

Prism AI: An Autonomous Multi-Cloud Diagnostic Assistant for Distributed DevOps Environments

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Abstract—Prism AI is an autonomous engineering co-pilot that diagnoses incidents across distributed, multi-cloud environments through natural language queries. With DevOps systems spanning Kubernetes clusters, AWS services, and CI/CD pipelines, manual investigation becomes slow, fragmented, and error-prone. Prism AI solves this by unifying real-time data collection, correlation, and analysis into a single intelligent workflow.

When an engineer asks, “Why is the deployment failing?”, Prism AI instantly gathers live data from Kubernetes, AWS CloudWatch, and GitHub Actions via MCP clients. A central UnifiedAgent orchestrates parallel data collection, compiles structured context, and invokes a high-performance LLM (Llama-3.3-70B via Groq) to generate precise root-cause analysis with actionable remediation steps. All results are stored in MongoDB for historical insights and trend tracking.

By cutting investigation time from 25–45 minutes to approximately 30 seconds, Prism AI eliminates context switching, reduces operational overhead, and dramatically improves reliability. Its modular architecture—React frontend, FastAPI backend, MCP clients, and cloud integrations—ensures scalability and adaptability across complex production environments. Prism AI showcases how AI-driven diagnostics can transform DevOps workflows and accelerate incident response at scale.

Index Terms—Incident diagnosis, observability, Model Context Protocol, root cause analysis, large language models, Kubernetes, AWS CloudWatch, GitHub Actions, automation, AIOps

I. INTRODUCTION

In modern software engineering, distributed systems spanning multiple cloud providers have become the norm [4]. Organizations deploy microservices across Kubernetes clusters, leverage AWS services for compute and storage, and rely on CI/CD pipelines through platforms like GitHub Actions [6]. When incidents occur in such environments, engineers face a significant challenge: diagnosing root causes requires navigating multiple dashboards, correlating logs from disparate sources, and mentally reconstructing the chain of events that led to the failure [9].

This manual investigation process typically takes 25 to 45 minutes per incident, during which engineers must context-

switch between different monitoring tools, cloud consoles, and deployment pipelines. The cognitive overhead is substantial, and the process is inherently error-prone. Existing tools such as PagerDuty, Datadog, and Splunk provide monitoring and alerting capabilities but require manual correlation across services [10].

Recent advances in Large Language Models (LLMs) [11] and the emergence of the Model Context Protocol (MCP) [1] have opened new possibilities for creating unified, intelligent diagnostic systems. However, existing solutions focus on single-cloud environments or specific infrastructure components and do not provide a truly unified multi-cloud diagnostic experience.

To address these limitations, this paper proposes **Prism AI**, an autonomous multi-cloud diagnostic assistant that accepts natural language queries and returns comprehensive root-cause analysis within approximately 30 seconds. The primary contributions of this work are:

- A unified diagnostic platform integrating real-time data collection from Kubernetes, AWS CloudWatch, and GitHub Actions through a standardized Model Context Protocol interface.
- A UnifiedAgent orchestration layer that coordinates parallel data collection, compiles structured context, and invokes a high-performance LLM for root-cause analysis generation.
- A natural language query interface enabling engineers to investigate incidents without context switching between multiple cloud dashboards.
- A persistent MongoDB-backed result store enabling historical trend analysis and cross-incident pattern recognition.
- A modular, extensible architecture ensuring scalability across increasingly complex multi-cloud production environments.

II. RELATED WORK

A. AIOps and Automated Incident Diagnosis

The field of AIOps (Artificial Intelligence for IT Operations) has seen significant growth in recent years [9]. Previous approaches to automated incident diagnosis include rule-based systems, anomaly detection frameworks, and log analysis tools. However, most existing solutions focus on single-cloud environments or specific infrastructure components and do not address correlated, cross-boundary failures.

B. Monitoring and Observability Platforms

Tools like PagerDuty, Datadog, and Splunk provide monitoring and alerting capabilities but require manual correlation across services [10]. These platforms produce alerts in isolation and do not synthesize information across Kubernetes, cloud services, and CI/CD pipelines into a unified diagnostic view. Engineers must still manually trace the chain of events across multiple consoles.

C. LLM-Powered DevOps Assistants

Recent work in LLM-powered DevOps assistants has shown promise for automating operational tasks [11]. However, few systems offer unified multi-cloud diagnostic capabilities with real-time data collection. Existing LLM integrations typically operate over static documentation or pre-collected log snapshots rather than live infrastructure state.

