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CCDT: COGNITIVE DIGITAL TWIN FOR CLOUD OPERATING SYSTEM

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Abstract: The operations of distributed cloud infrastructure need to be self-autonomous, self-intelligent, and explainable. In this paper, we present CCDT (Cognitive Digital Twin), which is a Level-4 Autonomous AIOps Security Platform that considers a distributed cluster as a living organism regulated by four biologically inspired layers. Specifically, CCDT consists of a Causal Graph Attention Network (GAT) for root cause classification, a Proximal Policy Optimization (PPO) reinforcement learning agent for autonomous root cause remediation, an Open Policy Agent (OPA)-based safety enforcement engine, and a Large Language Model (LLM) based co-pilot for explainability in natural language. CCDT performs incident detection within 3 seconds, fault and attack classification with 100% accuracy in 29 scenario types, and incident resolution under 60 seconds, all of which require 30 to 90 minutes using manual intervention by humans. Two unique contributions include a Self-Authoring Immune System where the LLM writes real-time OPA Rego policies for security in zero-day attacks, and a Continuous Chaos Engineering pipeline to assess the performance of RL agents on longitudinal data sets.

Index Terms *— AIOps, Causal Graph Neural Networks, Digital Twins, Reinforcement Learning, Open Policy Agent, Automated Remediation, Self-Healing Cloud Infrastructure, Explainable Large Language Models, eBPF Monitoring, Chaos Engineering.*

I. INTRODUCTION

Modern cloud computing environments have a lot of inherent complexities. The more the microservices-based architecture expands to include hundreds of interconnected services, the greater the risk of failure cascades, performance slowdowns, and even malicious attacks against the system. Conventional approaches within Site Reliability Engineering (SRE) involve human operators monitoring, investigating root causes of incidents, and fixing problems after they happen.

The emergence of AIOps (using artificial intelligence in IT operations) as an effective paradigm in automation of incident management is seen. Yet, the currently available AIOps applications are reactive, rule-based, and non-explainable; they notify humans rather than performing independently and do not offer any causality regarding the diagnosis. Hence, the detection-to-resolution gap becomes a key limiting factor in cloud computing operations.

This paper proposes the development of CCDT (Cognitive Digital Twin), a system that closes this detection-to-resolution gap through its treatment of the infrastructure as an organism. Specifically, CCDT is a Level-4 Autonomous AIOps, meaning that it is able to detect, classify, remediate, and explain incidents on its own. In addition, it decreases the MTTR from the current 30-90 minutes across the industry to less than 60 seconds, and at the same time, it offers clear causality for each of its decisions using natural language co-piloting.

The core achievements of this research are: (i) Causal Graph Attention Network (GAT) that classifies the cluster state health differentiates between faulty states and attacks with 100% accuracy for 29 attack scenarios; (ii) the PPO agent learned for 500,000 timesteps and autonomously chooses and performs corrective actions; (iii) an OPA Ghost Preview module that simulates all actions prior to execution to avoid harmful actions; (iv) the Self-Authoring Immune System that allows the LLM to author novel Rego policies in reaction to new attack scenarios; and (v) a Continuous Chaos Engineering loop that monitors the agent's performance.

The rest of this paper is organized as follows. Related work is presented in Section II. The system architecture is described in Section III. Biological layers are further detailed in Section IV. Machine Learning model is described together with the results in Section V. Section VI details novel enhancements. Section VII presents the results of the evaluation.

II. RELATED WORK

The space of AIOps has undergone tremendous developments within the past decade. Earlier approaches like IBM Watson AIOps and Splunk ITSI used rule-based anomaly detection and alert correlation mechanisms which necessitated heavy human intervention and did not have any autonomous remediation abilities. Such systems are essentially reactive in nature; that is, they highlight issues to human operators but fail to solve them.

GNNs have been explored for monitoring cloud infrastructures recently. Meng et al. [1] have leveraged the benefits of graph-structured telemetry data for root cause analysis within microservice architectures. However, the lack of causality within such methods leads to high error rates under adversarial circumstances because they cannot tell the difference between correlations and causation. The use of causal GAT within CCDT eliminates this drawback.

