting initial design concepts based on the requirements specified in Chapter 3.
2. Developing prototypes to explore the feasibility of design concepts.
3. Refining the system requirements and design through iterations, incorporating feedback from simulated deployments and stakeholder reviews.
4. Establishing design specifications that includes descriptions of system components, data flows, and interaction protocols.

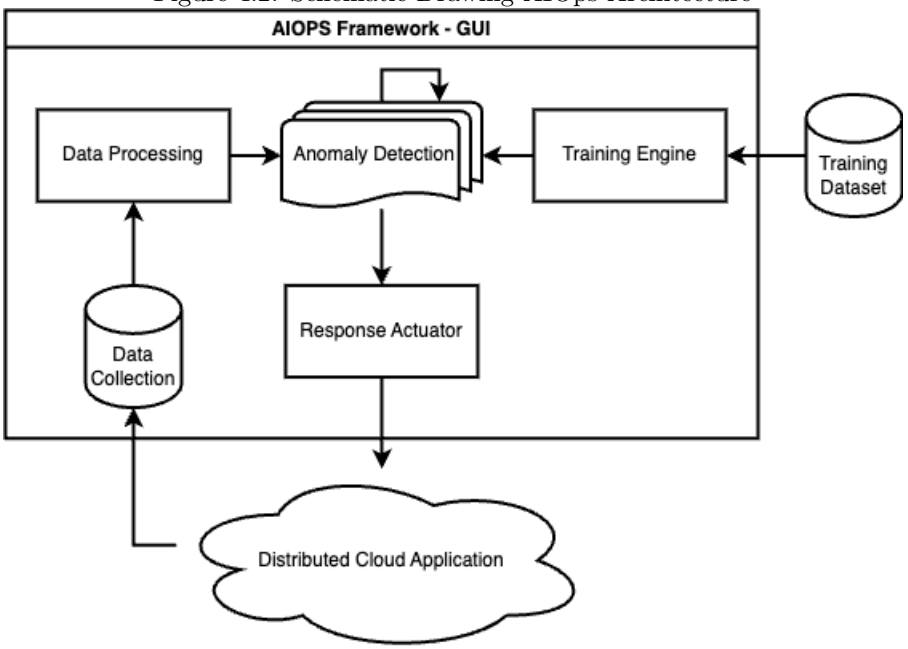
4.2 System Architecture

4.2.1 High-Level Architecture

The architecture of the AIOps framework presented in figure 4.2 integrates various components designed to enable performance monitoring, anomaly detection,

and automated response across distributed cloud applications.

Figure 4.2: Schematic Drawing AIOps Architecture



- Data Ingestion Layer - Responsible for collecting data from diverse sources, such as logs, metrics, and event streams.
- Data Processing Engine - Analyzes ingested data in real-time to detect potential issues.
- Anomaly Detection Modules - Utilize machine learning models to identify anomalies.
- Response Actuator - Execute responses based on detected anomalies.
- Training Engine - Facilitates the initial and ongoing training of AI models specific to the operational environment.
- User Interface - Provides users with tools to monitor and interact with the system.

4.2.2 Component Design

Each component of the AIOps framework is designed to meet the requirements discussed in Chapter 3:

Data Ingestion Layer Uses mechanisms to gather real-time and historical data from cloud infrastructure. It ensures data capture with minimal impact on system performance.

Data Processing Engine Process data streams efficiently, focusing on minimizing latency and maximizing throughput.

Anomaly Detection Modules These modules are equipped with various machine learning algorithms that are initially trained on historical data reflective of typical operational scenarios. They continuously refine their models based on new data to improve their predictive accuracy over time.

Response Actuator Implements a range of automated actions, from resource reallocation to triggering recovery protocols, based on the anomaly detected and predefined response strategies.

Training and Adaptation Engine Manages the initial training of AI algorithms for specific environments, using a dataset that reflects the characteristics of the deployment environment. It also supports ongoing retraining and model adaptation to allow for changes in system behavior or operational conditions.

User Interface Designed for ease of use allowing users to configure monitoring parameters, set anomaly thresholds, and view system analytics. The interface provides insights and facilitates interaction with the system for deeper analysis.

4.3 Data Management

4.3.1 Data Collection

The data collection design for the AIOps framework involves capturing an array of data types. These include performance metrics, logs, and event notifications from various cloud infrastructure components such as application servers, databases, and network systems as defined below.

Data Sources

- *Input Sources* - Application servers, databases, network devices
- *Monitoring Agents* - Interface with existing monitoring tools
- *Data Types Collected*:

  Metrics - CPU usage, memory usage, network bandwidth

  Logs - Error logs, transaction logs

Events - Real-time notifications, system alerts

- *Continuous Collection* - Ensures real-time data flow and coverage

4.3.2 Data Storage

The framework incorporates a structured data storage that categorizes data into short- and long-term storage according to their use cases. Short-term storage handles real-time data for immediate processing, while long-term storage archives data for historical analysis and training datasets for machine learning models. This layered storage strategy is important in managing the volume and variety of data, ensuring scalability and data integrity as defined below.

Data Storage

- *Short-term Storage*

  Purpose - Immediate processing for real-time analytics

  Characteristics - High speed, optimized for quick access

- *Long-term Storage*

  Purpose - Historical analysis, training data for AI models

  Characteristics - High capacity, durability, optimized for data integrity

- *Data Scaling*

  Dynamic Scaling - Adjusts storage resources based on data volume and velocity

  Layered Storage - Balances load between short- and long-term needs

4.3.3 Data Processing

Data processing within the AIOps framework is organized into real-time and batch processing. Real-time processing focuses on immediate anomaly detection and alerting, while batch processing handles comprehensive analyses like trend assessment and predictive modeling. Additionally, the framework includes a specialized workflow for managing and refining anomaly datasets used in AI training (table 4.3.3).

Data Processing

- *Real-Time Processing*

  Objective - Immediate anomaly detection and alert generation

  Process:

- Filter and prioritize incoming data
- Analyze data against predefined thresholds and patterns

- *Batch Processing*

  Objective - In-depth analysis for trends and predictive modeling

  Process:

  - Aggregate data over time
  - Perform complex analyses, such as machine learning model training

4.3.4 Anomaly Data Sets for AI Training

The framework's design includes a special mechanism for the management of anomaly data sets, used for training and refining AI models. This involves the collection and labeling of anomaly instances. These are then processed and stored in the long-term storage system. This data is composed to ensure high quality and relevance, with features and labels clearly defined to train the AI models effectively. The design supports ongoing learning and adaptation of AI algorithms by integrating new data into the training sets. This allows the models to evolve in response to new patterns and changes in the system. This training process is aids maintaining the accuracy and effectiveness of anomaly detection over time.

4.4 Machine Learning Models

4.4.1 Model Selection

The selection of machine learning models for the AIOps framework is guided by the specific needs for anomaly detection and automated responses within cloud environments. The framework uses a combination of supervised and unsupervised learning models to manage the variety of data and anomaly types encountered. The choice of models is determined by their ability to handle the scale of data, their accuracy in diverse operational scenarios, and their computational efficiency

Supervised Learning Models Used for scenarios where historical data on anomalies is labeled and abundant, enabling models like decision trees, support vector machines, and neural networks to learn and predict based on past incidents.

Unsupervised Learning Models Used in situations where anomaly labels are scarce or unavailable. Techniques such as clustering and principal component analysis help in identifying new or unknown types of anomalies by analyzing patterns and deviations in the data.

4.4.2 Model Training

Model training within the AIOps framework involves several key steps designed to optimize performance and accuracy:

1. Data Preparation: Involves cleaning, normalizing, and segmenting data into training and testing sets. Special attention is given to the management of anomaly data sets to ensure models are give a broad range of scenarios.

2. Feature Engineering: Enhancing model performance, this process involves selecting, modifying, or creating new features from raw data to improve the interpretability of models and their predictions on anomalies.

3. Training Environment: Facilitating the training of complex models on large datasets. The environment supports both continuous and batch training modes to accommodate ongoing learning and adaptation of models. Can utilizes cloud-based platforms to leverage scalable computing resources.

4.4.3 Model Deployment

Once trained, the models are deployed within the AIOps architecture where they continuously analyze incoming data streams for anomalies. The Models are integrated into the anomaly detection modules, ensuring seamless operation and immediate application of their insights. To maintain high accuracy and relevance, models are regularly evaluated against new data, and retrained or fine-tuned as necessary. This includes updating models with new anomaly data sets to adapt to evolving cloud environments. Continuous monitoring of model performance is implemented to quickly identify degradation or drift in predictions. Metrics such as precision, recall, and F1-score are tracked to ensure models meet operational standards.

4.5 Integration and Interfaces

4.5.1 System Integration

The AIOps framework intents to integrates with existing IT systems and platforms to enhance operational efficiency and align with known cloud services. Important to this integration capabilities are standard APIs and adherence to common data exchange protocols, which facilitate seamless interactions with existing cloud infrastructure, monitoring tools, and CI/CD pipelines.

CI/CD Pipeline Integration with CI/CD pipelines allows the AIOps framework to interact dynamically with software deployment processes. This interaction enables the framework to provide real-time feedback and automated

anomaly detection during various stages of software development and deployment, thus contributing to higher reliability and faster resolution of issues.

Cloud Services The framework's design will support integration with major cloud service providers like AWS, Azure, and Google Cloud. This ensures that the AIOps framework can operate within any cloud environment, usable for scaling and managing cloud-native applications.

4.5.2 User Interfaces

The user interfaces of the AIOps framework are designed to ensure that they are intuitive and accessible, providing users with a clear view of system analytics and operational statuses. These interfaces include dashboards that present data in an understandable format, allowing users to make informed decisions quickly.

Dashboards Several dashboards are designed to provide a provide overview of system performance, including real-time data on network traffic, resource utilization, and anomaly detection outcomes. These dashboards are customizable to adjust the specific needs of different users.

Configuration Tools Configuration tools within the UI allow users to adjust settings, such as thresholds for anomaly detection and data collection parameters, according to their requirements. These tools are designed to be user-friendly, enabling users without technical expertise to manage the AIOps framework.

Manual Anomaly Entry The user interface provides an option for users to manually input anomaly data into the Training and Adaptation Engine. This allows system operators to directly contribute to the training dataset, enhancing the learning process and refining the predictive accuracy of the AI models. Users can specify the type of anomaly, associated data, and circumstances, helping more targeted adjustments to AI behavior.

4.5.3 Data Interoperability

The framework adheres to standard protocols for data exchange, ensuring that data can be shared across different platforms without compatibility issues. This interoperability promotes collaborative operations and for maintaining data integrity across IT environments.

4.6 Scalability Strategies

The AIOps framework is designed with robust scalability strategies to handle varying loads and data sizes effectively. The aids maintaining performance and reliability in dynamic cloud environments. Scalability features include:

Vertical Scaling The framework can scale up its computational resources to handle increased data processing needs during heavy loads, such as adding more CPU or memory resources to existing servers.

Horizontal Scaling It also supports horizontal scaling, which involves adding more instances or nodes to distribute the workload more evenly. This is useful for data ingestion and processing tasks across distributed architectures.

4.7 Data Flow

Data Ingestion Data ingestion is the initial phase where the system acquires data from various sources. These sources include cloud infrastructure components like application servers, databases, and network devices, as well as external monitoring tools that provide metrics, logs, and event streams. The ingestion layer is designed to capture this data in real-time, maintaining a continuous flow into the processing engine.

Processing When data is ingested, it is directed to the data processing engine, where it undergoes initial filtering and prioritization. This stage identifies data that require attention and reducing noise from the operational data stream. The processing tasks are conducted in real-time to support quick insights and decision-making. Processes include data normalization, aggregation, and preliminary analysis to prepare the data for further examination.

Anomaly Detection At this stage, the data is analyzed using various anomaly detection techniques implemented within the anomaly detection modules. These techniques range from statistical methods to advanced machine learning models that identify deviations from normal operational patterns. Anomalies are flagged based on predefined thresholds and patterns of potential issues.

Response Mechanisms When an anomaly is detected, the response actuator component of the system is triggered. This component is responsible for executing response strategies based on the type and severity of the detected anomaly. Responses can include automated adjustments such as resource reallocation, recovery scripts, or triggering alerts for manual intervention.

Training and Adaptation At the same moment, the training and adaptation engine uses the data, to train and refine the machine learning models. This involves adjusting model parameters and incorporating new data into the learning algorithms to enhance their accuracy and adaptability to changing conditions.

Feedback Loop The entire process follows a feedback loop that continuously monitors the outcomes of the data processing and response actions. This feedback is used to improve data handling procedures, anomaly detection accuracy, and the effectiveness of response mechanisms. The system logs all actions and decisions for analysis, which aids in future learning and system improvement.

4.8 Conclusion

In this chapter, we detailed the design and architecture of an AIOps framework for cloud environments. We discuss the importance of an architecture that meets both functional and non-functional requirements, as well including usability, performance, continuous improvement, and security.

Key aspects of modularity and scalability were discussed for integration with existing cloud infrastructures and tools. Advanced technologies for real-time data processing, anomaly detection, and automated responses were discussed to ensure the framework maintains performance and reliability.

We addressed continuous improvement mechanisms to enable the framework's evolution and optimization over time. Security and compliance requirements were also considered to ensure data protection and adherence to regulatory standards.

The design principles and architectural considerations provide a foundation for developing the AIOps framework. This framework design allows for effective monitoring to optimizes cloud application performance and with that enhancing cloud operations. The principles ensure that the framework is adaptable and capable of meeting the demands of cloud environments.

In the next chapter, we will delve into the implementation of the proof of concept. This includes the development environment, tools, and technologies used, as well as the implementation details of each module implemented within the AIOps framework proof of concept.

Chapter 5

Implementation Proof of Concept

In this chapter, we transition from the theoretical framework and system architecture to the practical implementation of our AIOps framework within a cloud environment. We detail the development environment, the tools and technologies employed, and the step-by-step process of implementing the components we have implemented in the AIOps framework, as well as establishing a set of requirements for other algorithms to be implemented within the framework.

We provide a proof of concept that intents to validate several of the architectural choices and design principles discussed in the previous chapters. The implementation provides a foundation for further development and real-world deployment.

5.1 Development Environment

In this section, we describe the hardware and software configurations, tools, and technologies employed in the development of the AIOps framework.

5.1.1 Hardware and Operating System

We conduct our development activities on a MacBook Air with an ARM M1 processor. The operating system used is macOS, which provides compatibility with a range of development tools and frameworks necessary for this project.

5.1.2 Development Tools

We have used Visual Studio Code and Minokube to facilitate the development process. VSCode serves as the IDE and supports various aspects of development, including coding, debugging, and version control. Minikube is used to run

a local Kubernetes cluster on the development machine, allowing for local testing and development of Kubernetes deployments before moving to production environments.

5.1.3 Frameworks and Libraries

We utilize a combination of frameworks and libraries to support the development process:

- **Flask** Used for most modules due to its simplicity and flexibility in handling routing, request processing, and API development.
- **Django** Used for developing the user interface. The frameworks holds extensive features and modular design to build scalable and maintainable web applications.
- **Celery** Used for managing long-running tasks, supporting asynchronous task execution to improve the system's responsiveness.
- **Redis** Functions as the message broker for Celery, facilitating communication between different system components.
- **Docker** Used for containerizing applications, ensuring consistency across development and production environments.
- **Kubernetes** Used for orchestrating containerized applications, automating deployment, scaling, and management processes.
- **GitHub CI/CD** Utilized to automate building, and deployment processes.
- **Google Cloud** Chosen as the cloud platform for deploying the AIOps framework, providing a reliable and scalable infrastructure.

5.1.4 Programming Languages

The primary programming languages utilized in this project are Python, HTML and JavaScript. Python is used for backend development, including data processing, machine learning model implementation, and server-side logic. Python is chosen for its extensive libraries and strong support for data analysis and machine learning. Additionally this is the programming language the anomaly detection algorithms are written which, allowing for better compatibility. HTML and JavaScript are used for front-end development for an interactive and responsive user interface. HTML is used to structure web pages, while JavaScript for dynamic behavior and enhancement of we user interaction.

5.2 Justification of Technology Choices

The selection of specific technologies and frameworks for the AIOps framework was driven by several factors, including their suitability for the intended tasks, ease of integration, scalability, and the existing ecosystem of tools. Below, we provide the justification for the chosen technologies over alternatives.

5.2.1 Flask vs. Other Web Frameworks (e.g., Express.js, Spring Boot)

Flask was selected as the primary web framework for most of the modules due to its simplicity, flexibility, and Python compatibility. Flask's lightweight nature allows for rapid development, which is important for building the RESTful APIs that form the backbone of the AIOps framework. Unlike more heavyweight frameworks like Django (used here specifically for the UI), Flask provides greater control over component integration and customization, making it ideal for the microservices architecture employed in this project.

Express.js, based on Node.js, is known for its speed and non-blocking features. However, Flask's tight integration with Python's data processing libraries made it more suitable for our machine learning and data-intensive tasks. On the other hand, Spring Boot, a Java-based framework, provides extensive enterprise-level features but introduces more complexity and a steeper learning curve, which is unnecessary for the scope of this project.

5.2.2 Django for User Interface vs. Flask or React

Django was chosen for developing the user interface because of its comprehensive feature set, including built-in ORM and form handling. Django's approach simplifies the development of a scalable and maintainable web application.

While Flask could be used for the UI, it lacks the built-in features of Django, which would require additional libraries or custom development to match Django's capabilities. React, while useful in building dynamic, single-page applications, was deemed unnecessary given the scope and complexity of the required UI. Django's templating system and built-in tools were more than adequate for our needs.

5.2.3 Celery with Redis vs. RabbitMQ, Kafka, or SQS

Celery was selected for managing background tasks because of its seamless integration with Python and its ability to handle asynchronous task execution, which is important for non-blocking operations like data collection and processing.

Redis was chosen as the message broker for Celery because of its speed and ease of use. Redis's in-memory data structure is well-suited for the task queue's needs, where low latency is important. Although RabbitMQ is a robust message broker with advanced messaging features, Redis provides sufficient functionality

for our use case with lower operational overhead. Kafka is useful for large-scale, distributed messaging but introduces unnecessary complexity for the relatively straightforward task management needed in this project. AWS SQS could have been an alternative, especially for cloud-native environments, but Redis's integration with Celery and its ability to run locally during development made it the preferred choice.

5.2.4 Docker and Kubernetes vs. Virtual Machines or Docker Swarm

Docker and Kubernetes were chosen for containerization and orchestration because of their dominance in the industry, strong community support, and robust features for managing complex, distributed applications.

Virtual Machines offer isolation but lack the efficiency and flexibility of containers, particularly in environments where rapid scaling and microservices architecture are involved. Docker Swarm, while simpler than Kubernetes, lacks Kubernetes' extensive feature set, particularly for large-scale orchestration, self-healing, and auto-scaling.

5.2.5 Google Cloud vs. AWS or Azure

Google Cloud was selected as the cloud platform due to its strong support for Kubernetes (via Google Kubernetes Engine), data analytics, and machine learning services, which align well with the needs of the AIOps framework.

AWS offers a broader range of services, but Google Cloud's integration with Kubernetes and its managed services were more aligned with the project's requirements for simplicity and scalability. Azure also provides strong Kubernetes support, but Google Cloud's pricing and machine learning capabilities made it the preferred choice for this project.

5.2.6 Python for Backend Development vs. JavaScript or Java

Python was the natural choice for backend development due to its extensive libraries for data analysis and machine learning (e.g., Pandas, NumPy, Scikit-learn, PyTorch).

JavaScript (Node.js) is efficient for I/O operations but does not offer the same level of support for data science and machine learning tasks as Python. Java is powerful and has strong performance in enterprise applications, but Python's simplicity and the vast ecosystem of scientific computing libraries make it more suitable for this project.