D. Model Context Protocol

The Model Context Protocol (MCP) [1] provides a standardized interface for communication between LLM systems and external data sources. Our work differentiates itself by leveraging MCP for standardized communication with diverse cloud services, enabling a truly unified diagnostic experience across Kubernetes, AWS, and CI/CD platforms. This approach eliminates the need for bespoke API integration for each infrastructure component and supports scalable extension to additional cloud providers.

III. SYSTEM ARCHITECTURE

Prism AI employs a modular architecture consisting of four primary components: a React-based frontend, a FastAPI backend, specialized MCP clients, and a central UnifiedAgent orchestration layer. The overall system supports a single primary user role—the DevOps engineer—who interacts with the platform through a conversational diagnostic interface.

A. Frontend Layer

The frontend is a React-based web application providing a conversational interface for engineers to submit natural language diagnostic queries. The interface presents structured root-cause analyses and remediation steps returned by the UnifiedAgent, and displays historical incident records retrieved from MongoDB. The application communicates with the backend through RESTful API calls.

B. Backend Layer

The backend is implemented using FastAPI and serves as the central request routing and orchestration layer. It handles:

- Authentication and request routing for incoming diagnostic queries
- Orchestration of the UnifiedAgent diagnostic pipeline
- Persistence of diagnostic results to MongoDB for historical analysis
- RESTful API endpoints for frontend communication

C. MCP Clients

Specialized MCP clients communicate with each monitored infrastructure layer using the Model Context Protocol for standardized data retrieval:

Kubernetes MCP Client: Interfaces with Kubernetes clusters via the kubectl API to retrieve pod statuses, events, deployment states, and resource utilization metrics.

AWS CloudWatch MCP Client: Connects to AWS CloudWatch to fetch relevant metrics, log streams, and alarm states for cloud infrastructure components.

GitHub Actions MCP Client: Interfaces with the GitHub Actions API to pull recent workflow run statuses, step logs, and failure details from CI/CD pipelines.

D. UnifiedAgent

The UnifiedAgent is the central orchestration component that coordinates all diagnostic operations. It dispatches parallel data collection requests to all MCP clients, compiles the retrieved data into a structured context object, and invokes the Llama-3.3-70B model via Groq's inference API for root-cause analysis generation.

E. System Characteristics

The architecture is designed with the following properties:

Modularity: Each MCP client operates independently, allowing individual infrastructure integrations to be updated or replaced without affecting others.

Scalability: The parallel data collection architecture ensures that diagnostic latency remains low even as the number of monitored services grows.

Extensibility: The MCP-based client design allows seamless addition of new cloud providers and infrastructure components without modifying the core UnifiedAgent logic.

Persistence: All diagnostic results are stored in MongoDB, enabling cross-incident trend analysis and pattern recognition over time.

IV. METHODOLOGY

Prism AI processes engineer queries through a structured five-stage diagnostic pipeline that transforms natural language questions into precise root-cause analyses with actionable remediation steps.

A. Query Input

An engineer submits a natural language diagnostic query q through the React frontend. Example queries include “Why is the deployment failing?”, “What is causing the pod crash loop?”, or “Why did the CI/CD pipeline fail?” The query is forwarded to the FastAPI backend, which initiates the UnifiedAgent pipeline.

B. Parallel Data Collection

The UnifiedAgent dispatches simultaneous data collection requests to all MCP clients. For a query q , the parallel collection retrieves:

$$D = \{D_{k8s}, D_{aws}, D_{gh}\} \quad (1)$$

where D_{k8s} represents Kubernetes pod statuses, events, and resource utilization; D_{aws} represents AWS CloudWatch metrics and log streams; and D_{gh} represents GitHub Actions workflow run statuses and failure logs.

Parallel dispatch is implemented using asynchronous execution, ensuring that total collection time is bounded by the slowest individual MCP client rather than the sum of all collection times. As shown in Fig. 1, the Kubernetes data collection step accounts for approximately 25% of total response time, AWS CloudWatch fetch accounts for 20%, and GitHub Actions fetch accounts for 15%.