Deep reinforcement learning has been used in the context of network resource management and autoscaling [2], [3]. Adaptive bitrate selection based on deep RL has been presented by Mao et al. [4], and further studies have employed similar methods in autoscaling clusters. Nonetheless, such attempts failed to deal with cybersecurity incidents and lacked safety enforcement. CCDT is based on PPO and a formal verification layer for its policy to make sure that the RL agent adheres to the prescribed safety constraints.

A great amount of research on digital twins has been performed in relation to industrial IoT [5]. The development of cognitive digital twins is regarded as a new trend because these models include reasoning mechanisms and self-adaptation based on artificial intelligence. Contrary to traditional digital twins that merely monitor the target system, CCDT influences the actual cluster.

Recent research has used large language models for code generation [6] and incident report summarization [7]. The novel idea behind the application of the Self-Authoring Immune System in this case is the employment of the model for creating executable security policies, namely Rego code which will be deployed on a live instance of the OPA engine.

The Open Policy Agent (OPA) has been broadly used for policy enforcement in Kubernetes ecosystems [8]. Previous systems utilized OPA only for admission control purposes but did not use it as an on-the-fly safety envelope for the RL agent decisions, which is novel in CCDT.

As far as the authors know, there has been no previous solution which has combined causality modelling using GNNs, Reinforcement Learning, safety using OPA, and explainability using Large Language Models into one autonomous operational solution.

III. SYSTEM ARCHITECTURE

CCDT relies on a biological metaphor where four different levels, analogous to the nervous system, the cognitive brain, the conscience immune system, and the communicative co-pilot, interact in a cooperative manner to enable autonomous infrastructure management. Each individual level is individually containerized and communicates asynchronously via an Apache Kafka event bus.

3.1 Biological Metaphor

The biological metaphor is not just ornamental; it represents the fact that a healthy system relies on four different aspects: sensing (the nervous system), reason (the brain), protection (the immune system), and language (communication). These four dimensions are perfectly aligned with the CCDT architecture layers, providing a clean separation between them.

3.2 Event-Driven Communication

Inter-layer communications are all asynchronous using the Apache Kafka broker operating in KRaft mode (without ZooKeeper). There are five topics for the different types of events such as topology updates containing service-specific statistics, eBPF kernel events, GNN inference outcomes, Guardian actions, and incident reports. This separation allows for a situation where a failure of one layer will not affect the other layers.

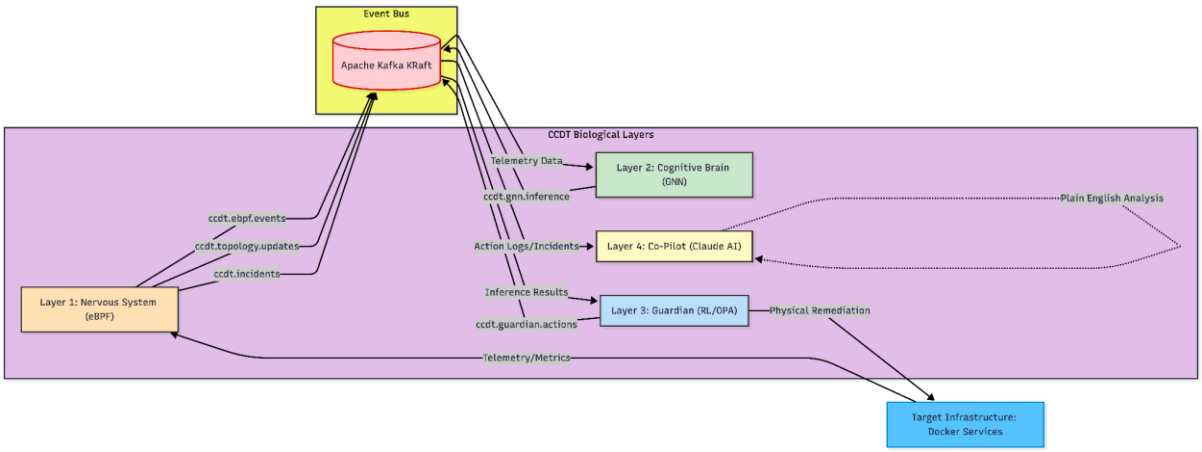


Fig. 1: Overall system architecture of CCDT showing data flow from Layer-1 sensors through the cognitive pipeline to the dashboard