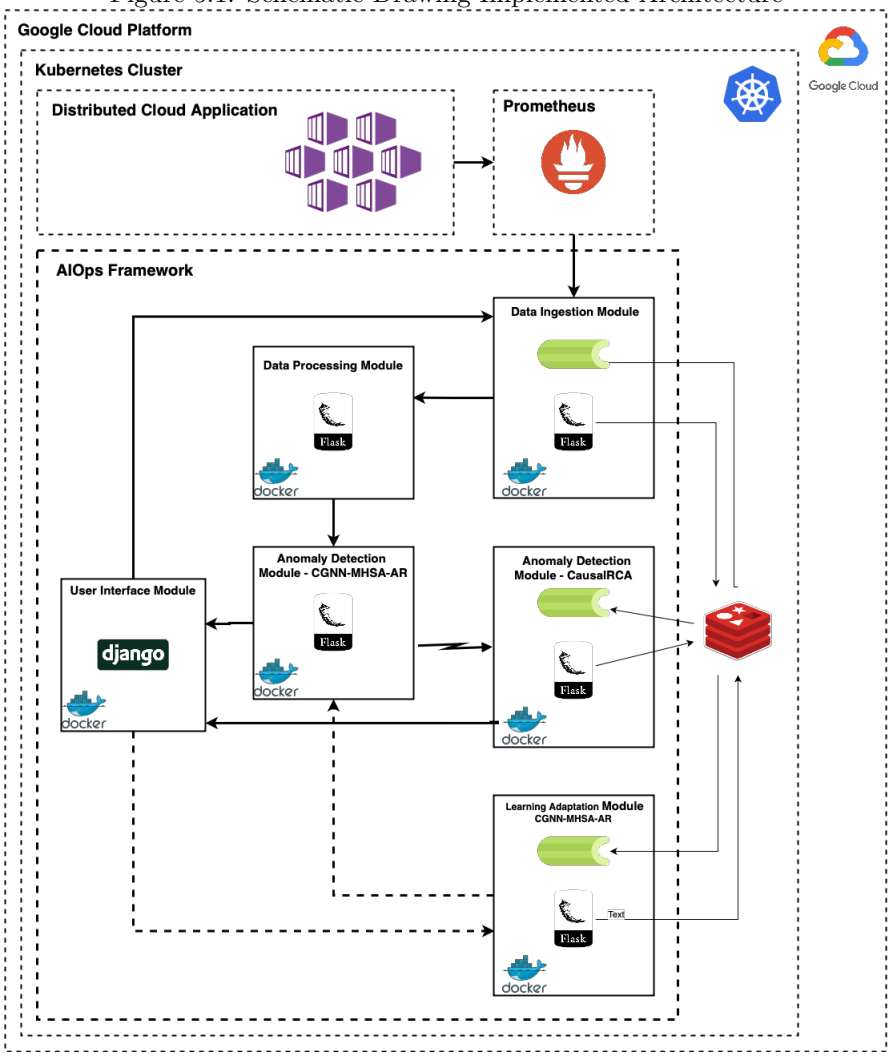
The technologies and frameworks were selected based on their ability to meet the project's specific needs, including performance, scalability, ease of development, and integration capabilities. Each decision was guided by the goal of creating a maintainable, and scalable AIOps framework that can handle the complexities of cloud environments and machine learning tasks. These choices

reflect a balance between leveraging cutting-edge tools and ensuring the framework remains manageable and aligned with industry best practices.

5.3 Implementation Details

In this section, we outline the implementation of our system architecture as shown in figure 5.8. We describe the key components, workflow and operational workflow for each module implemented.

Figure 5.1: Schematic Drawing Implemented Architecture



5.3.1 Data Collection Module

Overview

We utilize a Flask-based web server to manage data collection tasks within the Data Collection Module. To handle task scheduling, we employ Celery, with Redis acting as the message broker. The module interfaces with Kubernetes to fetch pod metrics and uses Prometheus for querying these metrics. The collected data is then processed and stored for anomaly detection.

Key Components

- **Flask Application:** Our Flask application serves as the main entry point for managing data collection tasks, providing RESTful APIs to start, stop, and monitor these tasks. This ensures external control and query capabilities for the system.
- **Celery:** We use Celery to manage background tasks, allowing continuous monitoring without blocking the main application. Redis is configured as the broker and backend for task management, facilitating communication and state management of these tasks.
- **Kubernetes Client:** The Kubernetes client interacts with the Kubernetes API to fetch pod details and metrics. This ensures real-time data collection from the distributed cloud environment, enabling us to monitor specific pods and their performance metrics accurately.
- **Prometheus:** We utilize Prometheus to query metrics from the Prometheus server. Specific PromQL queries are constructed to fetch the required metrics for each pod, allowing us to collect a wide range of performance data, such as CPU usage, memory usage, and network I/O.
- **Configuration Management:** Configuration settings for the metrics to be collected are stored in a configuration file (`metric_config.json`). Our module includes functions to update and retrieve these settings, ensuring flexibility and adaptability in the metrics collection process.

Workflow

1. **Starting Monitoring:** When the `/start_monitoring` endpoint is invoked, it accepts a JSON configuration detailing the monitoring requirements, including information on which pods to monitor, what metrics to collect, and the duration and frequency of data collection. A new Celery task is then initiated to start continuous monitoring based on this configuration.
2. **Data Collection:** The `monitoring_task` function in Celery handles the continuous collection of metrics. It periodically queries Prometheus for the specified metrics of the given pods. The collected data is processed into

a pandas DataFrame and sent to a processing API for further handling. This ensures continuous data collection, processing, and availability for anomaly detection.

3. **Fetching Metrics:** The `fetch_metrics` function constructs Prometheus queries using the configuration settings. It retrieves metric data within the specified time range and processes it into a pandas DataFrame. This function ensures that the data is formatted correctly, and any missing data is handled appropriately to maintain data integrity.

4. **Handling Kubernetes Integration:** Our module includes endpoints for loading Kubernetes configuration and fetching pod names. This integration allows the module to dynamically interact with the Kubernetes environment, ensuring accurate and up-to-date data collection.

5. **Configuration Management:** Configuration settings can be managed through endpoints provided by the Flask application. We have implemented functions to load, update, and set initial configurations for the metrics to ensure the system can adapt to changing monitoring requirements. This helps in maintaining flexibility and ensuring the relevant metrics are always being collected.

Operational Workflow

- **Task Initialization:** When a monitoring task is started, the system initializes with the provided configuration, ensuring that all necessary parameters are set for data collection.
- **Periodic Data Collection:** The Celery task periodically executes Prometheus queries, collecting and processing data at defined intervals.
- **Data Processing:** Collected data is formatted into a DataFrame, handling any missing or incomplete data to ensure accuracy.
- **API Interaction:** Processed data is sent to an external API for further processing, ensuring seamless integration with other components of the AIOps framework.
- **Continuous Monitoring:** The system runs continuously, handling data collection and processing in the background, and providing real-time monitoring and anomaly detection capabilities.

5.3.2 Data Processing Module

The Data Processing Module utilizes a Flask-based web server to handle preprocessing requests. It processes both CGNN-MHSA-AR and CausalRCA data, preparing them for anomaly detection tasks. The module normalizes data, manages training and test data sets, and interfaces with external APIs for further processing.

Key Components

- **Flask Application:** The Flask application serves as the main interface for preprocessing requests. It provides endpoints for handling CGNN-MHSA-AR training data and test data, and CausalRCA data. This structure ensures a standardized approach to data preprocessing within the AIOps framework.
- **Data Preprocessing Functions:** Functions for handling CGNN-MHSA-AR and CausalRCA requests manage data loading, normalization, and formatting. These functions prepare the data by converting it into a suitable format for subsequent anomaly detection processes.
- **Normalization:** The normalization process is important for ensuring that data values are scaled appropriately. MinMaxScaler from the scikit-learn library is used to normalize the data, which helps in maintaining consistency and accuracy in the anomaly detection models.
- **External API Interaction:** After preprocessing, the module sends the transformed data to external APIs for anomaly detection. This interaction ensures that the preprocessed data is seamlessly integrated into the anomaly detection workflow.

Workflow

1. **Preprocessing CGNN-MHSA-AR Training Data:** The `/preprocess_cgnn_train_data` endpoint handles requests for preprocessing CGNN-MHSA-AR training data. It accepts form-data containing the training files and related information. The `handle_cgnn_train_request` function processes the training, test, and anomaly label files, normalizes them, and formats them into CSV strings. The processed data is then sent to the learning and adaptation API for training the CGNN model.
2. **Preprocessing CGNN-MHSA-AR Test Data:** The `/preprocess_cgnn_data` endpoint manages requests for preprocessing CGNN-MHSA-AR test data. It accepts a test data file and related information. The `handle_cgnn_request` function processes and normalizes the test data, preparing it for anomaly detection. The processed data is sent to the CGNN-MHSA-AR anomaly detection API.
3. **Preprocessing CausalRCA Data:** The `/preprocess_crca_data` endpoint deals with requests for preprocessing CausalRCA data. It accepts a data file and related information. The `handle_crca_request` function normalizes the data and prepares it for anomaly detection. The processed data is sent to the CausalRCA anomaly detection API.
4. **Data Loading and Transformation:** The `load_data` function is responsible for loading and processing data files. It converts CSV data into

numpy arrays, handles missing values, and prepares the data for normalization. For CGNN, it handles both training and test data, as well as anomaly labels.

5. **Data Normalization:** The `normalize_data` function uses MinMaxScaler to scale the data values between 0 and 1. This step is for maintaining the accuracy and performance of the anomaly detection models.

6. **Error Handling:** The module includes robust error handling mechanisms to manage exceptions and ensure that errors are logged appropriately. This improves the stability and reliability of the preprocessing operations.

Operational Workflow

- **Request Handling:** The module receives preprocessing requests through the Flask application endpoints.
- **Data Loading:** The requested data files are loaded and converted into suitable formats (numpy arrays).
- **Data Normalization:** The data is normalized using MinMaxScaler to ensure consistent scaling across all data points.
- **Data Formatting:** The normalized data is formatted into CSV strings, making it ready for further processing.
- **API Interaction:** The formatted data is sent to external anomaly detection APIs, completing the preprocessing workflow.

5.3.3 Anomaly Detection Module

CGNN-MHSA-AR Module

Overview: The CGNN-MHSA-AR module is designed to detect anomalies in the collected data using advanced machine learning techniques. It employs a Flask-based web server to handle requests for anomaly detection and model management. The module integrates PyTorch for model operations, enabling robust and scalable anomaly detection capabilities.

Key Components:

- **Flask Application:** The Flask application serves as the primary interface for handling anomaly detection requests. It provides several endpoints for detecting anomalies, saving models, retrieving configurations, and managing results.
- **PyTorch Integration:** PyTorch is utilized for loading, saving, and using machine learning models. This integration supports the execution of complex neural network operations necessary for accurate anomaly detection.

- **Configuration Management:** The module uses a configuration file (`config.json`) to manage various settings and parameters related to model training and prediction. Functions are provided to set, update, and retrieve configurations, ensuring flexibility and ease of use.
- **Endpoints and Functionality:** Multiple endpoints are implemented to support different aspects of the anomaly detection process, including:
  - `/detect_anomalies`: Detects anomalies in the given data.
  - `/save_model`: Saves a trained model and its related information.
  - `/get_config`: Retrieves the current configuration settings.
  - `/update_config`: Updates the configuration settings.
  - `/get_available_models`: Retrieves information about available trained models.
  - `/get_results`: Retrieves results for a specific task ID.
  - `/get_all_results`: Retrieves results for all tasks.
  - `/delete_results`: Deletes results for a specific task ID.

Workflow:

1. **Anomaly Detection:**
   - The `/detect_anomalies` endpoint is invoked to detect anomalies in the provided test data. The endpoint accepts a CSV file containing the test data and a JSON object with additional information, including the model to use and thresholds for anomaly detection.
   - The `load_model_and_predict` function is called to load the specified model and run predictions on the test data. The predicted anomaly scores are compared against the specified threshold to determine if an anomaly has occurred.
   - If an anomaly is detected (i.e. the threshold is exceeded), additional information is prepared and possibly sent to the CausalRCA endpoint for further root cause localization.
2. **Model Management:**
   - The `/save_model` endpoint handles the saving of trained models. It accepts the model file and related information, saving the model parameters, configuration, and evaluation metrics to the filesystem.
   - The `/get_available_models` endpoint provides details about the available trained models, including their parameters and evaluation metrics, facilitating model management and selection.
3. **Configuration Management:**

- The `/get_config` and `/update_config` endpoints manage the configuration settings. These endpoints allow users to retrieve the current configuration and update it as needed, ensuring that the anomaly detection process can be tailored to specific requirements.

4. **Result Management:**
   - The `/get_results` and `/get_all_results` endpoints retrieve the results of anomaly detection tasks. These endpoints provide detailed insights into the performance and outcomes of the detection processes.
   - The `/delete_results` endpoint allows for the deletion of specific task results, ensuring that the system can manage storage and maintain relevance in the stored data.

Operational Workflow:

- **Data Input:** Test data and model information are submitted via the `/detect_anomalies` endpoint.
- **Model Prediction:** The specified model is loaded, and predictions are made on the test data to identify anomalies.
- **Threshold Comparison:** Anomaly scores are compared against predefined thresholds to determine if an anomaly is present.
- **Result Storage:** Detection results are stored, and relevant information is saved for further analysis and retrieval.
- **Model and Configuration Management:** Models and configuration settings are managed through dedicated endpoints to ensure flexible and efficient operation.
- **Result Management:** Detection results are retrieved, reviewed, and managed through the result management endpoints.

CausalRCA Module

The CausalRCA module leverages a combination of machine learning techniques and causal analysis to detect root causes of anomalies. It utilizes Flask for handling requests, Celery for task management, and various Python libraries for data processing and analysis.

Key Components

- **Flask Application:**
  - The Flask application serves as the entry point for initiating CausalRCA tasks, retrieving status, and managing results.

- **Celery Integration:**
  - Celery is used for managing asynchronous tasks, allowing CausalRCA analysis to be performed without blocking the main application flow.
- **Configuration Management:**
  - Configuration settings are managed through a configuration file (`config.json`), which can be updated and retrieved as needed.
- **Endpoints and Functionality:**
  - Several endpoints are provided to manage CausalRCA tasks and configurations:
    - `/crca`: Initiates a new CausalRCA task.
    - `/get_status/{task_id}`: Retrieves the status of a specific task.
    - `/results/{task_id}`: Retrieves results of a specific task.
    - `/delete_results/{task_id}`: Deletes results of a specific task.
    - `/get_config`: Retrieves the current configuration settings.
    - `/update_config`: Updates the configuration settings.

Workflow

1. **Initiating CausalRCA:**
   - The `/crca` endpoint accepts a CSV file containing CausalRCA data and additional information in JSON format. This data is used to initiate a task asynchronously via Celery.
2. **Task Management:**
   - The task is handled by Celery, which processes the data using the `run_crca_task` function. This function reads the data, performs CausalRCA analysis, and stores the results.
3. **Data Analysis:**
   - The `run_crca` function performs the core CausalRCA analysis, which involves multiple iterations of causal relation extraction, averaging the results, and matching column names based on the provided information. The analysis results, including scores and graphical representations, are saved and returned as JSON objects.
4. **Result Management:**
   - The results of the CausalRCA analysis are managed through various endpoints. The `/get_status/{task_id}` endpoint retrieves the status of a specific task, while the `/results/{task_id}` endpoint provides the detailed results. The `/delete_results/{task_id}` endpoint allows for the deletion of specific task results.

5. **Configuration Management:**

    - Configuration settings for the CausalRCA module are managed through the `/get_config` and `/update_config` endpoints. These endpoints provide the ability to retrieve and update settings dynamically, ensuring flexibility in the CausalRCA analysis process.

Operational Workflow

1. **Data Submission:** Users submit data and information via the `/crca` endpoint.
2. **Task Initiation:** The data is processed and a task is initiated asynchronously.
3. **Data Analysis:** The `run_crca` function performs CausalRCAon the submitted data, iteratively extracting causal relations and calculating scores.
4. **Result Storage:** Results, including scores and graphical representations, are stored and managed in the filesystem.
5. **Result Retrieval:** Users can retrieve task status and results through dedicated endpoints.
6. **Configuration Updates:** Configuration settings can be updated and retrieved as needed to adjust the CausalRCA analysis parameters.

5.3.4 Learning and Adaptation Module

The Learning and Adaptation Module is designed to facilitate the training and adaptation of models based on new data. This module incorporates Flask for API endpoints, Celery for task management, and various machine learning libraries for training and evaluating models.

Key Components

- **Flask Application:**
    - Serves as the interface for initiating training tasks, checking their status, retrieving available models, and managing datasets.
- **Celery Integration:**
    - Handles the asynchronous execution of training and evaluation tasks, ensuring that the system remains responsive.
- **Configuration Management:**
    - Manages configurations through a JSON file, which can be dynamically updated and retrieved as needed.

- **Endpoints and Functionality:**
  - Several endpoints manage model training, status checking, model retrieval, and dataset management:
    - `/cgnn_train_model`: Initiates a new training task.
    - `/get_status/{task_id}`: Retrieves the status of a specific task.
    - `/get_available_models`: Retrieves a list of available trained models.
    - `/save_to_detection_module`: Saves a trained model to the detection module.
    - `/cgnn_train_with_existing_dataset`: Trains a model using an existing dataset.
    - `/update_config`: Updates configuration settings.
    - `/get_config`: Retrieves the current configuration settings.
    - `/get_available_datasets`: Retrieves a list of available datasets.

Workflow

1. **Initiating Training:**
   - The `/cgnn_train_model` endpoint accepts training data, test data, and anomaly labels, along with training information in JSON format. This data initiates a training task asynchronously via Celery.
2. **Task Management:**
   - Celery handles the `train_and_evaluate_task`, which involves training a model and evaluating its performance. This task is executed in the background, allowing the main application to remain responsive.
3. **Model Training and Evaluation:**
   - The `train_and_evaluate_task` function processes the training data, trains the CGNN-MHSA-AR model, and evaluates its performance. The trained model and its configuration are saved for future use.
4. **Result and Model Management:**
   - The `/get_status/{task_id}` endpoint provides the status of ongoing training tasks.
   - The `/get_available_models` endpoint retrieves details of available trained models, including their parameters, configuration, and evaluation metrics.
   - The `/save_to_detection_module` endpoint saves a trained model to the detection module for anomaly detection purposes.
5. **Dataset Management:**

- The `/cgnn_train_with_existing_dataset` endpoint allows for training with existing datasets stored in the system. It retrieves relevant data, filters it based on user selection, and initiates the training process.
- The `/get_available_datasets` endpoint lists all available datasets and their details.

6. **Configuration Management:**
    - Configuration settings for the module are managed through the `/get_config` and `/update_config` endpoints, allowing for dynamic adjustments to training parameters and other settings.

Operational Workflow

1. **Data Submission:** Users submit training data, test data, anomaly labels, and training information via the `/cgnn_train_model` endpoint.
2. **Task Initiation:** The training task is initiated asynchronously, and its status can be monitored via the `/get_status/{task_id}` endpoint.
3. **Model Training:** The `train_and_evaluate_task` function trains the model using the submitted data, evaluates its performance, and saves the model and its configuration.
4. **Result Retrieval:** Users can retrieve the list of available trained models and their details through the `/get_available_models` endpoint.
5. **Model Deployment:** Trained models can be saved to the CGNN-MHSA-AR detection module via the `/save_to_detection_module` endpoint.
6. **Configuration Updates:** Configuration settings can be updated and retrieved as needed to adjust training parameters and other settings dynamically.

5.3.5 User Interface Module

The User Interface Module provides a front-end for interacting with the anomaly detection and monitoring system. It is implemented using Django and integrates with the various back-end APIs for anomaly detection, model training, and monitoring. This module aims to offer a seamless user experience for configuring, monitoring, and visualizing data and results.

Operational Workflow

Monitoring Users can set up and initiate monitoring, specifying parameters such as pods, models, and intervals. A monitoring dashboard provides an overview of tasks (figure 5.2 and 5.3).