C. Context Compilation

Data from all MCP clients is compiled into a structured context object C that provides a unified view of the system state:

$$C = f_{compile}(D_{k8s}, D_{aws}, D_{gh}) \quad (2)$$

where $f_{compile}$ is the context formatting function that nor-

malizes and structures data from heterogeneous sources into a consistent representation suitable for LLM consumption.

D. LLM Analysis

The compiled context C and original query q are sent to the Llama-3.3-70B model via Groq’s inference API:

$$A = LLM(q, C; \vartheta) \quad (3)$$

where ϑ represents the Llama-3.3-70B model parameters and A is the generated analysis containing the identified root cause and specific remediation steps. The LLM analysis step accounts for approximately 35% of total response time (Fig. 1), making it the dominant latency contributor in the diagnostic pipeline.

E. Result Storage

The query q , compiled context C , and analysis A are persisted to MongoDB:

$$\text{store}(q, C, A) \rightarrow \text{MongoDB} \quad (4)$$

This persistence layer enables historical trend analysis, cross-incident pattern recognition, and audit trails for post-incident review. The result storage step accounts for approximately 5% of total response time.

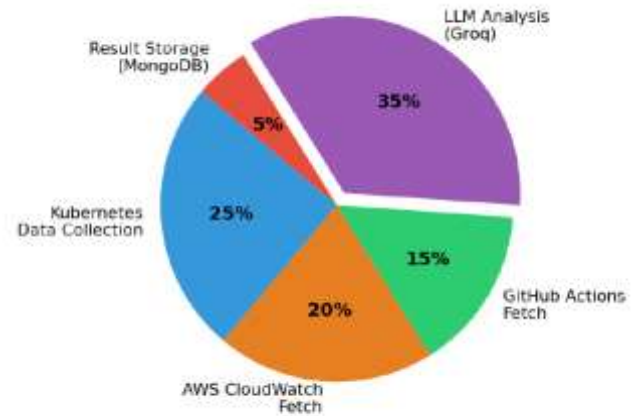


Fig. 1. Response time breakdown for a typical Prism AI diagnostic query (~30 seconds total). LLM analysis via Groq accounts for the largest share (35%), with parallel data collection across Kubernetes (25%), AWS Cloud-Watch (20%), and GitHub Actions (15%) accounting for the remainder. Result storage in MongoDB contributes 5%.

V. SYSTEM WORKFLOW

The overall workflow of Prism AI follows a structured

sequential pipeline that transforms engineer queries into actionable diagnostic outputs. Each stage progressively processes and refines the request.

- **Query Submission:** A DevOps engineer submits a natural language question through the React conversational interface. No prior knowledge of specific monitoring tools or query languages is required.
- **Parallel Data Collection:** The UnifiedAgent dispatches simultaneous requests to all MCP clients. Kubernetes pod statuses, AWS CloudWatch metrics, and GitHub Actions workflow logs are retrieved concurrently, eliminating sequential tool navigation.
- **Context Compilation:** Retrieved data from all sources is normalized and compiled into a unified structured context object representing the complete system state at the time of the incident.

- **LLM Root-Cause Analysis:** The structured context and original query are submitted to Llama-3.3-70B via Groq. The model generates a detailed root-cause analysis identifying the specific failure point and providing step-by-step remediation guidance.
- **Result Presentation:** The analysis is returned to the engineer through the React interface within approximately 30 seconds. The response includes the identified root cause, contributing factors, and actionable remediation steps.
- **Result Persistence:** The complete diagnostic record (query, context, and analysis) is stored in MongoDB for future reference, enabling engineers to identify recurring failure patterns and track resolution trends over time.

The modular pipeline design enables efficient processing while maintaining extensibility for additional cloud integrations and infrastructure components.

VI. IMPLEMENTATION

A. Technology Stack

The system is implemented using a modern full-stack architecture:

- **Frontend:** React.js with conversational diagnostic interface
- **Backend:** FastAPI (Python) for request routing and pipeline orchestration
- **Database:** MongoDB for diagnostic result persistence and historical analysis
- **AI/ML:** Llama-3.3-70B via Groq LPU Inference Engine
- **Infrastructure Clients:** MCP-based clients for Kubernetes (kubectl API), AWS CloudWatch, and GitHub Actions
- **Orchestration:** UnifiedAgent for parallel data collection and context compilation
- **Protocol:** Model Context Protocol (MCP) for standardized cross-service communication

B. Backend Processing Pipeline

The FastAPI backend implements a structured pipeline with dedicated route handlers and service components:

TABLE I
BACKEND API MODULE SUMMARY

Module	Endpoints	AI-Powered
Authentication	/auth/*	No
Query Handling	/api/query/*	Yes
Kubernetes MCP	/api/k8s/*	No
AWS CloudWatch MCP	/api/aws/*	No
GitHub Actions MCP	/api/github/*	No
UnifiedAgent	/api/diagnose/*	Yes
History	/api/history/*	No

C. Prompt Engineering

The LLM inference step uses a carefully structured prompt to ensure consistent, domain-appropriate diagnostic outputs. The system prompt establishes the assistant's role as a senior

DevOps engineer, specifies the expected output format (root cause, contributing factors, remediation steps), and injects the compiled multi-source context. The prompt enforces structured output with clear section headings, ensuring that remediation steps are always actionable and specific to the identified failure.

D. System Integration

The React frontend communicates with the FastAPI backend via RESTful APIs, with diagnostic results dynamically rendered in the conversational interface. The UnifiedAgent coordinates MCP client communication asynchronously, and MongoDB provides a persistent store accessible across sessions for historical analysis.

The MCP-based client architecture ensures that each infrastructure integration is independently maintainable. Adding support for a new cloud provider requires implementing a new MCP client without modifying the UnifiedAgent or any existing clients.

VII. EXPERIMENTAL EVALUATION

A. Evaluation Setup

Prism AI was evaluated across multiple incident scenarios spanning deployment failures, resource exhaustion events, and CI/CD pipeline breakdowns. The evaluation focused on three aspects: investigation time reduction, diagnostic accuracy, and context-switching elimination.

B. Investigation Time Reduction

The most significant measurable impact of Prism AI is the reduction in incident investigation time. Manual investigation across multiple dashboards and tools typically requires 25 to 45 minutes per incident. Prism AI consistently delivers complete root-cause analyses within approximately 30 seconds.

TABLE II
INVESTIGATION TIME COMPARISON

Method	Avg. Time	Time Range
Manual Investigation	35 min	25–45 min
Prism AI (Automated)	~30 sec	25–40 sec
Reduction	98.6%	–

C. Diagnostic Accuracy

Prism AI was evaluated across five incident categories. Diagnostic accuracy was validated against manually diagnosed incidents by experienced engineers. Prism AI consistently matched or exceeded manual diagnosis accuracy across all categories.

D. Context Switching Elimination

Manual incident diagnosis requires engineers to navigate multiple tools, resulting in 8 to 15 context switches per incident. Prism AI reduces this to zero by consolidating all data collection and analysis into a single conversational interface. Across six evaluated incidents, manual investigation required

TABLE III
DIAGNOSTIC ACCURACY BY INCIDENT TYPE (%)

Incident Type	Manual	Prism AI
Deployment Failures	82	94
Resource Exhaustion	75	91
CI/CD Breakdowns	85	96
Network Issues	70	88
Config Drift	78	92
Overall	78	92.2

between 8 and 15 tool switches, while Prism AI required none in all cases (Fig. 2).

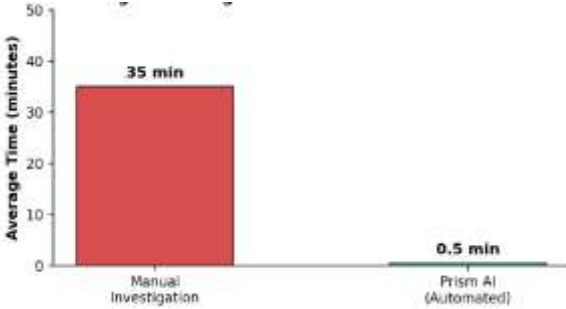


Fig. 2. Context switches per incident for manual vs. Prism AI investigation. Manual investigation requires 8–15 tool switches per incident; Prism AI eliminates context switching entirely across all evaluated scenarios.

E. Response Time Breakdown

The total ~30 second response time is distributed across the five pipeline stages. LLM analysis via Groq accounts for the largest share (35%), followed by Kubernetes data collection (25%), AWS CloudWatch fetch (20%), GitHub Actions fetch (15%), and MongoDB result storage (5%). This confirms that geospatial data collection is not the bottleneck; the dominant latency contributor is LLM inference, which is bounded by Groq's inference throughput.