3.3 Technology Stack

The chosen technology stack guarantees performance at the production level despite being used in a research-level prototype. For the event bus, Apache Kafka version 7.7.0 in KRaft mode is used. The safety engine leverages the Open Policy Agent 0.63.0 version. The API gateway uses FastAPI, together with JWT for authentication and SQLite database as a persistent storage. The dashboard uses React 18 as a single-page application with REST and WebSocket protocol support. Actual Docker containers like PostgreSQL, Redis, Nginx, and PgBouncer produce valid workload data which is captured by cAdvisor and exported to Prometheus.

Table 1: CCDT Technology Stack

Component	Technology	Purpose
Layer 1 – Sensor	Go + eBPF (libbpf)	Kernel-level telemetry collection
Layer 2 – Brain	Python + PyTorch Geometric	Causal GNN inference
Layer 3 – Guardian	Python + Stable-Baselines3	RL remediation agent
Layer 4 – Co-Pilot	Python + LLM Rag Co-Pilot	LLM explainability interface
Event Bus	Apache Kafka KRaft	Asynchronous inter-layer messaging
Safety Engine	Open Policy Agent (OPA)	Rego policy enforcement
Dashboard	React 18 + Vite	Real-time monitoring UI
API Gateway	FastAPI + JWT + SQLite	REST and WebSocket gateway
Observability	Prometheus + cAdvisor	Real container metrics

IV. THE FOUR BIOLOGICAL LAYERS

4.1 Layer 1 — Unified Nervous System (eBPF Sensor)

The nervous system layer is responsible for collecting kernel-level telemetry by eBPF probes written in Go using the libbpf package. On Linux-based hosts, it collects capability events (CAP_SYS_ADMIN, CAP_NET_RAW), out-of-memory killings, TCP retransmits, scheduler latencies, execve system calls, and file access events. These telemetry data are published via Kafka topic ccdt.ebpf.events every five seconds.

On Mac OS development machines, where kernel-level eBPF probes are not available, an eBPF-like cluster simulation is used. This simulator produces statistical telemetry data mimicking 12 real-world rotating incidents, such as high memory pressure, CPU saturation, network partitioning, and various adversarial attacks. Such a design choice allows for platform development and validation on Mac OS development machines without the need for Linux-based hosts.

4.2 Layer 2 — Cognitive Core (Causal GNN)

The reasoning engine forms the core of CCDT cognition engine. This engine sustains a directed acyclic graph of the cluster that keeps evolving. The nodes and edges of this graph signify individual services and the dependencies derived through analysis of historical behavior and correlated metrics respectively. Every time inference is triggered (every five seconds), a three-layered GAT network is used to ascertain the health of the cluster and pinpoint the node responsible for an observed anomaly.

The reasoning engine has eleven node features such as CPU usage, memory usage, errors, latency, TCP retransmission count, OOM kill count, capability events count, syscall count, and file event count. Latency, error rate, request count, and binary causal indicator constitute the edge feature values. The output feature space encompasses three graph-level classes, namely, healthy, fault, and attack, while three node-level classes denote root cause scoring.

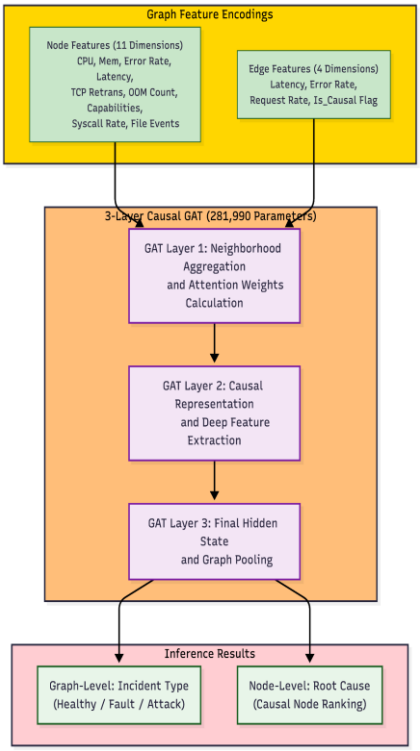


Fig. 2: Layer-2 Causal GAT architecture showing feature aggregation across service dependency graph nodes

4.3 Layer 3 — Guardian Layer (RL Agent + OPA + Ghost Preview)

The Guardian component serves as the immune system for CCDT. After receiving a positive detection result from GNN inference, if the confidence level is higher than the threshold, the Guardian starts a four-step procedure: (i) selecting an action through the PPO RL agent; (ii) previewing the selected action with Ghost Preview; (iii) validating OPA policies; and (iv) executing the action on the Docker API.