Figure 5.2: Monitoring Setup

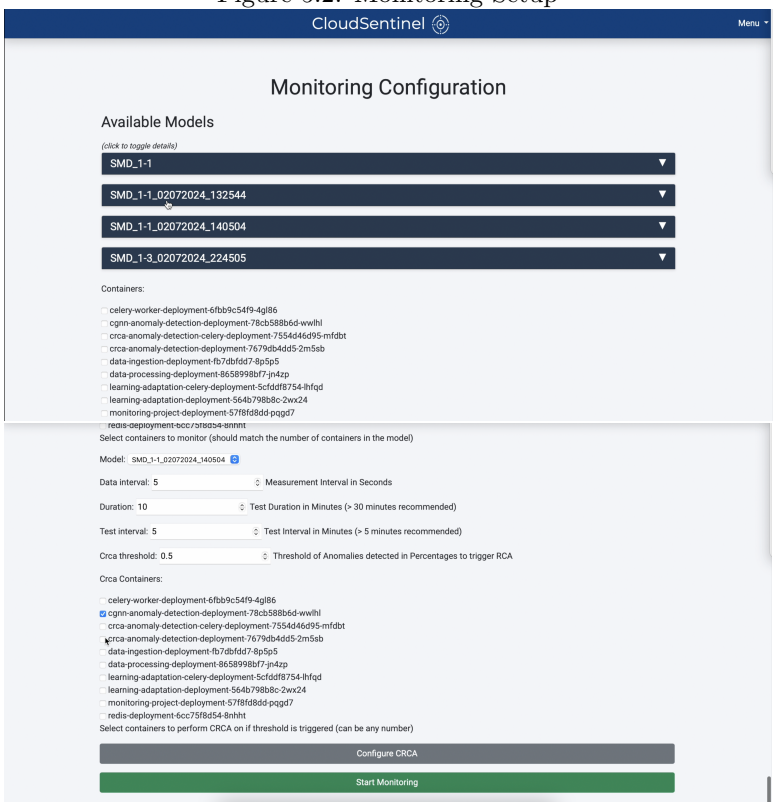
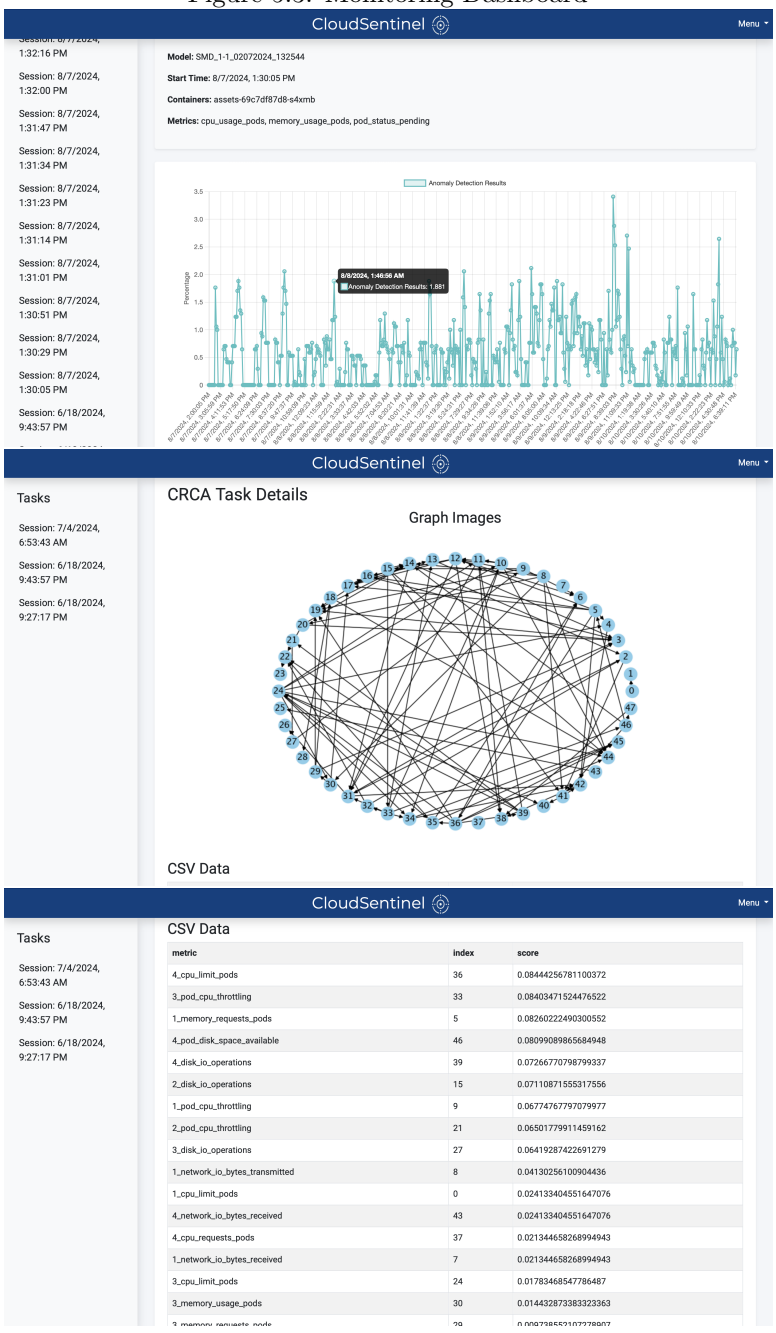


Figure 5.3: Monitoring Dashboard



metric	index	score
4_cpu_limit_pods	36	0.08444256781100372
3_pod_cpu_throttling	33	0.08403471524476522
1_memory_requests_pods	5	0.08260222490300552
4_pod_disk_space_available	46	0.08099089865684948
4_disk_io_operations	39	0.07266770798799337
2_disk_io_operations	15	0.07110871555317556
1_pod_cpu_throttling	9	0.06774767797079977
2_pod_cpu_throttling	21	0.06501779911459162
3_disk_io_operations	27	0.06419287422691279
1_network_io_bytes_transmitted	8	0.04130256100904436
1_cpu_limit_pods	0	0.024133404551647076
4_network_io_bytes_received	43	0.024133404551647076
4_cpu_requests_pods	37	0.021344658268994943
1_network_io_bytes_received	7	0.021344658268994943
3_cpu_limit_pods	24	0.01783468547786487
3_memory_usage_pods	30	0.014432873383323363

Model Training Users can train models using either existing datasets or by uploading new training data. The training process is initiated and managed via Celery tasks, with results available through the UI (figure 5.5 and 5.6).

Figure 5.4: Training Setup

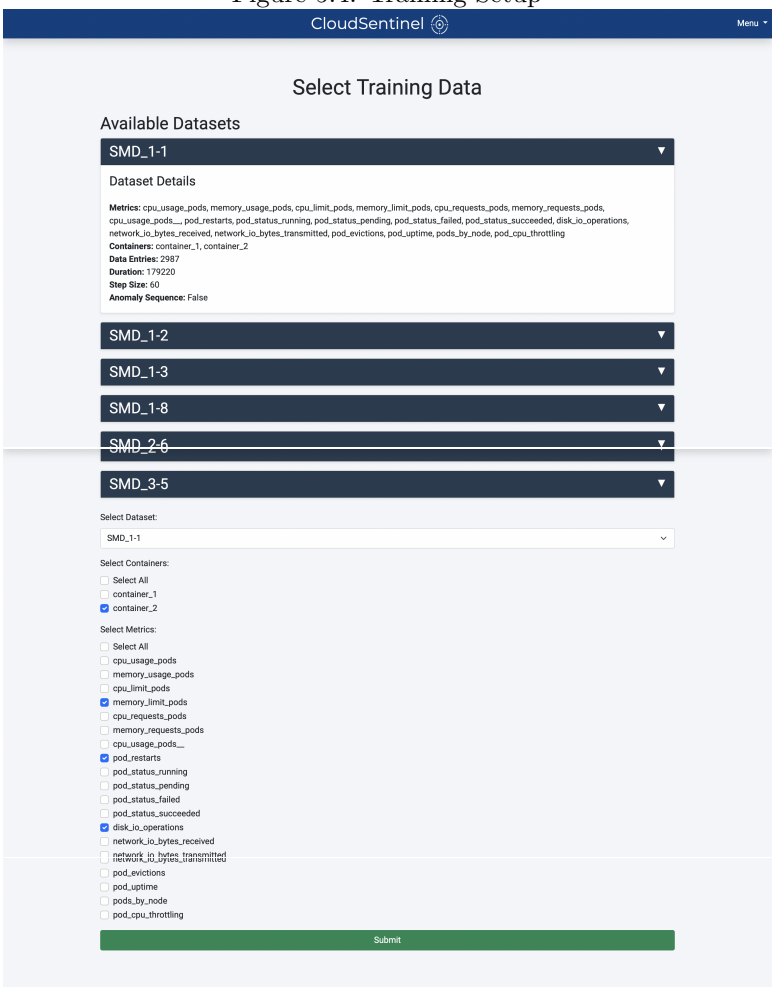


Figure 5.5: Training Feedback

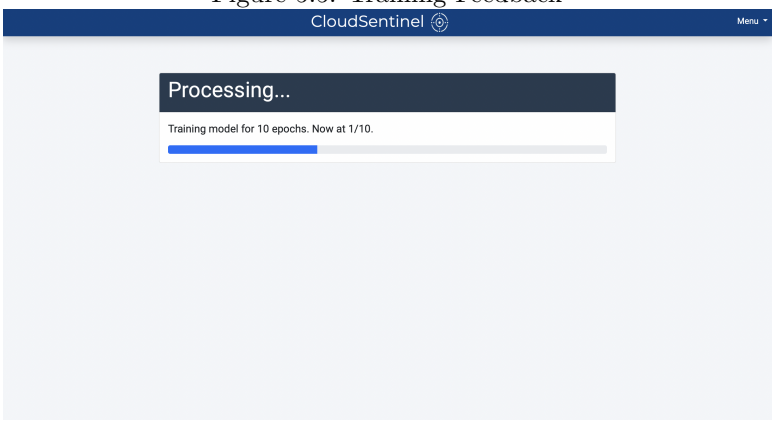
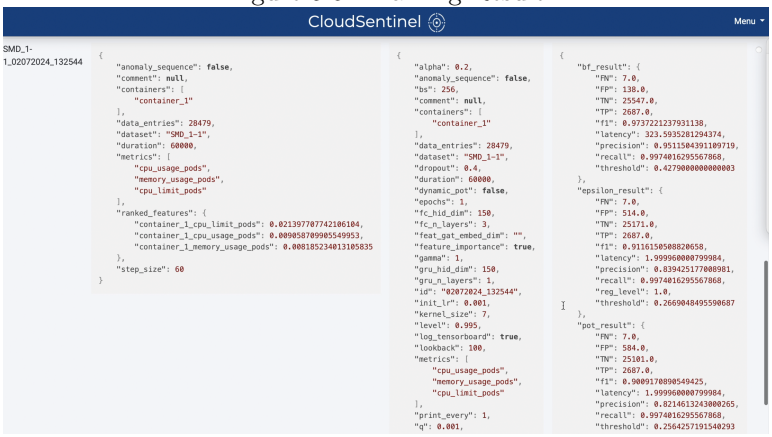


Figure 5.6: Training Result



Anomaly Detection

- Users can navigate to the home page for anomaly detection and select either CGNN-MHSA-AR or CausalRCA.
- For CGNN-MHSA-AR, users upload data files, which are processed and results displayed.
- For CausalRCA, users select pod names, date ranges, and upload files for processing and visualization.

Configuration Management Users can update configurations for anomaly detection, training, and monitoring through the UI. Configuration changes are saved and applied dynamically to the modules

Result Management Task results are fetched and displayed, including anomaly detection outcomes and training evaluations. Users can navigate to specific result based on task IDs (figure 5.7).

Figure 5.7: Manage Tasks

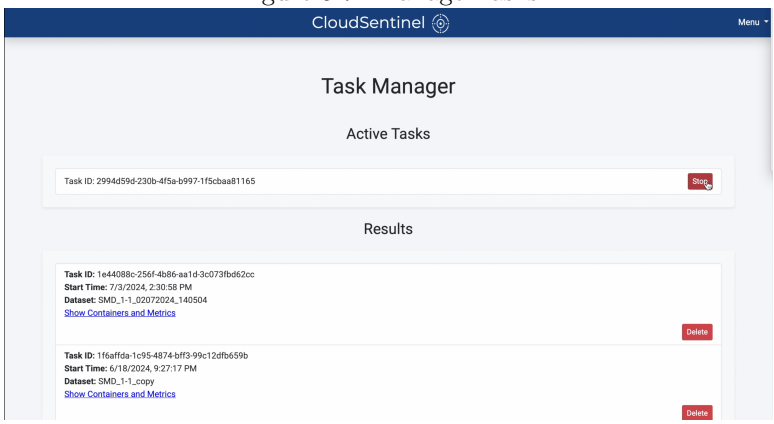
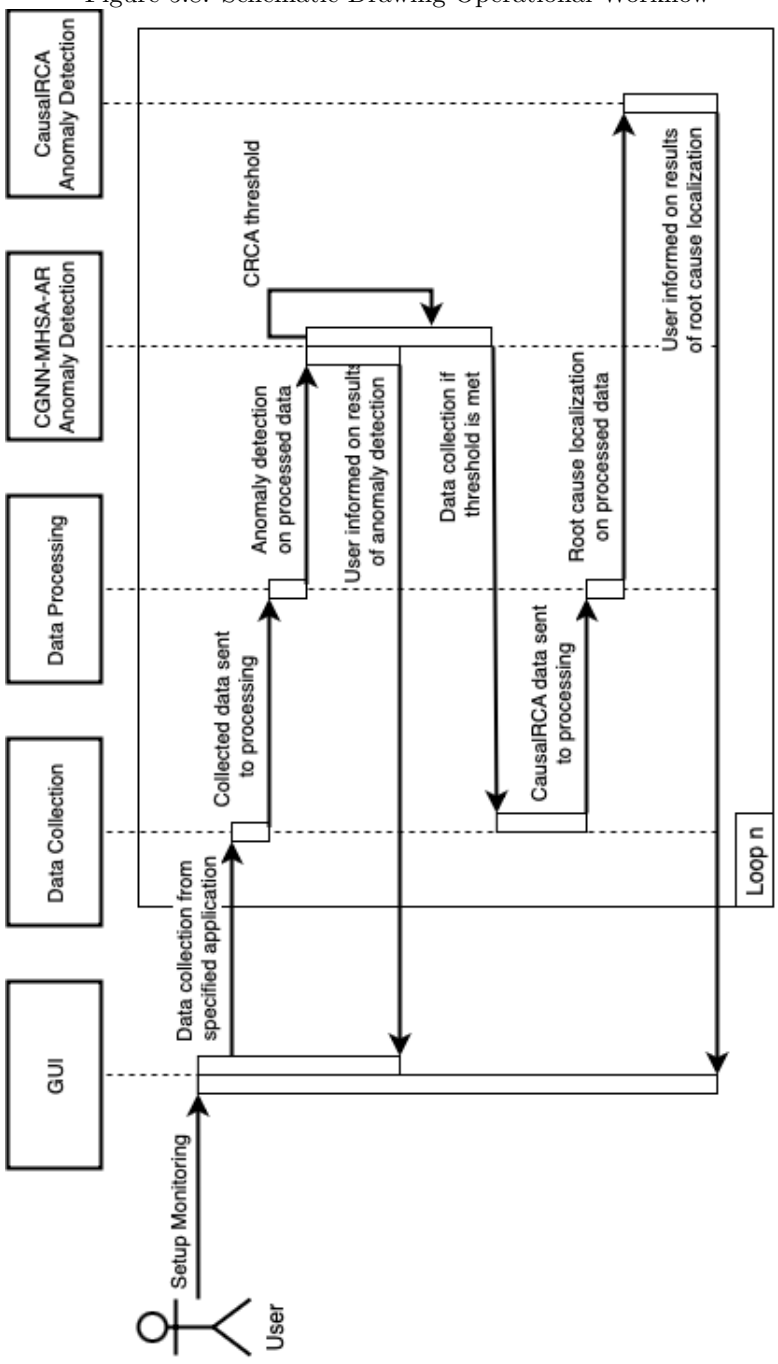


Figure 5.8: Schematic Drawing Operational Workflow



5.4 Interoperability Details

Data Exchange Standards and Protocols: We utilize JSON as the standard for all data exchanges across different platforms and tools. This choice ensures consistent and clear communication between systems, making data easily interpretable and manageable.

Ensuring Data Interoperability: To maintain interoperability, we adhere to a unified naming convention for all data elements. This practice helps prevent discrepancies and ensures that data remains consistent across various components and systems.

5.5 Requirements for Integrating Additional AI Anomaly Detection Algorithms

To extend the AIOps framework by integrating additional AI anomaly detection algorithms, several technical, architectural, and operational requirements must be considered. These requirements ensure that the new algorithms can be integrated into the existing framework, while maintaining compatibility, scalability, and performance.

5.5.1 Technical Requirements

Programming Language Compatibility The primary programming language for the new algorithms must be Python, as it is the language used throughout the framework. This compatibility ensures that the algorithms can leverage existing libraries and integrate smoothly with the backend processes. Additionally, the algorithms should be built using well-supported Python libraries, such as NumPy, Pandas, Scikit-learn, and PyTorch, which are compatible with the current environment. This approach minimizes dependencies and ensures long-term maintainability.

API Endpoints The algorithms must expose their functionalities through RESTful APIs, following the existing pattern in the framework. This includes developing endpoints for initiating anomaly detection, retrieving results, and managing configurations. All APIs should adhere to standardized input and output formats, specifically JSON, to ensure consistent data exchange across different modules.

Data Handling and Preprocessing The algorithms should include mechanisms for data normalization similar to the MinMaxScaler approach used in the existing modules. This ensures that input data is consistently scaled, which improves model performance and interoperability. Additionally, the algorithms should be flexible in terms of data input, accepting various formats, including

CSV, and converting them into structured data, such as NumPy arrays, for processing. This flexibility assists handling diverse data sources within the AIOps framework.

5.5.2 Architectural Requirements

Containerization The algorithms must be compatible with Docker, ensuring consistent deployment across development and production environments. Dockerfiles should be provided for build and deployment processes. Furthermore, the algorithms should be deployable in a Kubernetes environment, allowing them to be managed and scaled according to demand within the cloud infrastructure.

Modularity and Interoperability The design of the algorithms should emphasize modularity, enabling them to be developed as independent components that can be integrated into the existing framework without requiring significant changes to other modules. They should expose clear and consistent interfaces to interact with other components in the framework, such as the data processing module.

5.5.3 Operational Requirements

Scalability is another important consideration. The algorithms should support horizontal scaling to handle increasing loads, ensuring that the AIOps framework remains responsive and efficient as data volume grows. Additionally, the algorithms should be optimized for resource efficiency, minimizing memory and CPU overhead when deployed in cloud environments.

The algorithms must be accompanied documentation, including a detailed API documentation outlining the available endpoints, input/output formats, and example requests, ensuring that developers can easily integrate and use the algorithms within the AIOps framework. Additionally, user guides should be provided for configuring, deploying, and maintaining the algorithms, ensuring that they can be managed in production environment.

By adhering to these requirements, the integration of additional AI anomaly detection algorithms into the AIOps framework can be achieved smoothly, enhancing the framework's capabilities while maintaining its reliability, scalability, and ease of use.

5.6 Challenges

The development and deployment of the AIOps framework encountered several challenges, particularly during the testing phase. These challenges were systematically addressed to ensure that the framework operates as intended in diverse and dynamic cloud environments.

Testing Algorithms One of the primary challenges was ensuring that the algorithms, performed consistently and accurately. The goal was to replicate the results obtained in previous studies and to ensure that these algorithms integrated seamlessly into our framework.

The main issue were difficulties in getting the algorithm to perform as expected. To resolve this we conducted extensive testing to validate the algorithms' performance. This involved comparing results from our implementation with the baseline results from previous studies. Where discrepancies were found, we meticulously reviewed the algorithmic implementations and adjusted parameters to align performance metrics.

API Mismatches During the integration of various system components, we encountered mismatches in API responses. These mismatches caused disruptions in data flow and processing, leading to errors and inconsistencies in system operations.

The main issue were differences in expected and actual API responses. To resolve this we updated API endpoints and data handling logic to ensure compatibility and correct data exchange. This involved standardizing API responses and implementing robust error-handling mechanisms to manage unexpected data formats.

Data Format Inconsistencies Inconsistent data formats were a recurrent issue that affected the accuracy and reliability of data processing. These inconsistencies arose from variations in data sources and formats within the cloud environment.

The main issue were inconsistent data formats leading to errors in data processing. To resolve this we enforced strict adherence to JSON data format standards and implemented robust data validation mechanisms. By standardizing data formats and ensuring that all data conforms to predefined schemas, we minimized processing errors and ensured data integrity.