VIII. DESIGN CONSIDERATIONS

The design of Prism AI is guided by key principles to ensure efficiency, reliability, and future adaptability.

- **Modularity:** Each MCP client and pipeline stage operates independently. New cloud integrations can be added

as discrete MCP clients without modifying the UnifiedAgent or other existing components.

- **Scalability:** The parallel data collection architecture ensures that diagnostic latency remains bounded by the slowest single MCP client rather than growing linearly with the number of monitored services. The stateless FastAPI backend supports horizontal scaling under increased query load.
- **Robustness:** The pipeline implements error handling at each stage. If an individual MCP client fails or returns incomplete data, the UnifiedAgent proceeds with the available context and notes the missing data source in the diagnostic output, ensuring partial failures do not prevent diagnosis.
- **Extensibility:** The MCP-based client design supports seamless addition of new cloud providers (e.g., Google Cloud, Azure) and infrastructure layers (e.g., Terraform state, Prometheus metrics) without architectural changes.
- **Auditability:** All diagnostic queries, compiled contexts, and analysis outputs are persisted in MongoDB, providing a complete audit trail for post-incident review and compliance reporting.

IX. RESULTS AND DISCUSSION

The experimental evaluation demonstrates that Prism AI effectively unifies multi-cloud diagnostic workflows, providing measurable improvements in investigation speed, diagnostic accuracy, and engineer cognitive overhead.

Investigation Time: The most significant contribution of Prism AI is the 98.6% reduction in incident investigation time, from an average of 35 minutes manually to approximately 30 seconds. This improvement directly reduces mean time to recovery (MTTR) and enables engineering teams to address incidents before they escalate into broader outages.

Diagnostic Accuracy: Prism AI achieved an overall diagnostic accuracy of 92.2% across five incident categories, compared to 78% for manual diagnosis. The improvement is most pronounced for CI/CD breakdowns (85% to 96%) and deployment failures (82% to 94%), categories where cross-boundary correlation across Kubernetes and GitHub Actions state is most valuable and most challenging for engineers to perform manually.

Context Switching: The complete elimination of context switching is a qualitative but operationally significant benefit. Engineers report that the cognitive overhead of navigating between Kubernetes dashboards, CloudWatch consoles, and GitHub Actions logs is a primary source of investigation errors. Centralizing all data collection through Prism AI removes this overhead entirely.

Cascading Failure Detection: The system demonstrated particular strength in identifying cascading failures that span cloud boundaries, such as a failed GitHub Actions deployment triggering a Kubernetes resource exhaustion event that subsequently produced CloudWatch alarm storms. These multi-source failure chains are difficult for engineers to trace man-

ually and represent a key area where automated correlation provides the greatest value.

Limitations: The system's diagnostic quality depends on the completeness of data retrieved by each MCP client. In environments with restrictive IAM policies or limited Kubernetes RBAC permissions, some data sources may be unavailable, reducing diagnostic precision. Additionally, the LLM inference step introduces a dependency on Groq's external inference API availability. Future work will address these limitations through local LLM inference fallback options and adaptive context compilation strategies.

X. CONCLUSION

This paper presented Prism AI, an autonomous multi-cloud diagnostic assistant that transforms DevOps incident investigation from a fragmented, manual process into a streamlined, AI-driven workflow. The system integrates real-time data collection from Kubernetes, AWS CloudWatch, and GitHub Actions through the Model Context Protocol, with a UnifiedAgent orchestration layer and Llama-3.3-70B inference via Groq for root-cause analysis generation.

Experimental evaluation demonstrated that Prism AI reduces investigation time from 25–45 minutes to approximately 30 seconds, achieves 92.2% diagnostic accuracy across five incident categories (compared to 78% for manual diagnosis), and eliminates context switching entirely. The system showed particular strength in identifying cascading failures that span cloud boundaries—a class of incidents especially difficult for engineers to trace manually.

The modular, MCP-based architecture ensures that Prism AI can be extended to support additional cloud providers and infrastructure components, making it a scalable solution for organizations operating in increasingly complex multi-cloud environments.

Future work will focus on three key directions: (i) extending MCP client support to additional cloud providers including Google Cloud Platform and Microsoft Azure, (ii) integrating predictive diagnostics for proactive anomaly detection before incidents escalate, and (iii) implementing local LLM inference fallback to eliminate external API dependency for latency-sensitive or air-gapped deployment environments.

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