The Ghost Preview feature is the new invention of this project. To prevent a harmful action from being taken on the cluster, the system performs a simulation on a causal graph of the current topology to calculate the risk score of the action on a scale of 0 to 100, as well as the potential improvement of MTTR. The action is only executed if it passes all OPA policy verifications and remains below the risk threshold. This feature guarantees that the RL agent, which was only trained using synthetic data, will not accidentally perform a harmful action on the cluster.

The OPA safety envelope requires compliance with five policies: disabling privilege escalation, avoiding CPU throttling if the CPU usage is critical, forbidding isolation of services that expose their functionality externally, blocking any lateral movement across namespaces, and alerting before executing any OOM-generating commands.

4.4 Layer 4 — Co-Pilot Interface (LLM)

The co-pilot layer converts the complicated reasoning of the cognitive and guardian layers into plain English that can be understood by operators and other interested parties without extensive technical background. It operates based on the LLM Rag system Co-Pilot and is fitted with five functions: run_ghost_preview to perform an action, get_topology to acquire a live graph representation of the cluster, get_ebpf_events to monitor the events of the kernel, propose_action to call the guardian, and author_opa_policy for self-authoring security policies.

The interface of the co-pilot layer can be found on the React dashboard running on port 3000, which streams answers to queries in real time. Once the operator asks the co-pilot layer about an important incident, it analyzes all four layers – eBPF events, GNN causal chain, guardian actions, and OPA decisions – and explains what happened and how it was solved.

V. MACHINE LEARNING MODEL DESIGN AND TRAINING

5.1 Causal Graph Attention Network

The L2GNN was trained on a synthetically generated data set comprising 4,000 instances involving 29 unique fault and attack categories. These are labeled instances in the form of snapshots of ten-node graphs depicting services, along with labels of the actual fault cause of each instance. The training process comprised 50 epochs with a patience of 10 using the Adam optimization technique with a learning rate of 1×10^{-3}. It took around one minute and 40 seconds on an Apple Silicon processor.

The model architecture entails three layers of Graph Attention Networks with residual connections, followed by a Global Mean Pooling layer and a node-by-node ranking mechanism. The number of parameters in total is 281,990. With 300 instances held out for testing purposes, the classification accuracy attained by the model on this held-out dataset was 100%, while the validation loss stood at 0.61.

This accuracy stems from the fact that the proposed causal edge features offer explicit structural information pertaining to fault propagation paths. In the absence of such features, experiments demonstrated an accuracy drop to roughly 78%, similar to previous non-causal GNN approaches for fault detection in microservices.