Integration Failures Failures in communication between integrated components posed significant challenges. These failures often resulted from misconfigurations, network issues, or incompatibilities between system modules.

The main issue were failures in communication between integrated components. To resolve this we conducted root cause analysis to identify and resolve connectivity and configuration issues. This involved thorough testing of network configurations, updating connection parameters, and ensuring that all system components could communicate reliably.

5.7 Conclusion

In this chapter, we moved from theoretical concepts to practical implementation. We demonstrate the feasibility of our AIOps framework in a cloud environment.

The implementation realizes our architectural choices and design principles through a proof of concept approach. Through the development of key modules, we demonstrated how each component functions and interacts within the AIOps framework. The integration of machine learning algorithms like CGNN-MHSA-AR and CausalRCA showed the system's capability to handle real-time anomaly detection and root cause analysis, providing a foundation for further development and real-world deployment.

In the next chapter we will present the results and evaluation of the implemented system, focusing on the performance of key components and the validation of the machine learning algorithms.

Chapter 6

Results and Evaluation

In this chapter, we present the results and evaluation of our AIOps framework implementation. Following the detailed design and implementation outlined in previous chapters, we now assess the system performance and effectiveness. The evaluation covers the system's flexibility and portability.

First we provide an overview of the main components of the implemented system, highlighting their roles and interactions. Then we outlinte the evaluation metrics that were used in assessing framework. Through a series of structured experiments, we analyze the performance. These experiments are designed to test the system's capability to different configurations, its ability to maintain consistency across various operational conditions, and its capacity to scale efficiently with increasing workloads.

The results presented in this chapter are helpful for understanding the practical viability of the AIOps framework. By examining the system's response to different stressors and configurations, we identify its strengths and areas for improvement, offering insights that are valuable for future enhancements.

Through this evaluation, we aim to demonstrate the viability of our AIOps framework as a robust solution for automated anomaly detection and efficiency in cloud environments.

6.1 Overview of Implemented System

Given the constraints of our project timeline, we prioritized the implementation of several core components necessary to the functioning of our AIOps system. These components are designed to handle various tasks from data ingestion to anomaly detection and user interaction.

6.1.1 Main Components

Data Ingestion Module This module is responsible for scraping data from the deployed cloud environment. It handles the periodic scraping of data accord-

ing to the specified metrics and containers set up for monitoring. The collected data is subsequently passed to the Data Processing Module for further handling.

Data Processing Module This component processes the scraped data into a uniform format suitable for analysis. The processing methods vary depending on the anomaly detection algorithm in use. Once processed, the data is forwarded to the respective Anomaly Detection Module.

Anomaly Detection CGNN-MHSA-AR Utilizing a CGNN-MHSA-AR algorithm developed by Xin et al. 2022, this module detects anomalies within the processed data. Detected anomalies are stored locally within the module and are accessible via the user interface dashboard. When anomalies exceed a user-defined threshold, the CausalRCA Detection is triggered, reactivating the Data Ingestion Module to collect targeted data for detailed analysis.

Anomaly Detection CausalRCA This module performs CausalRCA on the flagged data. The algorithm, also developed in Xin et al. 2022, identifies specific containers and metrics responsible for anomalies. Like CGNN-MHSA-AR, this module stores its findings for display and management within the user interface dashboard.

User Interface The user interface module facilitates user interaction with the system. Users can configure and manage monitoring tasks for specific containers and metrics within the distributed cloud application. The interface allows users to manage tasks, train the CGNN-MHSA-AR module with either new data or existing datasets, and evaluate the performance of trained models. Successful models can then be integrated into the CGNN-MHSA-AR Anomaly Detection Module.

Training and Adaptation Engine This component supports the training of the CGNN-MHSA-AR algorithm. Post-training, and based on user selection, the model can be deployed to the CGNN-MHSA-AR Anomaly Detection Module for operational use.

System Architecture and User-Centric Design for Configurability

The systems architecture employs a user-centric design philosophy considering system's configurability. By default, the framework is configured with settings that are based on typical use cases, which allows the system to function effectively. This is intended to lift initial burden on users, sparing them complexity of configuring parameters before being able to use the system.

Aside from the default setup, the framework allows for more advanced configuration. It is designed to be fully customizable, allowing users to adjust a wide range of parameters such as anomaly detection thresholds, data collection frequencies, and specific monitoring metrics. This flexibility ensures that users

can fine-tune the system to better align with their specific requirements. How this is handled in the framwork is displayed in code snippet 6.1.

Addtionally, integration simplicity is another important component of configuration flexibility. In the framework, users are only required to specify the namespace within the Kubernetes cluster they wish to monitor. This singular requirement simplifies the integration process, as it abstracts the complexities associated with connecting to and monitoring distributed systems. It allows users to begin monitoring their applications with minimal setup, promoting a smoother adoption curve and reducing the initial technical barriers to entry.

```
def set_initial_config():
    """
    Sets initial configuration parameters based on environment variables
         or defaults.
    Writes the configuration to 'config.json' file.
    """
    config = {
         # --- Train params ---
         "epochs": os.getenv("EPOCHS", 10),
         "val_split": os.getenv("VAL_SPLIT", 0.1),
         "bs": os.getenv("BS", 256),
         "init_lr": os.getenv("INIT_LR", 1e-3),
         "shuffle_dataset": os.getenv("SHUFFLE_DATASET", True),
         "dropout": os.getenv("DROPOUT", 0.4),
         "use_cuda": os.getenv("USE_CUDA", True),
         "print_every": os.getenv("PRINT_EVERY", 1),
         "log_tensorboard": os.getenv("LOG_TENSORBOARD", False),
     }
    with open(config_file_path, 'w') as file:
        json.dump(config, file, indent=2)

    def set_config(new_config=None):
    """
    Updates the configuration parameters in 'config.json' file.
    If new_config is provided, it updates the existing configuration
         parameters.
    """
    config = get_config()
    if new_config:
        config.update(new_config)
    with open(config_file_path, 'w') as file:
        json.dump(config, file, indent=2)
```

Listing 6.1: Python Function for Setting Initial Configuration

Scalability

Scalability is an important attribute of the AIOps platform. It is intended to operate within dynamic and potentially expansive cloud environments. Our system's design anticipates the need for scalability to handle varying workloads.

The architectural framework of our AIOps framework is built to leverage Kubernetes' native capabilities for managing load variations. Kubernetes provides automatic scaling of resources, which is important in environments where application demands can fluctuate. This native support forms the foundation upon which our AIOps framework scalability is structured, allowing for both horizontal and vertical scaling.

Our system is designed to be configured to scale out horizontally, helping in managing increased data volumes and computational demands without a drop in performance.

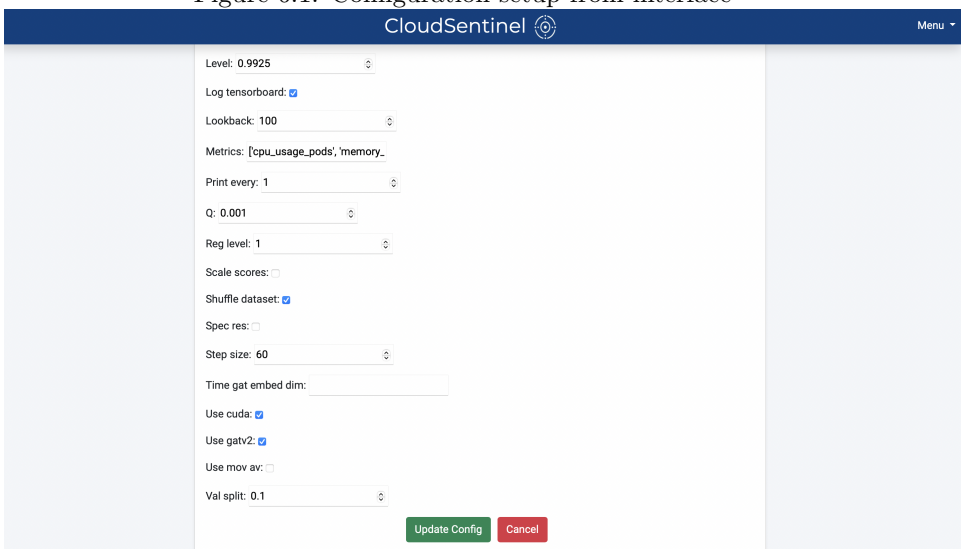
In scenarios where the complexity of the data or the intensity of the processing increases, our framework can be configured to scale up by utilizing more powerful machines or allocating more resources like CPU and memory to existing pods. This flexibility ensures that the system can handle more intensive computational tasks without lag or delay.

While the complete scalability features are not yet implemented, the design anticipates these needs and includes provisions for easy integration of these capabilities, as demonstrated in code snippet 6.2. For instance, the framework's modular design allows for components to be independently scaled according to the specific requirements of different parts of the system. This modular scalability ensures that each component can operate efficiently under varying loads without affecting the overall system performance.

```yaml
apiVersion: apps/v1
kind: Deployment
metadata:
  name: monitoring-project-deployment
  namespace: cloudsentinel
spec:
  replicas: 1  # This can be increased to scale out horizontally
  selector:
    matchLabels:
      app: monitoring-project
  template:
    metadata:
      labels:
        app: monitoring-project
    spec:
      containers:
      - name: monitoring-project
        image: ${{ secrets.DOCKER_USERNAME }}/monitoring_project:latest
        imagePullPolicy: Always
        ports:
        - containerPort: 8000
        env:
        # Namespace of application to be monitored
        - name: CLUSTER_NAMESPACE
          value: "cloudsentinel"
        # Resource requests and limits for vertical scaling
        resources:
          requests:
            memory: "512Mi"
            cpu: "500m"
          limits:
            memory: "1Gi"
            cpu: "1"
```

Listing 6.2: Sample Kubernetes Deployment and Service Configuration

Figure 6.1: Configuration setup from interface



Interoperability

Compatibility Our system is designed to integrate into existing Kubernetes clusters, which are commonly used for modern cloud infrastructure management. This compatibility is allows organizations looking to implement AIOps without disrupting their current operational frameworks This broad compatibility is achieved through the use of standard Kubernetes APIs and conventions, which are universally accepted and implemented across different Kubernetes deployments.

Ease of Deployment The system can be deployed as a set of containerized services within any existing Kubernetes cluster, utilizing Kubernetes' native management features to ensure that the framework scales and operates efficiently. This approach minimizes the setup time and reduces the complexity typically associated with deploying new software solutions, making it accessible. Our deployment setup is demonstrated in code snippet 6.2.

```
name: Infrastructure Setup Deployment

on:
  push:
    paths:
      - 'k8s/**'

jobs:
  setup-infrastructure:
    runs-on: ubuntu-latest

    steps:
    - name: Checkout code
```

```
14        uses: actions/checkout@v3
15
16      - name: Set up Google Cloud SDK
17        uses: google-github-actions/setup-gcloud@v0
18        with:
19          version: 'latest'
20          service_account_key: ${{ secrets.GCP_SA_KEY }}
21          export_default_credentials: true
22
23      # To be specified by the user
24      - name: Configure kubectl
25        run: |
26          gcloud container clusters get-credentials cluster-name --zone
                cluster-zone --project project-name
27
28      ...
```

Listing 6.3: GitHub Actions Workflow for Infrastructure Setup Deployment

API-Driven Interactions the framework employs RESTful API that allows it to communicate with other components within the cloud infrastructure. This API-driven approach ensures that the framework can retrieve necessary data from various sources but in future implementation can also interact with other systems for actions such as triggering alerts, initiating scaling procedures, or applying configuration changes. This interoperability extends the framework's utility and makes it a versatile tool.

6.1.2 Deployment Environment and Configuration

The AIOps system was deployed within the same Kubernetes cluster as the distributed cloud application to minimize latency and optimize data access. Google Cloud was selected as the deployment platform to showcase the framework's functionality within cloud environments, particularly its capacity to handle the demands of real-time data processing and anomaly detection in distributed cloud settings. The scalability experiments were conducted on a dedicated server running Linux, equipped with 8 vCPUs and 16 GB of RAM. This configuration provided sufficient resources to effectively demonstrate the initial capabilities of the proof-of-concept framework.

For detailed descriptions of each module's specific functionalities and workflows, we refer to Chapter 5, which covers implementation details extensively.

6.2 Data Sources

6.2.1 Configurability Experiment Data

For our configurability experiment, we engaged three experts from the field of cloud services:

- **Data Engineer in Cloud Services:** Provided insights into the data handling, processing requirements, and integration complexities.

- **Software Engineer in Cloud Services:** Offered a perspective on the implementation aspects, system configuration, and adaptability of the framework to various application needs.
- **Tech Consultant in Cloud Services Department:** Offered a broad perspective on the strategic integration and practical implications of deploying the AIOps framework within various cloud environments.

These experts were tasked with configuring the AIOps framework to meet specific operational and application requirements. Their feedback and performance data during the configuration process were collected to assess the ease of system configuration and the flexibility of the framework. The insights from these professionals helped us assess the configurability aspects of our system.

6.2.2 Consistency Experiment Data

For our consistency experiment, we selected datasets that are used for validating the accuracy and robustness of our AIOps implementation, particularly for the CGNN-MHSA-AR and CausalRCA models. These datasets include:

Server Machine Dataset (SMD) This dataset consists of a five-week-long real-time data collection from 28 cloud platform servers, featuring over 708,405 data points in the training set and 708,420 in the testing set, with an anomaly rate of 4.16%. From this dataset, we selected four subsets chosen for their complexity and relevance to real-world scenarios and because they have been previously used in validating similar algorithms, which allows for comparative analysis and benchmarking. These subsets were used for validating the CGNN-MHSA-AR algorithm. The four datasets include Machine-1-3 (the training set has 23,702 data points, and the testing set has 23,703 data points), Machine-1-8 (both the training and test sets have 23,698 data points each), Machine-2-6 (both the training and test sets have 28,743 data points each), and Machine-3-5 (the training set has 23,690 data points, and the testing set has 23,691 data points). These subsets were chosen because they did not perform well in many detection models due to irregular fluctuations in the data leading to false positives in anomaly detection, but they did perform well with the CGNN-MHSA-AR algorithm. This selection helps validate the performance of the algorithm in our framework.

Sock Shop Application Dataset To evaluate the CausalRCA algorithm in our framework, we used data gathered from the Sock Shop application, a microservice benchmark simulating an e-commerce website. The dataset includes data where an anomaly was simulated in the CPU of the frontend service to test the CRCA algorithm's ability to accurately identify and rank the root causes of anomalies within a microservices environment.

6.2.3 Scalability Experiment Data

Retail Store Sample Application Similar to the Sock Shop application, the Retail Store Sample application is designed to illustrate various concepts related to containers on AWS. It presents a sample retail store application including a product catalog, shopping cart, and checkout. The application provides a distributed component architecture in various languages and frameworks, utilization of a variety of different persistence backends for different components like MySQL, DynamoDB, and Redis, and the ability to run in various container orchestration technologies like Kubernetes. This deployment method runs the application in an Kubernetes cluster, ensuring that our AIOps framework can interact with and monitor a live, distributed application environment. For our scalabilty experiments, we used data collected from this deployment to test the framework's ability to scale up to demanding workloads.

6.3 Evaluation Metrics and Performance Indicators

In the development of AIOps systems, we prioritize both system flexibility and portability to ensure adaptability and seamless functionality across diverse operational environments and cloud applications. This section integrates these concepts into a unified framework. To evaluate the system, we employ the following criteria:

- **Configurability**: These metrics evaluate the ease of configuring the system to meet operational or application-specific requirements, including the adjustment of settings like anomaly detection thresholds and setting up monitoring tasks.
- **Consistency**: Metrics evaluating the accuracy and robustness of the CGNN-MHSA-AR and CausalRCA models, ensuring they produce reliable results in various cloud environments.
- **Scalability**: This criterion tests the system's capacity to handle varying loads. Scalability is quantified through stress testing, where the system is subjected to progressively increasing loads to identify performance.

6.3.1 Configurability

The configurability evaluation focuses on assessing the ease with which the AIOps framework can be adapted to meet specific operational and application requirements. This subsection details the methodology and metrics used to evaluate the configurability of our system. By involving domain experts and gathering detailed feedback, we aim to ensure that the AIOps framework is both flexible and user-friendly, facilitating its deployment in diverse cloud environments.

Methodology

To evaluate the configurability of our AIOps framework, we engaged three experts from the field of cloud services. These experts were tasked with configuring the AIOps framework to meet specific operational and application requirements. Their feedback and performance data during the configuration process were collected to assess the ease of system configuration and the flexibility of the framework. The experts were first given an overview of the system, after which they worked independently to configure the framework. Post-configuration, they were asked to fill out a detailed survey. The survey aimed to capture their experiences and evaluate different aspects of the configurability.

Survey Structure The survey consisted of two sections: Task Complexity, and Usability Feedback. The Task Complexity section focused on two primary areas: tailoring system strategies and configuring monitoring tasks. Experts rated the complexity of customizing the system for different types of anomalies on a scale from very easy to very difficult. This helped assess how flexible and adaptable the system is to various anomaly types. They also evaluated the difficulty of setting up monitoring tasks for specific containers and metrics, providing insight into the practicality of configuring the system for specific needs. The Usability Feedback section aimed to gather overall impressions of the configuration process. Experts rated the overall ease of use of the configuration process and provided qualitative feedback, offering suggestions for improvements and highlighting any challenges they faced during the configuration process.

Evaluation Metrics

The metrics used to evaluate configurability were derived from the survey responses and expert feedback. These metrics provide a comprehensive assessment of how adaptable and user-friendly the AIOps framework is. The Task Complexity Metrics included the average rating of complexity in customizing the system for various anomalies and the average rating of complexity in setting up monitoring tasks for specific containers and metrics. Lower scores in these metrics indicate greater ease of customization and configuration. The Usability Feedback Metrics included the overall average rating of the ease of use of the configuration process, with lower scores reflecting a more user-friendly and straightforward configuration experience. Additionally, qualitative feedback from the experts was analyzed to identify common themes and areas for improvement.

6.3.2 Consistency

We validate our implementation by replicating the results presented in Xin et al. 2022. This ensures that the CGNN-MHSA-AR and CausalRCA algorithms are reliable and produces consistent results when applied in the AIOps framework.

It confirms that any modifications or integrations into our broader AIOps framework have not compromised the core functionality of the algorithms. Moreover it provides a validated baseline from which further modifications or enhancements to the algorithm can be explored, ensuring that future developments are built on a stable and verified foundation.

CGNN-MHSA-AR

The primary objective of this validation step is to confirm the functionality and accuracy of the CGNN-MHSA-AR algorithm within our AIOps system. By utilizing the datasets and the results from previous experiments conducted by Xin et al. 2022, we aim to replicate those findings to ensure that our implementation of the CGNN-MHSA-AR algorithm behaves as expected.

The validation process involves a comparison between the performance metrics recorded during original experiments and those achieved by our system under similar conditions. This direct comparison is important for establishing the reliability of the CGNN-MHSA-AR algorithm when deployed in our AIOps environment.

Steps for Validation

1. **Dataset Preparation**: Utilize the same datasets used in the experiments, including the specific partitions into training and testing sets. This ensures that any differences in performance can be attributed to the system's configuration and not variations in the data.
2. **Algorithm Configuration**: Configure our CGNN-MHSA-AR algorithm using the same parameters and settings as those described in the study.
3. **Performance Metrics Comparison**: Evaluate the algorithm using the same metrics reported: precision, recall and F1 score. Collect these metrics from our system and align them side-by-side with the previously reported results.
4. **Result Interpretation**: Interpret the results to determine whether the CGNN-MHSA-AR algorithm is performing within expected parameters. Discrepancies would indicate potential issues in our implementation or environmental differences that might affect the algorithm's performance.

Accuracy Metrics These accuracy metrics provide the quantitative measure of the CGNN-MHSA-AR algorithm's performance in detecting anomalies:

- **True Positives (TP)**: Cases where the CGNN-MHSA-AR algorithm correctly identifies an actual anomaly. High values indicate effective recognition of genuine anomalies.
- **True Negatives (TN)**: Instances where the algorithm accurately identifies the absence of anomalies. This metric ensures that the system maintains stability.