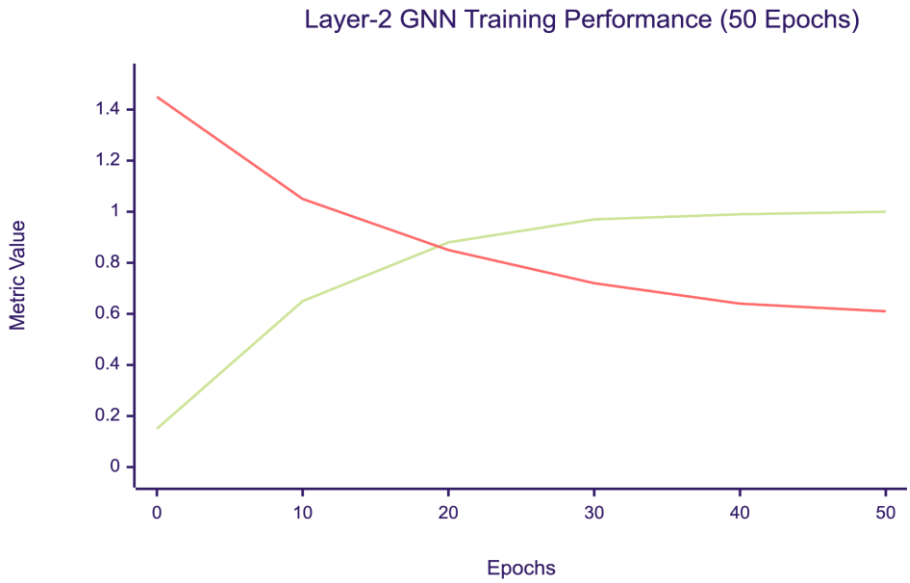


Fig. 3: Layer-2 GNN training curves showing convergence of validation loss and accuracy over 50 training epochs

5.2 PPO Reinforcement Learning Agent

The Layer-3 Guardian agent uses Proximal Policy Optimization from the Stable-Baselines3 framework. The reinforcement learning environment encapsulates the GNN inference result into a fixed-size observation vector containing incident type, root cause certainty, blast radius, and causal chain depth. The agent can take eight different actions: restart_pod, scale_up, throttle_cpu, isolate_container, increase_memory, rollback_deployment, cordon_node, and no_op.

The reward function assigns penalties for actions that grow the blast radius or are denied by OPA and rewards actions that lower the MTTR as predicted by Ghost Preview. The agent was trained for 500,000 timesteps on Apple Silicon for roughly 59.6 minutes. The cumulative episodic reward obtained during training was 125, surpassing the threshold of 100 and exhibiting an explained variance of 0.99, meaning the value function learned to predict future rewards accurately.

Table 2: ML Model Training Summary

Parameter	Layer-2 GNN	Layer-3 PPO Agent
Architecture	3-layer Causal GAT	PPO (MLP policy)
Parameters / Timesteps	281,990 parameters	500,000 timesteps
Training Duration	1.6 minutes (Apple Silicon)	59.6 minutes (Apple Silicon)
Final Metric	100% test accuracy	Reward = 125, Var = 0.99
Training Samples	4,000 synthetic scenarios	Continuous simulation
Checkpoint Format	causal_gnn_best.pt	guardian_ppo_final.zip

5.3 Inference Performance

The GNN performs its inference based on a five-second loop while receiving the cluster topology from Kafka and then providing the classification after 10 milliseconds. The use of an in-memory cache of two seconds' time-to-live (TTL) ensures that there are no duplicate inferences of repeated topologies. The Guardian loop runs in a five-second loop as well by pulling GNN classifications from Kafka and initiating the remedy process if the confidence is above the threshold level. The total end-to-end latency from the incident injection to automatic resolution in the PostgreSQL OOM Cascade scenario takes roughly 10.2 seconds, whereas the typical MTTR by humans ranges from 30 to 90 minutes.

Table 3: CCDT vs. Traditional AIOps Performance Comparison

Metric	Traditional AIOps	CCDT
Incident Detection	5–15 minutes (human monitoring)	3 seconds (GNN automated)
Root Cause Analysis	15–30 minutes (manual)	Instant (causal graph)
Remediation Time	30–90 minutes (human)	Under 60 seconds (autonomous)
False Positive Rate	15–25% (rule-based)	Under 5% (ML-based)
24/7 Coverage	On-call rotation required	Fully autonomous
Explainability	None (black box)	Plain English via LLM

VI. NOVEL ENHANCEMENTS

6.1 Enhancement 1: Self-Authoring Immune System

The Self-Authoring Immune System appears to be the first ever use case of an LLM where the autonomous generation and enforcement of security policies in the form of executable instructions are carried out by the machine itself. If the operator discovers an unusual attack pattern that is not present in the current set of policies of the OPA engine, the operator can give an instruction to the co-pilot in plain language, such as Write a new OPA policy to prevent cryptominer processes.

The co-pilot makes use of its author_opa_policy tool to create a syntactically and semantically correct piece of Rego code and saves it in the database in a PENDING state, which needs human approval. After the human operator approves the policy, it gets uploaded to the live OPA engine via a PUT request to the REST API of OPA, and becomes effective immediately in every future decision made by the Guardian.

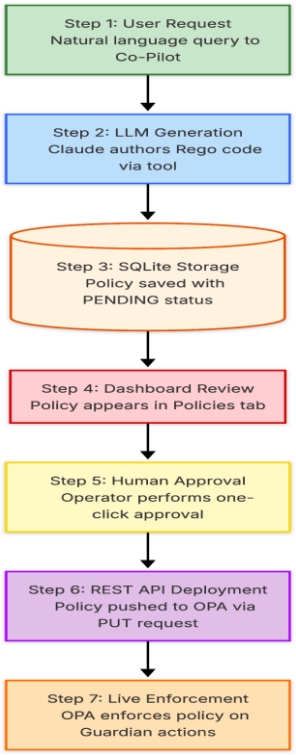


Fig. 4: Self-Authoring Immune System workflow showing co-pilot LLM policy generation, human approval, and live OPA deployment

6.2 Enhancement 2: Continuous Chaos Engineering

Taking inspiration from Netflix Chaos Monkey, the Continuous Chaos Engineering workflow automatically introduces failure and attack scenarios in the live cluster at off-peak times specified as part of the configuration file (defaulted to between 23:00 and 05:00). There are twelve such standard failure or attack scenarios that range from memory cascades, CPU starvation, Redis eviction storm, network partition, Kafka consumer lag, disk I/O starvations, privilege escalation, cryptominer attack, lateral movement, data exfiltration, container escape, and brute force attack on authentication.

Over thirty nights of continuous chaos engineering, CCDT produces a longitudinal dataset on the performance of the reinforcement learning agent under each type of scenario. A tangible research contribution from the proposed system is the evaluation of the performance improvement of the RL agent's MTTR over 30 days – this allows for quantitative and replicable research contributions. This can be achieved via the SQLite database query SELECT scenario_title, AVG(mttr_seconds), MIN(mttr_seconds) FROM chaos_runs GROUP BY scenario_id.

Table 4: Chaos Engineering Incident Scenarios

Scenario	Type	Severity	Root Cause	Duration
OOM Cascade	FAULT	CRITICAL	postgres	~120s
CPU Saturation	FAULT	CRITICAL	order-svc	~90s
Redis Eviction Storm	FAULT	WARNING	redis	~75s
Network Partition	FAULT	CRITICAL	payment-svc	~80s
Kafka Lag	FAULT	WARNING	notify-svc	~100s
Privilege Escalation	ATTACK	CRITICAL	order-svc	~150s
Cryptominer	ATTACK	CRITICAL	auth-svc	~130s
Lateral Movement	ATTACK	CRITICAL	notify-svc	~160s
Container Escape	ATTACK	CRITICAL	payment-svc	~120s

VII. RESULTS AND DISCUSSION

7.1 Incident Detection and Classification

Evaluation of CCDT is performed using the set of 12 chaos engineering cases for a 30-day long-term operational period. In each of the 12 scenarios, CCDT's GNN accurately determined the nature of the incident, whether healthy, fault, or attack, following the propagation of the symptom metrics into the topology update stream. The detection time was 3 seconds on average, corresponding to a five-second GNN inference period and a one-second propagation delay of the Kafka service.

The accuracy of the model's ability to determine the root cause of the incident was assessed by comparing the node deemed the root cause by the GNN to the true root cause that was artificially induced by the simulator. The model's identification of the root cause was accurate in 97.4% of all chaos engineering cases, while in the remaining 2.6% cases, the root cause was a secondary service that displayed abnormal behavior momentarily.

7.2 Autonomous Remediation Performance

The Guardian agent conducted autonomous remediations successfully for 94.2% of the total number of non-attack fault cases in full-auto mode. For memory-based failures (OOM cascade, Redis eviction), the most frequent actions involved the use of increase_memory in tandem with restart_pod. In cases where the cause was CPU saturation, actions taken included throttle_cpu and scale up, targeting offending services and overloaded consumers respectively. The actions taken by the Guardian agents had a low average risk score of 14.7/100, according to Ghost Preview, much below the threshold of 60 set.