- **False Positives (FP)**: Occurrences where the algorithm mistakenly identifies normal behavior as anomalous. Minimizing false positives avoid unnecessary interventions and maintain operational efficiency.
- **False Negatives (FN)**: Instances where the algorithm fails to detect actual anomalies. This metric directly impacts the system's reliability in safeguarding against potential disruptions.

Key Indicators From these counts, we derive the following key indicators:

- **Precision**: Measures the accuracy of the anomaly detection, defined as the ratio of true positives to the sum of true positives and false positives. High precision indicates a low rate of false alarms.

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

- **Recall (Sensitivity)**: Assesses the algorithm's ability to detect all relevant instances of anomalies, to ensure no critical anomaly is missed.

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

- **F1 Score**: Harmonic mean of Precision and Recall, providing a balanced measure that considers both false positives and false negatives.

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

Validation of the CausalRCA Algorithm

The goal of validating the CausalRCA algorithm is to confirm its effectiveness and accuracy within our AIOps framework. Using data and results from previous experiments conducted in Xin et al. 2022, we aim to reproduce those results to ensure that our implementation of the CausalRCA algorithm correctly performs root cause localization based on real-time monitoring data.

The CausalRCA algorithm's validation involves comparing its ability to model anomaly paths, rank metrics, and identify root causes as outlined in the research. This comparison ensures that our system can effectively utilize CausalRCA for practical operational decisions and recovery actions.

Steps for Validation

1. **Dataset Acquisition**: Use the identical datasets that were employed in the original experiments. This ensures consistency in the validation process, allowing us to focus on the algorithm's performance in our environment.

2. **Algorithm Configuration**: Set up the CausalRCA algorithm using the same configuration parameters detailed in the studies.

3. **Performance Metrics Comparison**: Evaluate the effectiveness of the CausalRCA algorithm by using the same evaluation metrics applied in the validation. This holds the accuracy of root cause identification of the hogged metric.

4. **Analysis**: Conduct analysis to compare our results with those obtained in the baseline study. This analysis will help identify any significant deviations and understand the underlying causes.

for this experiment we calculate this by taking the average of 10 iterations and ranking the metrics based on that. next we compare the accuracy to identify the hogged metric.

6.3.3 Scalability

Scalability is the performance indicator that reflects the AIOps system's ability to handle increasing workloads without compromising its functionality or efficiency. In the context of this experiment, scalability is evaluated by monitoring how the system manages additional monitoring tasks under progressively increasing loads. This assessment helps demonstrate the ability of the AIOps framework to effectively operate in environments where the demand on system resources grows over time.

Methodology

To evaluate the scalability of our AIOps framework, we set up monitoring tasks incrementally, beginning with 10 tasks and increasing by 10-task intervals up to a maximum of 50 tasks. These tasks were configured with the following parameters:

- **Data Points:** 1-second intervals.
- **Data Window:** 30 minutes, which corresponds to 1800 data points.
- **Task Interval:** 5 minutes.
- **CausalRCA Threshold:** 1.5% of anomalous data entries.

The monitored application was the Retail Store Sample Application, which provided a realistic and complex environment for assessing the scalability of the AIOps framework. Each of the 10 tasks monitors a different component of the application.

Each increment represents a more substantial load on the system, allowing us to observe how the framework adapts to varying levels of demand. We monitored the memory usage and CPU usage of the AIOps framework over a period of two hours for each increment using Grafana and Prometheus. Additionally,

we focused on the performance of the most active pods within the system, specifically the Data Ingestion pod, the CGNN-MHSA-AR algorithm pod, and the CausalRCA pod.

The system used for this test environment was equipped with 8 vCPUs and 16 GB of memory, providing a robust platform to assess how the framework scales with increased tasks. The goal was to identify the threshold at which the system's performance begins to degrade and to determine its capacity to handle multiple concurrent tasks efficiently.

Performance Metrics To quantify scalability, we monitored the following performance metrics across the system and individual pods:

- **CPU Usage**: This metric provides insight into the processing power consumed by the AIOps framework and its components as the number of monitoring tasks increases. High CPU usage indicates a heavy processing load, which can lead to slower response times if the system becomes overburdened.
- **Memory Usage**: Monitoring memory consumption identifies potential bottlenecks. As the system handles more tasks, increased memory usage can signal stress on the framework, especially if it approaches the system's maximum capacity.
- **System Load**: The overall load on the system is an important indicator of scalability. We observe how the framework manages the cumulative resource demand as more tasks are added, ensuring that it remains stable and responsive.
- **On-Time Delivery of CausalRCA Results**: This indicator measures the ability of the CausalRCA algorithm to deliver results within the expected time frame as the system load increases. Delays in delivery can indicate scalability issues.
- **Task Schedule Adherence**: This metric assesses whether the monitoring tasks remain on schedule as the number of tasks increases. Any deviations from the schedule could signal that the system is struggling to handle the additional load.

Steps for Evaluation

The scalability evaluation was conducted through the following steps:

1. **Incremental Task Setup**: Start with 10 monitoring tasks and increase the number of tasks by 10 at each step, up to 50 tasks. Each set of tasks is configured with 1-second data points, a 30-minute data window, and a 5-minute task interval.

2. **Resource Monitoring**: Utilize Grafana to continuously monitor the CPU and memory usage of the AIOps framework, focusing on the overall system as well as the Data Ingestion pod, CGNN-MHSA-AR algorithm pod, and CausalRCA pod. This monitoring is carried out over two-hour periods for each task increment.

3. **Data Collection**: Record the CPU and memory usage at each task increment, alongside the system load metrics. This data provides a basis for evaluating how the framework scales under increasing loads.

4. **Analysis**: Analyze the collected data to identify trends and thresholds where the system's performance begins to degrade. Specifically, assess how the additional tasks impact the CPU and memory usage, and determine the framework's maximum sustainable load before significant performance degradation occurs. Additionally, evaluate the on-time delivery of CausalRCA results and whether the monitoring tasks remained on schedule.

Analysis

The analysis focuses on identifying the point at which the AIOps framework's performance becomes unsustainable under the given load conditions. We compare CPU and memory usage across the different task increments to observe how the system scales and identify any potential bottlenecks or inefficiencies.

In particular, we scrutinize the performance of the most active pods—Data Ingestion, CGNN-MHSA-AR, and CausalRCA—to determine how well these critical components manage increased demand. We also evaluate key indicators such as the on-time delivery of CausalRCA results and the ability of the monitoring tasks to remain on schedule. The results from this analysis will guide future optimizations of the AIOps framework, ensuring that it can maintain high performance even as the number of monitoring tasks scales up in real-world deployment scenarios.

6.4 Results of Experiments

6.4.1 Configurability Evaluation Results

The configurability of the AIOps framework was evaluated based on feedback from three experts in the field of cloud services. Their insights and ratings provide valuable information on the system's ease of use, flexibility, and areas for improvement.

Survey Responses

Feedback was collected from a Data Engineer, an IT Consultant, and a Staff Software Engineer. Detailed survey results are provided in Appendix B.2. The survey captured ratings on task complexity and ease of use, along with qualitative feedback.

Analysis of Results

The feedback from the respondents highlights several aspects of the AIOps framework's configurability.

Task Complexity The ratings for tailoring system strategies varied, with some respondents finding it easy while others rated it as neutral. This suggests that while the system is relatively straightforward for some users, there may be aspects that could benefit from further simplification or better documentation. Configuring monitoring tasks received consistently high marks for ease, indicating that this aspect of the system is well-designed and user-friendly.

Ease of Use All respondents found the overall configuration process easy to use, which underscores the effectiveness of the system's user-centric design. However, there were suggestions for improvements, such as offering advanced options for those who want more control and automating certain aspects of the configuration to reduce manual input requirements.

Qualitative Feedback The qualitative feedback provided valuable insights into potential enhancements. For instance, allowing users to upload custom models for the CRCA algorithm and improving the visualization of cause-and-effect relationships were notable suggestions. Additionally, simplifying the training process by integrating with tools like Prometheus and automating data input could further enhance user experience.

Theoretical and Practical Implications

The theoretical implications of these findings suggest that while the AIOps framework is robust and user-friendly, there is room for improvement in terms of customization and automation. These enhancements could make the system even more adaptable and easier to use across a wider range of applications.

Practically, the feedback indicates that the system's default configurations are effective for initial use, reducing the initial burden on users. The ability to customize parameters and integrate seamlessly with existing tools like Kubernetes and Prometheus highlights the framework's flexibility and ease of integration. These features can significantly reduce the time and effort required to deploy and manage the AIOps framework in diverse cloud environments.

6.4.2 Consistency

CGNN-MHSA-AR Algorithm

The evaluation of the CGNN-MHSA-AR algorithm within our AIOps framework was structured to assess its performance across various machines, focusing on precision, recall, and F1 score as primary metrics. These metrics are integral for understanding the effectiveness of anomaly detection within distributed

cloud applications, reflecting the algorithm's ability to identify true anomalies (precision), capture all potential anomalies (recall), and balance these aspects (F1 score).

Table 6.1: CGNN-MHSA-AR Performance Metrics Comparison

Machine	Metric	Baseline	AIOps Framework	% Change
Machine 1-3	Precision	0.837	0.829	-0.96%
	Recall	0.870	0.841	-3.33%
	F1 Score	0.853	0.835	-2.11%
Machine 1-8	Precision	0.712	0.713	+0.14%
	Recall	0.956	0.957	+0.10%
	F1 Score	0.816	0.817	+0.12%
Machine 2-6	Precision	0.777	0.754	-2.96%
	Recall	0.999	1.000	+0.10%
	F1 Score	0.875	0.860	-1.71%
Machine 3-5	Precision	0.918	0.893	-2.72%
	Recall	0.955	0.955	0.00%
	F1 Score	0.936	0.923	-1.39%

Performance Overview

The results detailed in Table 6.1 demonstrate the CGNN-MHSA-AR algorithm's performance variability across different machines. Notably, the performance metrics slightly decreased for most machines compared to the baseline, with changes within an acceptable error margin. These variations are attributed to the inherent complexities of deploying CGNN-MHSA-AR in a real-world operational environment where data variability and dynamic conditions influence algorithm behavior.

Precision and Recall Analysis For Machine 1-3, a slight decrease in precision and recall was observed, indicating a marginal reduction in the algorithm's accuracy and coverage in anomaly detection. However, the changes were minimal, highlighting the algorithm's robustness. Machine 1-8 showed an improvement, albeit small, which can be considered interesting given the challenging nature of maintaining performance in varying operational contexts. This improvement shows some level of adaptability of our framework when handling different types of anomalies and operational data.

F1 Score Consistency The F1 scores across the machines confirm that the integrated CGNN-MHSA-AR algorithm maintains a high level of performance efficacy, with most reductions being within the range of 1-2%. Such consistency is important for ensuring reliability in automated anomaly detection within

cloud applications, where precise and accurate anomaly identification can significantly impact operational efficiency and system stability.

Theoretical and Practical Implications

The slight deviations in performance metrics are consistent with the expected variability of deploying machine learning algorithms in heterogeneous environments. Theoretical considerations suggest that such variability can stem from differences in operational conditions, and algorithm sensitivity to unseen anomalies.

Machine learning models, particularly in anomaly detection, expect variability due to the dynamic nature of cloud environments. The slight deviations observed are consistent with the expected behavior of such models when applied outside of ideal conditions. The AIOps framework's performance in real-world settings, showing only minor variations, shows robustness and capability to generalize effectively across different scenarios. Moreover, in practical applications, a small margin of error in detection metrics is acceptable if it does not compromise the overall system performance or the detection of critical anomalies. These results suggest that the system maintains reliability and effectiveness with slight performance dips. Additionally the resilience of the AIOps system in maintaining performance close to the baseline under real operational stresses show that it is suitable for performance monitoring and anomaly detection in infrastructure settings.

Practically, the results affirm the framework's capability to function effectively, aligning with the system's design objectives for robustness and adaptability. The performance of the CGNN-MHSA-AR algorithm within the AIOps framework demonstrates the system's capacity to adapt and perform, validating the design choices and operational strategies employed in its development. The results also provide a foundation for improvements and refinements, aligning with the system's continuous learning and adaptation capabilities.

CausalRCA Algorithm

In our evaluation of the CausalRCA algorithm within the AIOps framework, the focus was on measuring the algorithm's precision in identifying and ranking the impact of various container metrics under anomalous conditions. The experiments, consistently configured across ten iterations, targeted specific metrics, notably the CPU usage of the front-end container, identified as the primary anomalous metric. To ensure the robustness of our findings, each experiment was repeated ten times under the same conditions, and the results were averaged. This was for validating the CausalRCA's efficacy and stability in a controlled setup.

Analyzing Results

Results summarized in Table 6.2 to 6.5 compare baseline performance metrics against those obtained from our AIOps framework. The average rankings

derived from multiple iterations provide a detailed view of the algorithm's performance, emphasizing its ability to accurately rank metrics according to their impact on system functionality, with a special focus on the identified anomalous metric, 'front-end ctn cpu.'

The 'front-end ctn cpu' was systematically observed to maintain a consistent rank across multiple iterations of the experiment, which indicates that the CausalRCA algorithm effectively recognizes and prioritizes this metric as having a significant impact on system performance. This consistency demonstrates the algorithm's reliability in detecting and responding to anomalies that could potentially disrupt system operations.

The integration of the CausalRCA algorithm within our AIOps framework has proven effective in detecting and analyzing the root causes of performance anomalies, particularly with the 'front-end ctn cpu' as the primary anomalous metric. While some variability in the results is expected due to the inherent variability of the CausalRCA algorithm, the outcomes are within acceptable limits and confirm the algorithm's utility in enhancing operational reliability and responsiveness. These findings are helpful for further refinements and ensuring the algorithm's adaptability across various operational scenarios, reinforcing the overall flexibility and portability of the system.

cpu-hog1-frontend-file

Metric	Baseline	AIOps Framework	AIOps Rank	Rank Difference
front-end_ctn_cpu	0.0053	0.0054	1	0
user_ctn_write	0.0053	0.0054	2	0
catalogue_ctn_latency	0.0061	0.0069	4	-1
orders_ctn_mem	0.0113	0.0054	3	1
front-end_ctn_mem	0.0128	0.0134	6	-1
user_ctn_latency	0.0129	0.0216	14	-8
shipping_ctn_latency	0.0142	0.0144	7	0
front-end_ctn_latency	0.0177	0.0154	9	-1
front-end_ctn_net_out	0.0191	0.0152	8	1
shipping_ctn_net_out	0.0220	0.0327	20	-10
payment_ctn_net_out	0.0223	0.0294	18	-7
orders_ctn_write	0.0227	0.0161	11	1
carts_ctn_latency	0.0233	0.0133	5	8
payment_ctn_latency	0.0290	0.0237	16	-2
carts_ctn_write	0.0315	0.0205	13	2
front-end_ctn_net_in	0.0333	0.0233	15	1
payment_ctn_net_in	0.0343	0.0200	12	5
shipping_ctn_cpu	0.0355	0.0374	21	-3
orders_ctn_latency	0.0358	0.0157	10	9
carts_ctn_net_out	0.0362	0.0542	29	-9
orders_ctn_cpu	0.0371	0.0466	26	-5
user_ctn_net_out	0.0379	0.0623	32	-10
catalogue_ctn_net_in	0.0384	0.0377	22	1
carts_ctn_cpu	0.0402	0.0638	33	-9
orders_ctn_net_out	0.0403	0.0286	17	8
carts_ctn_net_in	0.0404	0.0512	27	-1
catalogue_ctn_cpu	0.0405	0.0413	24	3
catalogue_ctn_net_out	0.0406	0.0460	25	3
user_ctn_net_in	0.0426	0.0537	28	1
orders_ctn_net_in	0.0430	0.0297	19	11
shipping_ctn_net_in	0.0497	0.0385	23	8
payment_ctn_cpu	0.0524	0.0558	31	1
user_ctn_cpu	0.0663	0.0554	30	3

Table 6.2: Performance metrics for CausalRCA original and AIOps Framework - gamma 0.25 eta 100.

Metric	Baseline	AIOps Framework	AIOps Rank	Rank Difference
user_ctn_write	0.0055	0.0055	1	0
catalogue_ctn_latency	0.0063	0.0092	2	0
front-end_ctn_cpu	0.0111	0.0109	3	0
shipping_ctn_latency	0.0139	0.0161	7	-3
orders_ctn_mem	0.0141	0.0139	5	0
front-end_ctn_mem	0.0147	0.0136	4	2
user_ctn_latency	0.0196	0.0185	9	-2
carts_ctn_latency	0.0203	0.0141	6	2
orders_ctn_write	0.0207	0.0251	13	-4
payment_ctn_latency	0.0217	0.0306	19	-9
front-end_ctn_net_out	0.0219	0.0195	11	0
front-end_ctn_latency	0.0224	0.0172	8	4
shipping_ctn_net_out	0.0224	0.0241	12	1
orders_ctn_latency	0.0243	0.0260	15	-1
payment_ctn_net_out	0.0272	0.0188	10	5
orders_ctn_net_out	0.0293	0.0387	25	-9
orders_ctn_net_in	0.0295	0.0429	28	-11
carts_ctn_write	0.0303	0.0286	18	0
catalogue_ctn_net_in	0.0327	0.0284	17	2
front-end_ctn_net_in	0.0331	0.0343	21	-1
catalogue_ctn_net_out	0.0335	0.0255	14	7
payment_ctn_net_in	0.0343	0.0372	24	-2
orders_ctn_cpu	0.0357	0.0552	30	-7
carts_ctn_net_in	0.0371	0.0368	23	1
carts_ctn_cpu	0.0376	0.0416	27	-2
user_ctn_net_out	0.0405	0.0279	16	10
carts_ctn_net_out	0.0410	0.0319	20	7
user_ctn_net_in	0.0488	0.0438	29	-1
payment_ctn_cpu	0.0491	0.0562	31	-2
catalogue_ctn_cpu	0.0498	0.0361	22	8
shipping_ctn_net_in	0.0512	0.0407	26	5
shipping_ctn_cpu	0.0521	0.0676	33	-1
user_ctn_cpu	0.0681	0.0634	32	1

Table 6.3: Performance metrics for CausalRCA original and AIOps Framework - gamma 0.25 eta 1000.

Metric	Baseline	AIOps Framework	AIOps Rank	Rank Difference
user_ctn_write	0.0050	0.0049	2	-1
catalogue_ctn_latency	0.0064	0.0058	4	-2
front-end_ctn_cpu	0.0079	0.0049	1	2
orders_ctn_mem	0.0079	0.0049	3	1
user_ctn_latency	0.0092	0.0074	5	0
shipping_ctn_latency	0.0097	0.0093	7	-1
front-end_ctn_mem	0.0103	0.0177	14	-7
front-end_ctn_latency	0.0128	0.0115	9	-1
shipping_ctn_net_out	0.0129	0.0171	13	-4
carts_ctn_latency	0.0154	0.0094	8	2
front-end_ctn_net_out	0.0180	0.0265	16	-5
carts_ctn_write	0.0192	0.0149	11	1
payment_ctn_latency	0.0221	0.0088	6	7
orders_ctn_write	0.0230	0.0130	10	4
front-end_ctn_net_in	0.0247	0.0311	20	-5
payment_ctn_net_out	0.0262	0.0275	17	-1
orders_ctn_latency	0.0274	0.0160	12	5
payment_ctn_net_in	0.0279	0.0312	21	-3
shipping_ctn_net_in	0.0287	0.0278	18	1
carts_ctn_net_out	0.0387	0.0580	31	-11
catalogue_ctn_net_in	0.0406	0.0523	26	-5
carts_ctn_net_in	0.0409	0.0558	29	-7
orders_ctn_cpu	0.0438	0.0561	30	-7
catalogue_ctn_cpu	0.0448	0.0414	22	2
shipping_ctn_cpu	0.0454	0.0541	27	-2
catalogue_ctn_net_out	0.0465	0.0518	24	2
user_ctn_net_out	0.0483	0.0507	23	4
carts_ctn_cpu	0.0509	0.0663	33	-5
user_ctn_net_in	0.0524	0.0519	25	4
user_ctn_cpu	0.0536	0.0545	28	2
orders_ctn_net_out	0.0552	0.0257	15	16
payment_ctn_cpu	0.0613	0.0618	32	0
orders_ctn_net_in	0.0630	0.0296	19	14

Table 6.4: Performance metrics for CausalRCA original and AIOps Framework - gamma 0.5 eta 10.

Metric	Baseline	AIOps Framework	AIOps Rank	Rank Difference
front-end_ctn_cpu	0.0051	0.0079	4	-3
user_ctn_write	0.0051	0.005	1	1
orders_ctn_mem	0.0051	0.0079	5	-2
shipping_ctn_latency	0.0056	0.0115	10	-6
orders_ctn_write	0.0058	0.0141	13	-8
catalogue_ctn_latency	0.0061	0.0057	2	4
shipping_ctn_net_out	0.0085	0.0096	7	0
front-end_ctn_net_out	0.0104	0.0123	11	-3
front-end_ctn_net_in	0.0131	0.0192	17	-8
carts_ctn_write	0.0165	0.014	12	-2
user_ctn_latency	0.0167	0.0067	3	8
payment_ctn_net_out	0.0182	0.0185	16	-4
front-end_ctn_latency	0.0214	0.0112	9	4
carts_ctn_latency	0.0216	0.008	6	8
shipping_ctn_net_in	0.0256	0.0247	19	-4
payment_ctn_latency	0.0265	0.0157	14	2
orders_ctn_latency	0.0312	0.0166	15	2
payment_ctn_net_in	0.0332	0.0237	18	0
front-end_ctn_mem	0.0333	0.0101	8	11
carts_ctn_net_out	0.0342	0.0457	22	-2
catalogue_ctn_cpu	0.0352	0.0465	23	-2
catalogue_ctn_net_out	0.0404	0.0481	24	-2
user_ctn_net_out	0.0444	0.0568	28	-5
carts_ctn_net_in	0.0455	0.0414	20	4
catalogue_ctn_net_in	0.0463	0.0448	21	4
orders_ctn_net_out	0.0463	0.0608	31	-5
user_ctn_net_in	0.0495	0.0525	26	1
shipping_ctn_cpu	0.0521	0.0581	30	-2
orders_ctn_cpu	0.0542	0.0482	25	4
orders_ctn_net_in	0.0566	0.0567	27	3
user_ctn_cpu	0.0574	0.0568	29	2
carts_ctn_cpu	0.0617	0.068	32	0
payment_ctn_cpu	0.0668	0.0731	33	0

Table 6.5: Performance metrics for CausalRCA original and AIOps Framework - gamma 0.75 eta 10.

Theoretical and Practical Implications

From a theoretical perspective, the CausalRCA algorithm is designed to leverage principles of causality to analyze the interdependencies within cloud architectures. Theoretically, this aligns with models of complex systems where individual components can have disproportionate impacts on operational integrity. However, the variable performance and occasional inaccuracies in ranking and identifying anomalous metrics demonstrate the challenges of applying these theoretical models to dynamic and complex real-world environments.

Practically, while the CausalRCA algorithm effectively highlights critical metrics under certain conditions, its inconsistent performance across different

iterations and configurations suggests limitations in its current implementation. The differences observed, especially in the shifts in metric rankings and the identification of anomalous metrics, underline the practical challenges in achieving reliable anomaly detection in distributed systems. Such variability can complicate the tasks of system administrators and could potentially lead to overlooked anomalies or misprioritized responses, affecting the system's reliability and operational efficiency.

The practical impact of these inconsistencies is significant, particularly in environments where precision in anomaly detection and causality analysis is important. The variations in the algorithm's performance may require additional safeguards, such as manual oversight or additional monitoring tools, to ensure system stability and performance are maintained.

Furthermore, these results show the need for adjustments and enhancements to the CausalRCA algorithm. By refining its analytical models and improving adaptability to different system architectures and conditions, the algorithm's alignment with practical necessities can be improved. This ongoing development can ultimately enhance the effectiveness of the AIOps framework.

6.4.3 Scalability

his section evaluates our framework's ability to scale by gradually increasing the number of monitoring tasks and examining the system's response in terms of CPU and memory usage, as well as task processing efficiency. By simulating varying loads, we identify performance thresholds and potential bottlenecks, providing insights into the system's capacity to maintain high performance under increasing demands.

CPU Usage Analysis

The CPU usage analysis across various task levels provides insights into the performance and scalability of the AIOps framework and its critical components:

CGNN-MHSA-AR Pod The CPU usage for the CGNN-MHSA-AR pod increases progressively as the task load rises. Up to 30 tasks, the pod maintains stable CPU consumption, reflecting its capability to handle moderate workloads effectively. However, from 40 tasks onward, there is a noticeable rise in CPU consumption, suggesting that the pod begins to experience strain as the number of tasks grows. The significant increase at 50 tasks indicates that the pod is approaching its operational limits, which could lead to potential performance bottlenecks under further load. Additionally, while the CGNN-MHSA-AR pod met its deadlines up to 30 tasks, it began slightly missing deadlines at 40 tasks and took double the time to process tasks at 50 tasks. This highlights a critical point where the pod's efficiency sharply declines as the load increases.

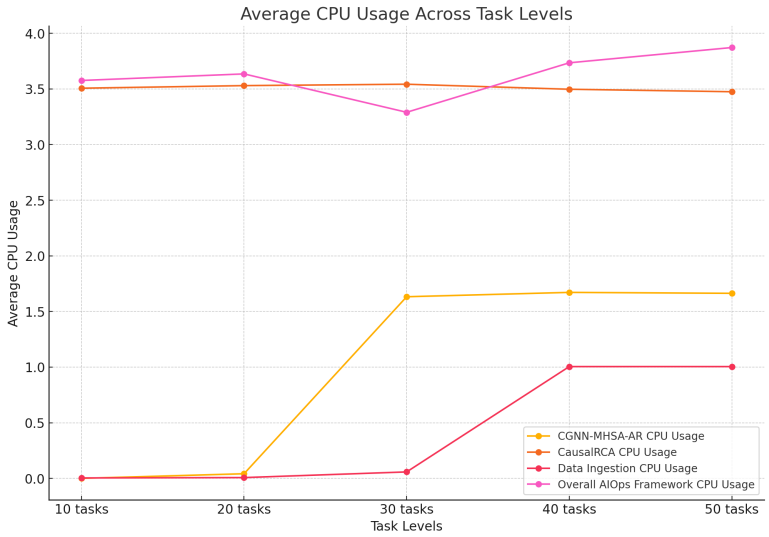
CausalRCA Pod The CausalRCA pod exhibits a similar pattern, with CPU usage rising steadily as task levels increase. Up to 20 tasks, CPU usage re-

mains within manageable limits, indicating efficient processing. However, as the task load increases to 30 and beyond, there is a significant jump in CPU consumption, particularly at 50 tasks. This suggests that the CausalRCA pod becomes increasingly resource-intensive under higher loads, potentially impacting its ability to deliver results in a timely manner. While the CausalRCA was able to deliver on time up to 20 tasks, its performance began to degrade incrementally as the number of tasks increased beyond this point, resulting in delayed deliveries. The sharp rise in CPU usage and the delay in result delivery both show the need for optimization to maintain performance under heavy workloads.

Data Ingestion Pod The Data Ingestion pod shows stable CPU usage up to 30 tasks, but a substantial rise is observed from 40 tasks onward, with a particularly sharp increase at 50 tasks. This trend indicates that the data ingestion process becomes more CPU-demanding as the number of tasks increases. The significant rise at higher task levels suggests that the pod may be nearing its processing capacity, which could affect the overall data processing capabilities of the AIOps framework.

Overall AIOps Framework CPU Usage The overall CPU usage of the AIOps framework increases steadily as the task load rises. The framework handles up to 30 tasks efficiently, with moderate CPU usage. However, the increase becomes more pronounced at 40 tasks, and there is a significant spike at 50 tasks. This trend suggests that while the AIOps framework can manage moderate workloads effectively, it starts to experience strain at higher task levels. The spike at 50 tasks indicates that the framework is nearing its maximum CPU capacity, which could lead to slower processing times and increased latency.

Figure 6.2:



Memory Usage Analysis

Memory usage across the different components of the AIOps framework further highlights its scalability characteristics:

CGNN-MHSA-AR Pod Memory usage for the CGNN-MHSA-AR pod increases linearly as the task load rises. Up to 30 tasks, the pod manages memory efficiently, with only a slight rise beyond this point. The linear increase suggests that the pod's memory requirements scale predictably with the task load. However, the rise at 40 and 50 tasks indicates that the pod is starting to experience pressure on its memory resources, which could lead to memory-related bottlenecks if the load continues to grow. The additional strain on memory at higher task levels likely contributes to the pod's reduced ability to meet deadlines, as noted in the CPU analysis.

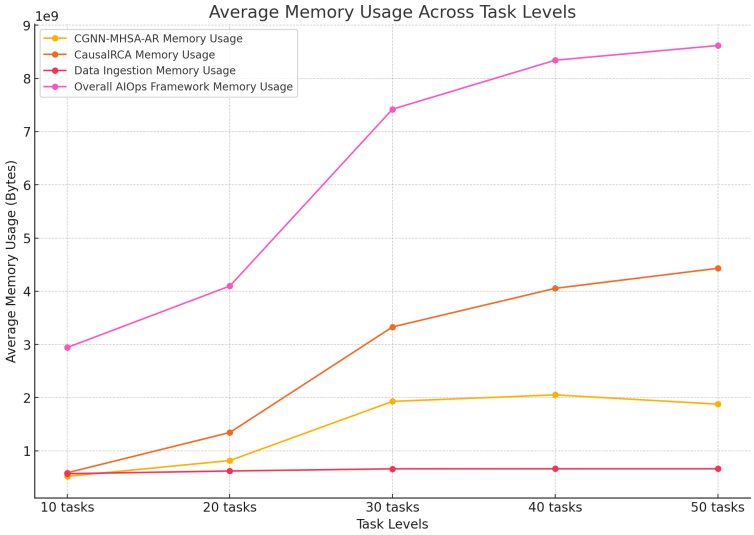
CausalRCA Pod The CausalRCA pod shows a substantial increase in memory usage as the task count rises from 20 to 50 tasks. Memory usage remains within acceptable limits up to 20 tasks, but it begins to increase significantly at 30 tasks and beyond. This pattern suggests that the CausalRCA pod is particularly memory-intensive at higher task levels, which could impact its processing efficiency and the overall performance of the AIOps framework. The steep rise at 50 tasks, coupled with the noted delays in result delivery, underscores the importance of optimizing memory management for this pod to ensure scalability.

Data Ingestion Pod Memory usage for the Data Ingestion pod remains stable across all task levels, with only a slight increase at 50 tasks. This stability

indicates that while the pod's CPU usage increases significantly with the task load, its memory requirements do not rise as dramatically. This suggests that the data ingestion process is more CPU-bound than memory-bound, and its scalability challenges are more related to processing power than memory capacity.

Overall AIOps Framework Memory Usage The overall memory usage of the AIOps framework increases steadily as the task load rises, particularly after 30 tasks. The rise is more linear compared to CPU usage, suggesting that while memory usage does increase with the task load, it does so in a more controlled manner. This trend indicates that the AIOps framework is managing memory efficiently even as the task load increases. However, the rise in memory usage at 40 and 50 tasks suggests that the framework is approaching its memory capacity, which could lead to slower processing and potential memory-related issues if the load continues to increase.

Figure 6.3:



Theoretical and Practical Implications

The findings from the scalability analysis practically emphasize the need for optimizing resource allocation, especially as the task load increases. The significant rise in CPU and memory usage in the CGNN-MHSA-AR and CausalRCA pods beyond 30 tasks suggests that the system must dynamically scale resources to prevent performance degradation. The observed delays in these pods show the importance of timely delivery of insights, as delays could hinder an organization's ability to respond quickly to anomalies, potentially leading to extended downtime or unresolved performance issues. This analysis also highlights the

necessity of careful capacity planning and system scaling in enterprise environments to ensure that the AIOps framework can continue to operate effectively as it scales. Prioritizing optimization efforts for the most resource-intensive components, such as the CGNN-MHSA-AR and CausalRCA pods, is helpful for maintaining system performance.

Theoretically, the performance degradation observed beyond 30 tasks provides insights into the scalability limits of the current framework, informing the design of more scalable architectures. The delays in task processing suggest that the current algorithms may require further optimization, highlighting the need for research into more efficient algorithms capable of maintaining performance under heavy loads. Additionally, the increase in resource consumption at higher task levels offers valuable information on how resource constraints impact system behavior, contributing to a better understanding of the trade-offs between resource allocation, system performance, and task load. This knowledge can be used to refine theoretical models that predict system behavior under varying workloads, aiding in the development of more robust and efficient AIOps solutions.

6.5 Conclusion

In this chapter, we have presented the results and evaluation of our AIOps framework implementation, focusing on its flexibility, portability, and overall performance under various conditions. The structured experiments provided a detailed analysis of the system's capability to handle different configurations, maintain consistency across operational conditions, and scale efficiently with increasing workloads. Through this evaluation, we identified key strengths, such as the robustness of the algorithms within the framework and the framework's ability to integrate seamlessly with existing cloud environments, as well as areas for improvement, particularly in terms of scalability and resource optimization.

The insights gained from this evaluation demonstrate practical viability of the AIOps framework and also offer guidance for future enhancements. By understanding how the system performs under different stressors, we can better optimize its components to improve efficiency and reliability in real-world deployments.

The next chapter will address our research questions, discuss the limitations of our study, and outline future directions for the development and refinement of our AIOps framework.

Chapter 7

Discussion

In this chapter, we explore the implications and broader context of our findings, by reflecting on the research questions that guided our study. Additionally, we address the limitations encountered during our research and propose future directions to enhance the framework's capabilities. Through this, we aim to provide the potential and challenges of implementing an AIOps framework for anomaly detection and performance monitoring in distributed cloud applications, while also identifying paths for future advancements.

7.1 Research Questions

SQ1 How can the AIOps framework be designed for seamless integration with existing cloud infrastructures while ensuring a user-friendly interface that supports flexibility and configurability for diverse operational needs?

Our AIOps framework is built with technologies that ensure it can be easily integrated into existing cloud environments. The framework leverages Kubernetes for managing its distributed components. This allows it to integrate with cloud infrastructures that already use Kubernetes, ensuring that it can scale dynamically based on workload demands. Kubernetes also facilitates the orchestration of the various microservices within the AIOps framework, such as data collection, processing, and anomaly detection.

Flask serves as the backbone for handling API requests across different modules, making it easy to interface with other cloud services. Celery, paired with Redis, handles asynchronous task management, allowing the framework to process data and run anomaly detection algorithms without disrupting other operations. This modular design supports the smooth integration of additional components as needed.

The integration of Prometheus enables real-time data collection and monitoring within cloud environments. This ensures that the AIOps framework can tap into existing monitoring setups, reducing the need for additional configurations and making the deployment process more straightforward.

To ensure the framework supports a wide range of operational needs, the user interface is designed with flexibility and ease of use in mind. The user interface, built with Django, allows users to interact with the AIOps framework intuitively. It provides straightforward tools for configuring monitoring tasks, training models, and visualizing results. This approach ensures that even users with limited technical expertise can effectively manage the system.

The framework's components are designed to be configurable. For instance, users can easily adjust monitoring parameters, set anomaly detection thresholds, and manage data processing workflows through the interface. This flexibility ensures that the framework can be tailored to specific operational requirements without requiring complez customization.

Configurability Experiment

We validated the configurability of the AIOps framework through an experiment involving three domain experts. These experts were tasked with configuring the framework to meet specific scenarios. The feedback showed that the system is easy to configure, particularly for common tasks like setting up monitoring. However, there were opportunities identified for further simplifying the process, particularly for more complex configurations. This experiment confirmed that the framework is both flexible and user-friendly, while also highlighting areas for enhancement.

To validate the configurability of our AIOps framework, we conducted an experiment involving three domain experts. These experts were tasked with configuring the AIOps framework to meet specific operational and application requirements. This experiment aimed to assess how flexible and user-friendly the framework is when it comes to adapting to different needs.

The feedback from the experts indicated that the framework is generally easy to configure, with high ratings for the simplicity of setting up monitoring tasks. However, there was some variation in how complex they found the process of tailoring the system for different types of anomalies. This suggests that while the AIOps framework is user-friendly for most tasks, there could be room for improvement in simplifying the configuration for more complex scenarios.

Qualitative feedback highlighted the importance of offering more advanced options for users who need greater control over system settings. Some experts suggested automating certain aspects of the configuration process to reduce manual effort.

Overall, the experiment validated that our AIOps framework is configurable and accessible to users. The positive responses to the ease of setting up monitoring tasks show the framework's flexibility, while the suggestions for improvement provide a insights on future enhancements.

SQ2 What are the components and technologies necessary for developing and validating an AIOps framework in a cloud environment, and how do they interact to achieve effective anomaly detection?

To develop and validate an effective AIOps framework in a cloud environment, several key components are found to be necessary. These components work together to achieve reliable and accurate anomaly detection:

Data Collection Module For gathering metrics and performance data from various sources within the cloud environment. It serves as the entry point for all data that will be analyzed by the AIOps framework. Without comprehensive data collection, the framework would lack the information needed to detect anomalies. This module ensures that data is captured in real-time from a range of cloud services, providing the material for subsequent processing and analysis.

Data Processing Module Responsible for transforming the data collected into a format suitable for analysis. This includes tasks such as data normalization, cleaning, and aggregation. Effective anomaly detection requires high-quality, consistent data. The Data Processing Module ensures that the data fed into the anomaly detection algorithms is clean, structured, and comparable across different time periods and metrics.

Anomaly Detection Module Core component of the AIOps framework. It uses advanced algorithms to identify patterns in the data that deviate from the norm, signaling potential issues within the cloud environment. This module must be robust and capable of identifying deviations that could indicate underlying problems. Accurate detection is necessary for preemptively addressing issues before they escalate.

Learning and Adaptation Module Improves the framework's performance by training the anomaly detection models on new data. It allows the system to adapt to changes in the environment and learn from new patterns of normal and anomalous behavior.

User Interface Module Provides a platform for users to interact with the AIOps framework. It allows operators to configure the system, monitor its performance, and review the results of anomaly detection and root cause analysis. A user-friendly interface is necessary for making the complex operations of the AIOps framework accessible.

Interaction of Components

These components are designed to work in an integrated manner to ensure effective anomaly detection. The process begins with the Data Collection Module gathering metrics from the cloud environment. The Data Processing Module then cleans and structures this data, preparing it for analysis. The Anomaly Detection Module examines the processed data for any deviations from expected patterns. Once an anomaly is detected, the Root Cause Analysis Module identifies the specific factors contributing to the issue. This integrated approach

ensures that their origins are also clearly understood, allowing for effective resolutions. The Learning and Adaptation Module feeds back into the system, refining the anomaly detection models based on new data. This creates a cycle of ongoing improvement, ensuring the framework remains effective as the environment evolves.

Consistency Experiment

To validate the effectiveness and reliability of our AIOps framework, particularly the consistency of its anomaly detection capabilities, we conducted an experiment to test how well the framework performs in identifying and analyzing anomalies under different conditions.

We used two algorithms, CGNN-MHSA-AR and CausalRCA, and validated their performance using datasets from different machines within a cloud environment. The goal was to replicate and compare the results with baseline performance metrics to ensure that the framework's anomaly detection capabilities were consistent and reliable.

We evaluated the CGNN-MHSA-AR algorithm using datasets that had been previously tested in similar studies. Key performance indicators, including precision, recall, and F1 score, were measured to assess the accuracy of anomaly detection. We compared these results with baseline metrics to ensure consistency.

The CausalRCA algorithm was tested by determining its ability to accurately identify the root causes of detected anomalies. The experiment involved running multiple iterations to observe how consistently the algorithm ranked and identified the most important metrics, such as CPU usage in specific containers. The results were compared to baseline rankings to validate the reliability of the root cause analysis.

The consistency experiment confirmed that our AIOps framework reliably detects anomalies and accurately identifies their root causes. The CGNN-MHSA-AR algorithm demonstrated consistent performance across different machines, with only minor variations from the baseline metrics, which is expected in dynamic cloud environments. Similarly, the CausalRCA algorithm showed consistent accuracy in identifying metrics, though there were some variations in ranking under different conditions, which highlights the complexity of real-world deployments.