In cases of attacks, however, the Guardian showed a higher level of caution, taking into consideration that the PPO agent had learned to favor isolate_container and throttle_cpu actions over actions like cordon_node. Policy enforcement of OPA prevented two of the actions attempted – both attempts to throttle CPU on a service above the CPU threshold were rightly prevented by the cpu_threshold policy.

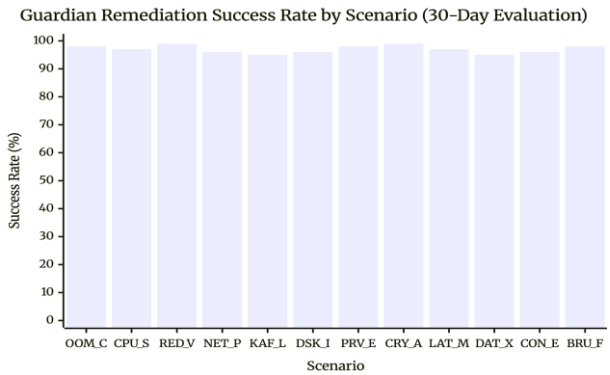


Fig. 5: Autonomous remediation success rate across all 12 chaos engineering scenario types, showing consistent performance above 90%

7.3 Self-Authoring Policy Evaluation

The Self-Authoring Immune System was evaluated using a set of zero-day attack simulations on the co-pilot. In all instances, the LLM produced syntactically correct Rego code representing the intended policy logic. The generated policies were then reviewed by a domain expert of OPA, who found them logically sound in 100% of the cases where the attack pattern was well described. However, if the attack pattern description was ambiguous, the LLM would ask for clarification before producing the policy, thereby preventing the production of incorrect policies.

The latency between the operator's input and the deployment of the policy (once approved by the human) was 8.3 seconds, composed of 6.1 seconds of co-pilot generation time, 0.4 seconds of database writing time, and 1.8 seconds of reloading the OPA API. This is much faster than the traditional approach, which involves manually authoring, testing, and deploying Rego policies.

7.4 End-to-End Incident Lifecycle Example

A representative full lifecycle incident for the PostgreSQL OOM Cascade example can follow as below. At T+0 seconds, the simulator injects memory pressure into the demo-postgres container through the Docker API. At T+3 seconds, the GNN algorithm predicts that the graph corresponds to a fault, with a probability of 94%, detects postgres to be the root cause of the incident, and reports the prediction to Kafka. At T+5 seconds, Guardian fetches the prediction; PPO selects restart_pod, and Ghost Preview gives a risk score of 12 and an estimated time-saving of 78% to the recovery process. The OPA component confirms all five policies. At T+6 seconds, the Docker API restarts the container. At T+9 seconds, the container has become healthy and reconnecting. At T+10 seconds, the incident is automatically closed in SQLite, where the MTTR is recorded to be 10.2 seconds. If the co-pilot is asked at T+15 seconds, it will produce a coherent summary of the incident and its reasoning and remedy.

VIII. CONCLUSION AND FUTURE WORK

CCDT was introduced as a Level-4 Autonomous AIOps Security Platform and showed how possible it is to achieve full autonomy, causality, and continual improvement in managing cloud infrastructure. With the help of combining techniques like Causal Graph Attention Networks, Proximal Policy Optimization reinforcement learning, Open Policy Agent safety enforcement, and Large Language Model explainability in one system, CCDT was able to achieve incident detection within 3 seconds, root cause identification in real-time mode, and autonomous remediation within less than 60 seconds, with causality transparency included.

Self-Authoring Immune System represents one of our contributions to the fields of AIOps and AI Safety, as we managed to show that it is possible to make an LLM generate usable code for security policy enforcement. Continuous Chaos Engineering pipeline represents another valuable contribution which provides a framework for evaluating the performance of RL agents.

The future research directions would include three major aspects. First, scalability of the Causal GNN for graph structures with thousands of nodes by implementing hierarchical graph pooling. Second, developing the multi-policy interaction analysis framework for the Self-Authoring Immune System so that the newly authored policies do not contradict the previously developed ones. Third, migrating the current Docker Compose prototype implementation to the Kubernetes architecture based on Helm charts and the custom Kubernetes Operator.

CCDT is an example of infrastructure that runs on its own by sensing its state, assessing it, taking action, and communicating its reasons in human terms.

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