SQ3 How does the AIOps framework perform under varying workloads, and what strategies can be employed to ensure its scalability and responsiveness in a dynamic cloud environment?

To understand how the AIOps framework performs under varying workloads, and to explore strategies for ensuring its scalability and responsiveness in a dynamic cloud environment, we examined both the framework's design and its performance in real-world scenarios. Several strategies are implemented to ensure the AIOps framework remains scalable and responsive:

The framework is designed to take advantage of both horizontal and vertical scaling. Kubernetes automates the deployment, scaling, and management of containerized applications, ensuring that the system can dynamically adjust to workload changes. Kubernetes' auto-scaling features enable the framework to scale resources up or down based on real-time demand.

By using Celery for asynchronous task management, the framework can handle long-running tasks in the background, which prevents bottlenecks and maintains system responsiveness. This is particularly important during periods of high demand, where tasks such as data processing or model training could otherwise slow down the system.

The framework's data processing pipeline is optimized for efficiency, ensuring that data is normalized and prepared for analysis quickly, even as the volume of incoming data increases. This helps maintain the speed and accuracy of anomaly detection under varying workloads.

Scalability Experiment

To validate the scalability of the AIOps framework, we conducted an experiment designed to test how well the system performs as the number of monitoring tasks increases. This experiment aimed to identify the framework's limits and evaluate its ability to maintain responsiveness under heavy workloads.

We incrementally increased the number of monitoring tasks from 10 to 50, observing the system's performance at each stage. Each task involved monitoring specific components of a cloud-based application, with data collected at one-second intervals over 30-minute windows.

Key performance metrics monitored during the experiment included CPU Usage were we measured the the overall framework and specific components, such as the CGNN-MHSA-AR, CausalRCA, and Data Ingestion pods and Memory Usage was tracked to assess how resource demands grew with the increasing workload. Additionally, we monitored how quickly the framework could process tasks and whether it maintained its schedule as the workload increased.

The experiment showed that the AIOps framework handled up to 30 monitoring tasks efficiently, with stable CPU and memory usage. However, as the number of tasks increased to 40 and beyond, we observed significant increases in resource consumption, particularly in the CGNN-MHSA-AR and CausalRCA pods. At 50 tasks, the framework began to show signs of strain, with delays in task processing and a marked increase in CPU and memory usage.

These findings indicate that while the AIOps framework is capable of handling moderate workloads effectively, its performance begins to degrade as the workload approaches its upper limits. The system's scalability is supported by Kubernetes' ability to manage resources, but additional optimization may be required to handle very high workloads without sacrificing responsiveness.

7.2 Limitations of the Study

While our research and development of the AIOps framework have yielded promising results, several limitations should be acknowledged. First, due to time and resource constraints, we were unable to implement several advanced features of the AIOps framework in our proof of concept. Specifically, the strategies for fault tolerance, load testing, and resource limitation tests were outlined but not executed, limiting our ability to fully validate the framework's robustness and reliability in real-world scenarios.

Additionally, the proof of concept did not include the implementation of automated response mechanisms or advanced training and adaptation processes for the algorithms. Currently, the framework lacks options for automated responses to detected anomalies. Addressing these features enables the AIOps framework to automatically improve the performance of the monitored application. While we proposed methods for integrating automated training processes and user-driven anomaly labeling, these components were not fully realized in the proof of concept. This absence limits the framework's ability to continuously learn and adapt based on new data and user inputs.

The datasets used for training and evaluating our anomaly detection models were limited in size and diversity. This constraint may affect the generalizability of our results, necessitating testing with larger and more diverse datasets in future work to ensure the framework's effectiveness across different environments and use cases. Although we discussed the importance of testing in diverse cloud environments, our current implementation was primarily validated within a single cloud platform. This limits our understanding of the framework's performance across various cloud providers and configurations.

While the framework includes basic security measures, comprehensive security features discussed in chapter 3 were not implemented, limiting the framework's ability to provide a robust security for cloud environments. Additionally, the study did not address the energy efficiency of the framework's operations. As sustainability becomes increasingly important, future research could consider optimizing the framework to minimize its footprint.

Addressing these limitations will be help to better realize the potential of the AIOps framework and to enhance its effectiveness and reliability in practical deployments.

7.3 Future Directions

To continue to develop and refine our AIOps framework, several directions are present for enhancing the system's capabilities and utility. These future directions aim to address current limitations, leverage emerging technologies, and better meet the evolving needs of distributed cloud applications.

To improve the robustness and reliability of the AIOps framework, several metrics and strategies should be implemented and utilized continuously. Introducing faults or failures into the system will help us observe how well it can

continue to operate without disruption. Examples include simulating server failures, network disconnections, or database crashes to ensure the system can gracefully handle these issues without losing its capability to detect and respond to anomalies. Additionally, stressing the system by feeding it data at higher volumes and velocities than expected during normal operations will help determine if it can handle sudden spikes in data without degradation in performance or accuracy.

Artificially limiting the system's resources, such as CPU and memory, will allow us to evaluate its performance under constrained conditions, helping us understand how resource bottlenecks affect the system's operational capabilities. Measuring how quickly and effectively the system can recover from crashes or failures is also important. This includes assessing the time it takes to return to full operational status after an incident and how well it restores any data processes that were interrupted.

Testing the system's performance under different configurations and conditions is another strategy. This involves deploying the system on various cloud platforms, using different operating systems, and changing network configurations to ensure consistent performance across diverse infrastructures. Ensuring that increases in load do not compromise the system's robustness will involve conducting both vertical and horizontal scalability tests. By utilizing these strategies and continuously monitoring their effectiveness through metrics, the AIOps framework can maintain its robustness and enhance its reliability over time.

Our thesis presents strategies for integrating automated training processes into the AIOps framework, along with implementing mechanisms for user-driven anomaly labeling. Developing methodologies for integrating automated training processes that leverage both supervised and unsupervised learning techniques will involve determining the types of data and features that are most effective for training the model to accurately identify performance anomalies across different distributed cloud applications. Creating mechanisms for users to interact with the framework by labeling detected anomalies enable the framework to refine its detection algorithms and improve accuracy over time.

Setting a continuous learning cycle where the framework evolves based on new data and user inputs will involve mechanisms for retraining the model with labeled data and updating its detection capabilities without significant manual intervention. Ensuring that the integration of automated training and user feedback leads to measurable improvements in the accuracy and precision of anomaly detection will enhance the overall effectiveness of the performance diagnosis process. Balancing the benefits of automation in training and anomaly detection with the need for human oversight and input will ensure that the framework benefits from the strengths of both machine learning algorithms and user insights.

Future work can focus on integrating robust auto-scaling features that leverage Kubernetes' native functionalities. Effective scalability requires careful planning regarding resource allocation. Determining the optimal resource limits and requests in Kubernetes to prevent over-provisioning or under-provisioning. As

the system scales, load balancing becomes more important. Developing intelligent auto-scaling policies based on predictive analytics could enhance the scalability of our framework.

Developing more advanced algorithms for automated root cause analysis can be an interesting direction. Integrating causal inference and other AI-driven diagnostic tools to automatically diagnose underlying causes of anomalies will significantly reduce resolution times and improve system reliability.

Improving the system's customization capabilities will allow users to tailor AIOps solutions more closely to their specific operational contexts. Creating user-friendly interfaces for defining custom monitoring parameters, anomaly detection thresholds, and automated response actions will enhance usability. Offering more automation options for routine maintenance and complex deployment scenarios will further reduce the operational burden on IT teams.

To further enhance flexibility, the framework can implement an adaptive configuration approach. The system dynamically adjusts its monitoring parameters based on the observed environment and operational feedback, improving precision and reducing the need for manual reconfiguration. Expanding configurability to include automated suggestions for optimal configuration settings based on machine learning analysis of historical performance data will provide tailored advice on configurations that best suit each unique environment.

By pursuing such future directions, the AIOps framework can continue to evolve and adapt, offering more efficient, and proactive solutions for managing distributed cloud applications. These advancements will ensure the framework remains robust, reliable, and capable of meeting the demands of modern IT environments.

7.4 Conclusion

In this chapter examined the implications of our findings, addressing research questions, limitations, and potential future directions. Through this chapter, we explored the design principles necessary for a user-friendly and flexible AIOps framework, adaptable across various distributed cloud applications. We detailed the methodologies for validating the framework's effectiveness and the strategies for ensuring its robustness and reliability.

Our research questions guided us in creating a modular and scalable system capable of integrating with existing cloud infrastructure. We proposed automated training processes to enhance the accuracy of anomaly detection, though these were not fully implemented in our proof of concept. The limitations of our study, such as the lack of comprehensive testing and the implementation of advanced features, show areas for future development.

Chapter 8

Conclusion

In our thesis, we have successfully developed and evaluated an AIOps framework aimed at improving performance monitoring and anomaly detection in distributed cloud environments. Our research focused on integrating advanced machine learning models, such as CGNN-MHSA-AR and CausalRCA, which have demonstrated robust capabilities in identifying and responding to performance anomalies with precision and reliability.

We employed an iterative design process, which was helped refining the framework to meet the complex demands of modern cloud applications. Through this process, we ensured that the framework is both adaptable and scalable, capable of maintaining performance under varying operational conditions. Our real-world testing and empirical evaluations confirmed that the framework can handle operational stresses while maintaining performance, validating its practical suitability.

Our research contributes to the theoretical foundations of AIOps by addressing challenges related to scalability, adaptability, and robustness. We explored the integration of machine learning algorithms and their application in real-time anomaly detection and automated response systems. This integration supports the continuous improvement and learning mechanisms essential for maintaining the efficiency of cloud-based systems.

We have also prioritized the development of a user-friendly interface, ensuring that the framework is not only technically robust but also accessible to users with varying levels of technical expertise. This aligns with DevOps practices, facilitating broader applicability within different organizational settings. Our framework's design supports seamless integration with existing IT infrastructure and operational tools, enhancing the overall effectiveness of performance monitoring systems.

The practical implications of our work are that, by applying and testing the AIOps framework in real operational environments, we have provided valuable insights into its effectiveness and adaptability. Our empirical results demonstrate that the framework can identify performance issues, maintaining accuracy and efficiency. This adaptability is important for ensuring that the framework

remains relevant and effective as cloud environments are inherently diverse.

Looking ahead, there are several directions for future research and development. One area is the further refinement of the learning algorithms to enhance their accuracy and efficiency. Additionally, expanding the framework's applicability to other types of cloud environments and operational contexts can be interesting. Exploring the integration of additional machine learning techniques and improving the user interface for better usability are also important future directions.

Our research sets a foundation for ongoing advancements in AIOps. The developed framework promises improvement and adaptation, contributing to the field of distributed cloud application performance monitoring. We believe that our work can inspire further innovations and enhancements in AIOps, ultimately leading to more efficient and reliable cloud-based systems.

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Appendices

Appendix A

Survey Identifying Key Requirements

A.1 Initial Key Requirements

Table A.1: Key Requirements

No.	Category	Description
1. Functional Requirements		
1.1	**Data Collection and Management**	Automated data collection for cloud applications monitoring. Collects metrics, logs, and event streams from various sources.
1.1.1	*Data Sources*	Integration with cloud infrastructure and monitoring tools for continuous data capture.
1.1.2	*Data Management and Storage*	Data management to handle volumes in real-time with dynamic storage.
1.2	**Real-time Data Processing**	Timely insights and responses.
1.2.1	*Stream Processing*	Technologies for real-time data stream analysis and anomaly detection.
1.2.2	*Low Latency Processing*	Minimizes latency for operational continuity.
1.3	**Anomaly Detection**	Accurate performance issue identification.
1.3.1	*Multifaceted Anomaly Detection Techniques*	Use various methods
1.3.2	*High Precision and Recall*	Minimize false positives and maximizes true positive rates.

Table A.1: Key Requirements

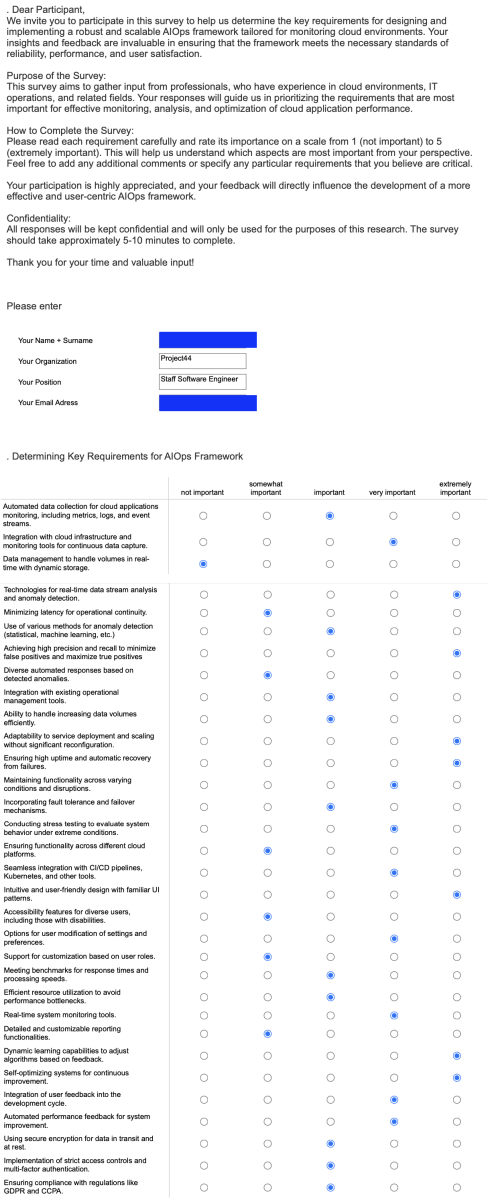
No.	Category	Description
1.4	**Automated Response and Resolution**	Automates interventions for issue mitigation and resolution.
1.4.1	*Diverse Automated Responses*	Varied responses based on detected anomalies.
1.4.2	*Integration with Operational Tools*	Compatibility with existing management tools.
2. Non-functional Requirements		
2.1	**Scalability**	Scales with increased data and operational size without performance loss.
2.1.1	*Data Volume Scalability*	Handles increasing data volumes.
2.1.2	*Operational Scalability*	Adapts to service deployment and scaling without reconfiguration.
2.2	**Reliability and Robustness**	Maintains uptime and robust performance under varying conditions.
2.2.1	*Reliability*	Operations with automatic recovery from failures.
2.2.2	*Robustness*	Maintains functionality across conditions and disruptions.
2.2.3	*Fault Tolerance and Failover Mechanisms*	Redundancy and error handling.
2.2.4	*Stress Testing*	Tests system behavior under extreme conditions.
2.3	**Portability and Integration**	Portable across cloud environments and integrates with existing tools.
2.3.1	*Portability*	Functions across different cloud platforms.
2.3.2	*Integration*	Integrates with tools like CI/CD pipelines and Kubernetes.
2.4	**User Interface and Experience**	Intuitive UI for easy access to features and data.
2.4.1	*Intuitive Design*	User-friendly design with familiar UI patterns.
2.4.2	*Accessibility*	Features for usability by diverse users.
2.5	**Configuration and Customization**	Configuration options for varied operational needs.
2.5.1	*Configuration*	Allows user modification of settings and preferences.
2.5.2	*Customization*	Supports customization.

Table A.1: Key Requirements

No.	Category	Description
2.6	**System Performance**	Meets benchmarks for response times, processing speeds, and resource utilization.
2.6.1	*Response Times*	Requires rapid responses.
2.6.2	*Processing Speeds*	High processing speeds for real-time data analysis.
2.6.3	*Resource Utilization*	Efficient resource use to avoid bottlenecks.
2.7	**Monitoring and Reporting**	For transparency and improvement.
2.7.1	*Real-time Monitoring*	Includes tools for real-time system monitoring.
2.7.2	*Detailed Reporting*	Provides comprehensive reporting.
2.8	**Adaptability**	Allows framework to learn and adjust.
2.8.1	*Dynamic Learning Capabilities*	Adjusts algorithms based on performance feedback.
2.8.2	*Self-Optimizing Systems*	Framework to self-optimize through learning.
2.9	**Feedback Mechanisms**	Mechanisms to capture inputs and outputs for refinement.
2.9.1	*User Feedback Integration*	User feedback integration into development cycle.
2.9.2	*Automated Performance Feedback*	Collects data and generates insights for system improvement.
2.10	**Data Security**	Protects data against unauthorized access and loss.
2.10.1	*Encryption*	Uses secure encryption for data in transit and for data at rest.
2.10.2	*Access Controls*	Implements access controls.
6.11	**Regulatory Compliance**	Complies with regulations like GDPR and CCPA.

A.2 Survey + Results

Figure A.1: Respondent #1



. Dear Participant,
We invite you to participate in this survey to help us determine the key requirements for designing and implementing a robust and scalable AIOps framework tailored for monitoring cloud environments. Your insights and feedback are invaluable in ensuring that the framework meets the necessary standards of reliability, performance, and user satisfaction.

Purpose of the Survey:
This survey aims to gather input from professionals, who have experience in cloud environments, IT operations, and related fields. Your responses will guide us in prioritizing the requirements that are most important for effective monitoring, analysis, and optimization of cloud application performance.

How to Complete the Survey:
Please read each requirement carefully and rate its importance on a scale from 1 (not important) to 5 (extremely important). This will help us understand which aspects are most important from your perspective. Feel free to add any additional comments or specify any particular requirements that you believe are critical.

Your participation is highly appreciated, and your feedback will directly influence the development of a more effective and user-centric AIOps framework.

Confidentiality:
All responses will be kept confidential and will only be used for the purposes of this research. The survey should take approximately 5-10 minutes to complete.

Thank you for your time and valuable input!

Please enter

Your Name + Surname [redacted]
Your Organization Project44
Your Position Staff Software Engineer
Your Email Adress [redacted]

. Determining Key Requirements for AIOps Framework

	not important	somewhat important	important	very important	extremely important
Automated data collection for cloud applications monitoring, including metrics, logs, and event streams.	○	○	◉	○	○
Integration with cloud infrastructure and monitoring tools for continuous data capture.	○	○	○	◉	○
Data management to handle volumes in real-time with dynamic storage.	◉	○	○	○	○
Technologies for real-time data stream analysis and anomaly detection.	○	○	○	○	◉
Minimizing latency for operational continuity.	○	◉	○	○	○
Use of various methods for anomaly detection (statistical, machine learning, etc.)	○	○	◉	○	○
Achieving high precision and recall to minimize false positives and maximize true positives	○	○	○	○	◉
Diverse automated responses based on detected anomalies.	○	◉	○	○	○
Integration with existing operational management tools.	○	○	◉	○	○
Ability to handle increasing data volumes efficiently.	○	○	◉	○	○
Adaptability to service deployment and scaling without significant reconfiguration.	○	○	○	○	◉
Ensuring high uptime and automatic recovery from failures.	○	○	○	○	◉
Maintaining functionality across varying conditions and disruptions.	○	○	○	◉	○
Incorporating fault tolerance and failover mechanisms.	○	○	◉	○	○
Conducting stress testing to evaluate system behavior under extreme conditions.	○	○	○	◉	○
Ensuring functionality across different cloud platforms.	○	◉	○	○	○
Seamless integration with CI/CD pipelines, Kubernetes, and other tools.	○	○	○	◉	○
Intuitive and user-friendly design with familiar UI patterns.	○	○	○	○	◉
Accessibility features for diverse users, including those with disabilities.	○	◉	○	○	○
Options for user modification of settings and preferences.	○	○	○	◉	○
Support for customization based on user roles.	○	◉	○	○	○
Meeting benchmarks for response times and processing speeds.	○	○	◉	○	○
Efficient resource utilization to avoid performance bottlenecks.	○	○	◉	○	○
Real-time system monitoring tools.	○	○	○	◉	○
Detailed and customizable reporting functionalities.	○	◉	○	○	○
Dynamic learning capabilities to adjust algorithms based on feedback.	○	○	○	○	◉
Self-optimizing systems for continuous improvement.	○	○	○	○	◉
Integration of user feedback into the development cycle.	○	○	○	◉	○
Automated performance feedback for system improvement.	○	○	○	◉	○
Using secure encryption for data in transit and at rest.	○	○	◉	○	○
Implementation of strict access controls and multi-factor authentication.	○	○	◉	○	○
Ensuring compliance with regulations like GDPR and CCPA.	○	○	◉	○	○

. Ordering most important Requirements

Ensuring high uptime and automatic recovery from failures.	1
Adaptability to service deployment and scaling without significant reconfiguration.	2
Technologies for real-time data stream analysis and anomaly detection.	3
Achieving high precision and recall to minimize false positives and maximize true positives	4
Dynamic learning capabilities to adjust algorithms based on feedback.	5
Intuitive and user-friendly design with familiar UI patterns.	6
Self-optimizing systems for continuous improvement.	7

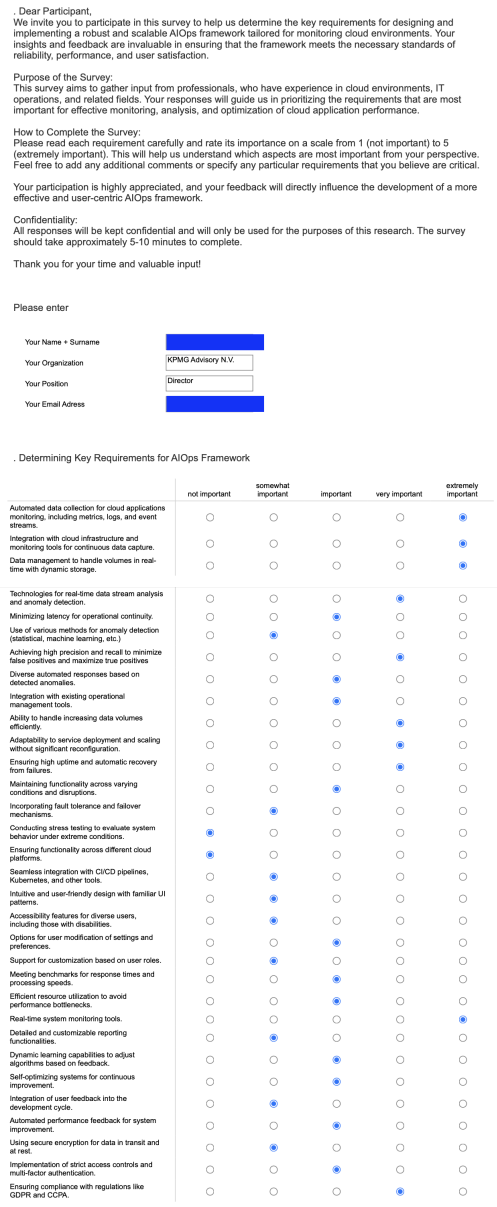
. Comments

Location Data

Location: (52.3672, 4.918)

Source: GeoIP Estimation

Figure A.2: Respondent #2



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Purpose of the Survey:
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How to Complete the Survey:
Please read each requirement carefully and rate its importance on a scale from 1 (not important) to 5 (extremely important). This will help us understand which aspects are most important from your perspective. Feel free to add any additional comments or specify any particular requirements that you believe are critical.

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Confidentiality:
All responses will be kept confidential and will only be used for the purposes of this research. The survey should take approximately 5-10 minutes to complete.

Thank you for your time and valuable input!

Please enter

Your Name + Surname	[redacted]
Your Organization	KPMG Advisory N.V.
Your Position	Director
Your Email Adress	[redacted]

. Determining Key Requirements for AIOps Framework

	not important	somewhat important	important	very important	extremely important
Automated data collection for cloud applications monitoring, including metrics, logs, and event streams.	○	○	○	○	◉
Integration with cloud infrastructure and monitoring tools for continuous data capture.	○	○	○	○	◉
Data management to handle volumes in real-time with dynamic storage.	○	○	○	○	◉
Technologies for real-time data stream analysis and anomaly detection.	○	○	○	◉	○
Minimizing latency for operational continuity.	○	○	◉	○	○
Use of various methods for anomaly detection (statistical, machine learning, etc.)	○	◉	○	○	○
Achieving high precision and recall to minimize false positives and maximize true positives	○	○	○	◉	○
Diverse automated responses based on detected anomalies.	○	○	◉	○	○
Integration with existing operational management tools.	○	○	◉	○	○
Ability to handle increasing data volumes efficiently.	○	○	○	◉	○
Adaptability to service deployment and scaling without significant reconfiguration.	○	○	○	◉	○
Ensuring high uptime and automatic recovery from failures.	○	○	○	◉	○
Maintaining functionality across varying conditions and disruptions.	○	○	◉	○	○
Incorporating fault tolerance and failover mechanisms.	○	◉	○	○	○
Conducting stress testing to evaluate system behavior under extreme conditions.	◉	○	○	○	○
Ensuring functionality across different cloud platforms.	◉	○	○	○	○
Seamless integration with CI/CD pipelines, Kubernetes, and other tools.	○	◉	○	○	○
Intuitive and user-friendly design with familiar UI patterns.	○	◉	○	○	○
Accessibility features for diverse users, including those with disabilities.	○	◉	○	○	○
Options for user modification of settings and preferences.	○	○	◉	○	○
Support for customization based on user roles.	○	◉	○	○	○
Meeting benchmarks for response times and processing speeds.	○	○	◉	○	○
Efficient resource utilization to avoid performance bottlenecks.	○	○	◉	○	○
Real-time system monitoring tools.	○	○	○	○	◉
Detailed and customizable reporting functionalities.	○	◉	○	○	○
Dynamic learning capabilities to adjust algorithms based on feedback.	○	○	◉	○	○
Self-optimizing systems for continuous improvement.	○	○	◉	○	○
Integration of user feedback into the development cycle.	○	◉	○	○	○
Automated performance feedback for system improvement.	○	○	◉	○	○
Using secure encryption for data in transit and at rest.	○	◉	○	○	○
Implementation of strict access controls and multi-factor authentication.	○	○	◉	○	○
Ensuring compliance with regulations like GDPR and CCPA.	○	○	○	◉	○

. Ordering most important Requirements

Real-time system monitoring tools.	1
Automated data collection for cloud applications monitoring, including metrics, logs, and event streams.	2
Integration with cloud infrastructure and monitoring tools for continuous data capture.	3
Data management to handle volumes in real-time with dynamic storage.	4

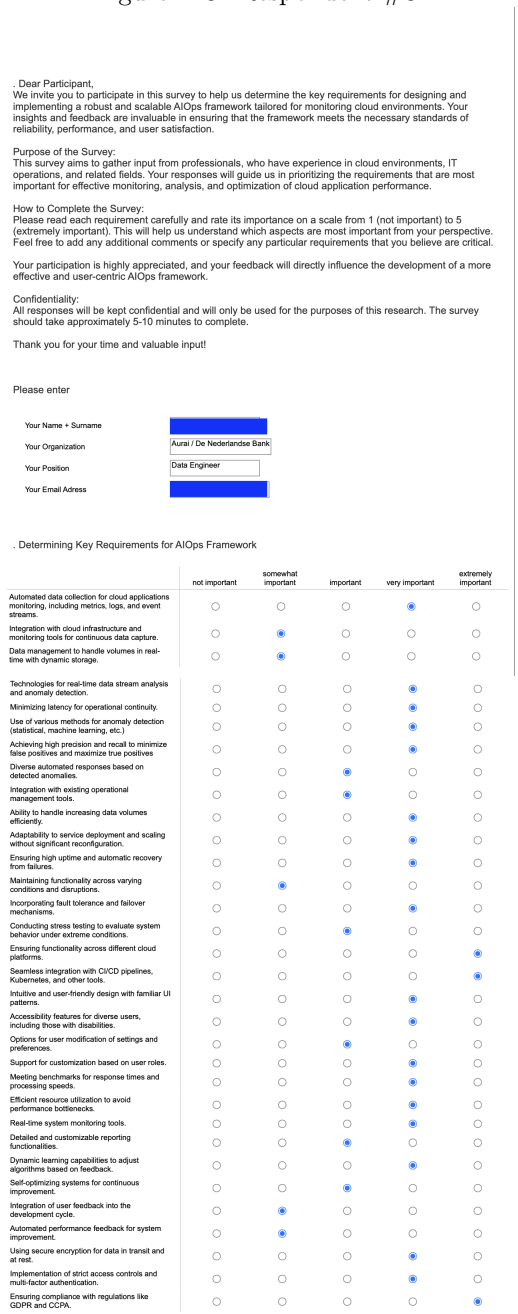
. Comments

Location Data

Location: (52.3759, 4.8975)

Source: GeoIP Estimation

Figure A.3: Respondent #3



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Confidentiality:
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Thank you for your time and valuable input!

Please enter

Your Name + Surname	[redacted]
Your Organization	Aurai / De Nederlandse Bank
Your Position	Data Engineer
Your Email Adress	[redacted]

. Determining Key Requirements for AIOps Framework

	not important	somewhat important	important	very important	extremely important
Automated data collection for cloud applications monitoring, including metrics, logs, and event streams.	○	○	○	◉	○
Integration with cloud infrastructure and monitoring tools for continuous data capture.	○	◉	○	○	○
Data management to handle volumes in real-time with dynamic storage.	○	◉	○	○	○
Technologies for real-time data stream analysis and anomaly detection.	○	○	○	◉	○
Minimizing latency for operational continuity.	○	○	○	◉	○
Use of various methods for anomaly detection (statistical, machine learning, etc.)	○	○	○	◉	○
Achieving high precision and recall to minimize false positives and maximize true positives	○	○	○	◉	○
Diverse automated responses based on detected anomalies.	○	○	◉	○	○
Integration with existing operational management tools.	○	○	◉	○	○
Ability to handle increasing data volumes efficiently.	○	○	○	◉	○
Adaptability to service deployment and scaling without significant reconfiguration.	○	○	○	◉	○
Ensuring high uptime and automatic recovery from failures.	○	○	○	◉	○
Maintaining functionality across varying conditions and disruptions.	○	◉	○	○	○
Incorporating fault tolerance and failover mechanisms.	○	○	○	◉	○
Conducting stress testing to evaluate system behavior under extreme conditions.	○	○	◉	○	○
Ensuring functionality across different cloud platforms.	○	○	○	○	◉
Seamless integration with CI/CD pipelines, Kubernetes, and other tools.	○	○	○	○	◉
Intuitive and user-friendly design with familiar UI patterns.	○	○	○	◉	○
Accessibility features for diverse users, including those with disabilities.	○	○	○	◉	○
Options for user modification of settings and preferences.	○	○	◉	○	○
Support for customization based on user roles.	○	○	○	◉	○
Meeting benchmarks for response times and processing speeds.	○	○	○	◉	○
Efficient resource utilization to avoid performance bottlenecks.	○	○	○	◉	○
Real-time system monitoring tools.	○	○	○	◉	○
Detailed and customizable reporting functionalities.	○	○	◉	○	○
Dynamic learning capabilities to adjust algorithms based on feedback.	○	○	○	◉	○
Self-optimizing systems for continuous improvement.	○	○	◉	○	○
Integration of user feedback into the development cycle.	○	◉	○	○	○
Automated performance feedback for system improvement.	○	◉	○	○	○
Using secure encryption for data in transit and at rest.	○	○	○	◉	○
Implementation of strict access controls and multi-factor authentication.	○	○	○	◉	○
Ensuring compliance with regulations like GDPR and CCPA.	○	○	○	○	◉

. Ordering most important Requirements

Ensuring compliance with regulations like GDPR and CCPA.	1
Ensuring functionality across different cloud platforms.	2
Seamless integration with CI/CD pipelines, Kubernetes, and other tools.	3

. Comments

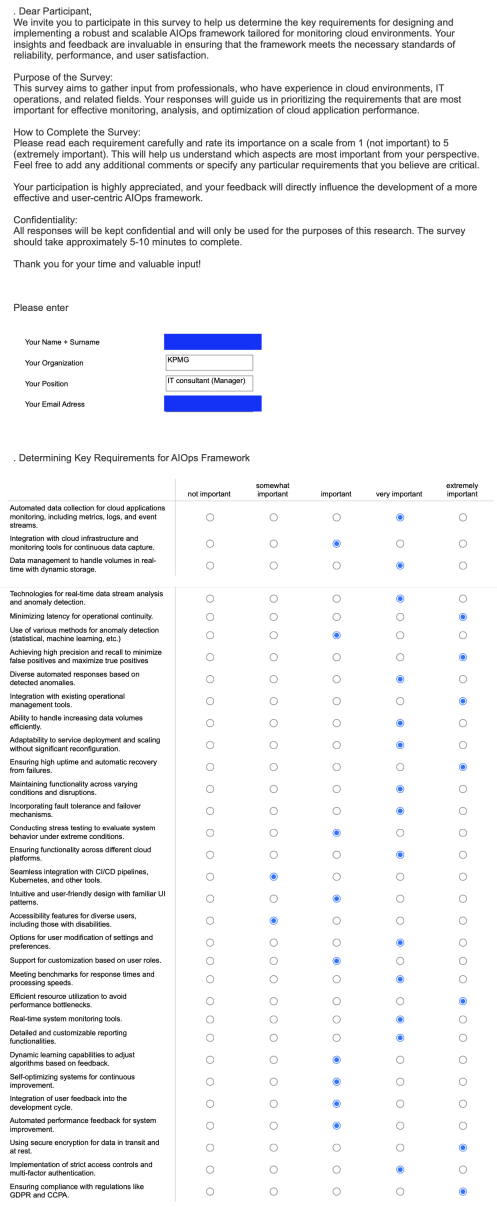
All are highly important

Location Data

Location: (52.3297, 4.8625)

Source: GeoIP Estimation

Figure A.4: Respondent #4



. Dear Participant,
We invite you to participate in this survey to help us determine the key requirements for designing and implementing a robust and scalable AIOps framework tailored for monitoring cloud environments. Your insights and feedback are invaluable in ensuring that the framework meets the necessary standards of reliability, performance, and user satisfaction.

Purpose of the Survey:
This survey aims to gather input from professionals, who have experience in cloud environments, IT operations, and related fields. Your responses will guide us in prioritizing the requirements that are most important for effective monitoring, analysis, and optimization of cloud application performance.

How to Complete the Survey:
Please read each requirement carefully and rate its importance on a scale from 1 (not important) to 5 (extremely important). This will help us understand which aspects are most important from your perspective. Feel free to add any additional comments or specify any particular requirements that you believe are critical.

Your participation is highly appreciated, and your feedback will directly influence the development of a more effective and user-centric AIOps framework.

Confidentiality:
All responses will be kept confidential and will only be used for the purposes of this research. The survey should take approximately 5-10 minutes to complete.

Thank you for your time and valuable input!

Please enter

Your Name + Surname	[redacted]
Your Organization	KPMG
Your Position	IT consultant (Manager)
Your Email Adress	[redacted]

. Determining Key Requirements for AIOps Framework

	not important	somewhat important	important	very important	extremely important
Automated data collection for cloud applications monitoring, including metrics, logs, and event streams.	○	○	○	◉	○
Integration with cloud infrastructure and monitoring tools for continuous data capture.	○	○	◉	○	○
Data management to handle volumes in real-time with dynamic storage.	○	○	○	◉	○
Technologies for real-time data stream analysis and anomaly detection.	○	○	○	◉	○
Minimizing latency for operational continuity.	○	○	○	○	◉
Use of various methods for anomaly detection (statistical, machine learning, etc.)	○	○	◉	○	○
Achieving high precision and recall to minimize false positives and maximize true positives	○	○	○	○	◉
Diverse automated responses based on detected anomalies.	○	○	○	◉	○
Integration with existing operational management tools.	○	○	○	○	◉
Ability to handle increasing data volumes efficiently.	○	○	○	◉	○
Adaptability to service deployment and scaling without significant reconfiguration.	○	○	○	◉	○
Ensuring high uptime and automatic recovery from failures.	○	○	○	○	◉
Maintaining functionality across varying conditions and disruptions.	○	○	○	◉	○
Incorporating fault tolerance and failover mechanisms.	○	○	○	◉	○
Conducting stress testing to evaluate system behavior under extreme conditions.	○	○	◉	○	○
Ensuring functionality across different cloud platforms.	○	○	○	◉	○
Seamless integration with CI/CD pipelines, Kubernetes, and other tools.	○	◉	○	○	○
Intuitive and user-friendly design with familiar UI patterns.	○	○	◉	○	○
Accessibility features for diverse users, including those with disabilities.	○	◉	○	○	○
Options for user modification of settings and preferences.	○	○	○	◉	○
Support for customization based on user roles.	○	○	◉	○	○
Meeting benchmarks for response times and processing speeds.	○	○	○	◉	○
Efficient resource utilization to avoid performance bottlenecks.	○	○	○	○	◉
Real-time system monitoring tools.	○	○	○	◉	○
Detailed and customizable reporting functionalities.	○	○	○	◉	○
Dynamic learning capabilities to adjust algorithms based on feedback.	○	○	◉	○	○
Self-optimizing systems for continuous improvement.	○	○	◉	○	○
Integration of user feedback into the development cycle.	○	○	◉	○	○
Automated performance feedback for system improvement.	○	○	◉	○	○
Using secure encryption for data in transit and at rest.	○	○	○	○	◉
Implementation of strict access controls and multi-factor authentication.	○	○	○	◉	○
Ensuring compliance with regulations like GDPR and CCPA.	○	○	○	○	◉

. Ordering most important Requirements

Using secure encryption for data in transit and at rest.	1
Ensuring compliance with regulations like GDPR and CCPA.	2
Achieving high precision and recall to minimize false positives and maximize true positives	3
Ensuring high uptime and automatic recovery from failures.	4
Efficient resource utilization to avoid performance bottlenecks.	5
Minimizing latency for operational continuity.	6
Integration with existing operational management tools.	7

. Comments

I think for people to truly start using this tool it is important that it is compliant with data protection regulations (this is a deal breaker) Next it is important that it adds something to monitoring landscape, and thus that the results are reliable (someone could be called out of bed based on its outcomes). With the increasing cloud costs it is also important that the energy cost (which usually corresponds with monetary cost) is in line with the overall costs of the application, to prevent this from becoming a prohibitive factor.

Location Data

Location: (52.3759, 4.8975)

Source: GeoIP Estimation

Appendix B

Survey Experiment 2 - Configurability

B.1 Survey

Administrator Information

- **Name:** _____
- **Role:** _____
- **Date:** _____

Task Complexity

1. **Tailoring System Strategies**
   - On a scale of 1 to 5, how would you rate the complexity of tailoring the system for different types of anomalies?
     - 1: Very Easy
     - 2: Easy
     - 3: Neutral
     - 4: Difficult
     - 5: Very Difficult
2. **Configuring Monitoring Tasks**
   - On a scale of 1 to 5, how would you rate the complexity of configuring monitoring tasks for specific containers and metrics?
     - 1: Very Easy
     - 2: Easy
     - 3: Neutral

    - 4: Difficult
    - 5: Very Difficult

Usability Feedback

3. **Ease of Use**
    - On a scale of 1 to 5, how would you rate the overall ease of use of the configuration process?
        - 1: Very Easy
        - 2: Easy
        - 3: Neutral
        - 4: Difficult
        - 5: Very Difficult
4. **Additional Comments**
    - Please provide any additional comments or suggestions to improve the configuration process.

B.2 Results

Respondent #1

- **Role:** Data Engineer
- **Date:** 22-07-24

1. 2 - Easy
2. 1 - Very Easy
3. 2 - Easy
4. Great application! I would love to be able to change the CRCA model to a custom model that I could upload.

Respondent #2

- **Role:** IT Consultant (Manager)
- **Date:** 31-7-2024

1. 3 - neutral
2. 2 - easy
3. 2 - easy

4. – For the CRCA I would by default not offer the users the opportunity to tweak the parameters, but have them select this offer specifically.
   – Additionally for the CRCA the use of colour in the diagram indicating the relations between possible causes could make it slightly more readable.

Respondent #3

- **Role:** Staff Software Engineer
- **Date:** 04-08-24

1. 3 - Neutral
2. 1 - Very Easy
3. 2 - Easy
4. – Using a pretrained model seems very easy, as long as you accept the defaults
   – Could be an idea to hide the default config options behind an "advanced options" button or something - to make it less daunting
   – Training on your own data seems a bit harder but made more sense to me after explaining what each of the options was, i.e. from reading a manual
   – For training it would be nice if you can just point it at historical data, e.g. directly in Prometheus without having to manually input things as CSV. Try to automate as much of the configuration as possible. Having a human manually label things makes it difficult.