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Agentic Generative AI Framework for Predictive Fault Detection in Self-Healing Cloud Environments

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Abstract: The increasing complexity of cloud-native systems has made fault detection and recovery a critical challenge for modern IT operations. Traditional AIOps approaches rely on static rules and data-driven models, which often lack adaptability in dynamic and large-scale environments. To address these limitations, this paper proposes the ARCH (Autonomous Reasoning and Contextual Healing) framework, an intelligent self-healing architecture that integrates Large Language Models (LLMs) with Retrieval-Augmented Generation (RAG) for context-aware fault detection and autonomous remediation. The proposed framework adopts a layered design consisting of perception, cognition, knowledge, and action components, enabling continuous monitoring, intelligent reasoning, and automated recovery. By leveraging agentic reasoning strategies such as Chain-of-Thought and action-oriented decision-making, the system analyzes telemetry data and identifies root causes with minimal human intervention. The integration of RAG enhances contextual awareness by incorporating historical incident knowledge, thereby improving diagnosis accuracy and reliability. In addition, the framework supports predictive fault detection by utilizing historical telemetry patterns to anticipate potential failures. The performance of the ARCH framework is evaluated using key metrics, including Mean Time to Repair (MTTR), Autonomous Success Rate (ASR), and system efficiency. Experimental results demonstrate that the proposed approach achieves up to 82% reduction in MTTR and 89.5% autonomous success rate compared to baseline approaches. These results highlight the effectiveness of LLM-driven agentic architectures in enabling scalable, intelligent, and autonomous self-healing cloud systems.
Keywords: AIOps, Large Language Models (LLMs), Retrieval-Augmented Generation (RAG), Self-Healing Systems, Cloud Computing, Agentic AI, Predictive Fault Detection, Autonomous Remediation

I. INTRODUCTION

Cloud computing has become a fundamental backbone for modern digital services, enabling scalable, distributed, and highly available applications. However, the increasing adoption of cloud-native architectures, microservices, and containerized environments has significantly increased system complexity. As a result, fault detection, diagnosis, and recovery have become critical challenges in maintaining system reliability and performance. Traditional approaches based on manual intervention, static rules, or conventional machine learning techniques often struggle to adapt to dynamic and large-scale environments.

Artificial Intelligence for IT Operations (AIOps) has emerged as a promising solution to automate monitoring and anomaly detection in cloud systems. While existing AIOps solutions improve operational efficiency, they are generally limited by their dependence on predefined rules or data-driven models, which lack contextual understanding and adaptive reasoning capabilities. These limitations restrict their effectiveness in handling complex, multi-step failure scenarios.

Recent advancements in Generative Artificial Intelligence, particularly Large Language Models (LLMs), have introduced new opportunities for intelligent automation. LLMs enable advanced reasoning, contextual understanding, and decision-making capabilities. Techniques such as Chain-of-Thought prompting and agentic reasoning allow systems to analyze problems in a structured manner and generate step-by-step solutions. Furthermore, Retrieval-Augmented Generation (RAG) enhances LLM performance by incorporating external knowledge sources, enabling context-aware and informed decision-making.

Motivated by these advancements, this paper proposes the ARCH (Autonomous Reasoning and Contextual Healing) framework, a novel agentic architecture designed for predictive fault detection and autonomous remediation in cloud environments. The framework integrates LLM-based reasoning with RAG-driven knowledge retrieval in a layered structure consisting of perception, cognition, knowledge, and action components. This design enables continuous monitoring, context-aware analysis, and intelligent decision-making through a closed-loop self-healing mechanism.

Unlike traditional reactive systems, the proposed approach also incorporates predictive capabilities by leveraging historical telemetry patterns to anticipate potential failures before they impact system performance. This predictive aspect enhances system resilience and reduces downtime in large-scale cloud environments.

The main contributions of this paper are summarized as follows:

1) A novel ARCH framework integrating LLMs and RAG for intelligent cloud self-healing.
2) An agent-based reasoning mechanism enabling context-aware fault diagnosis and decision-making.
3) A closed-loop architecture supporting both reactive and predictive fault detection.
4) A comprehensive evaluation demonstrating improvements in MTTR, ASR, and system efficiency.

The remainder of this paper is organized as follows. Section 2 presents the literature review. Section 3 describes the proposed ARCH architecture. Section 4 details the methodology and implementation. Section 5 discusses experimental results and analysis. Section 6 outlines challenges and future scope, followed by the conclusion in Section 7.

II. RELATED WORK

The rapid evolution of cloud computing has led to increasingly complex and distributed system architectures, creating significant challenges in fault detection and system reliability. Traditional approaches to IT operations relied on rule-based monitoring and manual intervention, which are often insufficient in dynamic cloud environments. To address these limitations, Artificial Intelligence for IT Operations (AIOps) has emerged as a promising paradigm for automating anomaly detection and fault management.

Early AIOps solutions primarily utilized machine learning and statistical techniques to analyze logs, metrics, and system behavior. These approaches improved anomaly detection accuracy; however, they often lacked contextual understanding and struggled to adapt to unseen failure scenarios. Recent studies have explored deep learning-based methods for log analysis and anomaly detection, demonstrating improved performance in identifying complex patterns. Despite these advancements, such models typically depend on large amounts of labeled data and lack reasoning capabilities.

With the emergence of Large Language Models (LLMs), a new direction has been introduced for intelligent automation. LLMs provide advanced reasoning and contextual understanding, enabling systems to analyze complex scenarios and generate step-by-step decisions. Techniques such as Chain-of-Thought prompting and ReAct-based reasoning have further enhanced the ability of LLMs to perform structured problem-solving and dynamic decision-making.

To improve the reliability of LLM-based systems, Retrieval-Augmented Generation (RAG) has been proposed as an effective approach for integrating external knowledge sources. RAG enables models to retrieve relevant information from historical logs, incident databases, and documentation, thereby enhancing contextual awareness and reducing hallucination issues. This approach has shown promising results in knowledge-intensive applications and is increasingly being adopted in intelligent agent systems.

Recent research has also focused on agent-based and multi-agent architectures for autonomous cloud operations. These systems leverage multiple intelligent agents to monitor, analyze, and manage cloud environments collaboratively. Such frameworks have demonstrated improvements in automation and system resilience; however, challenges related to coordination complexity, latency, and scalability still persist.

Although significant progress has been made in AIOps, LLM-based reasoning, and RAG integration, most existing solutions address these components in isolation. There is a lack of a unified framework that combines perception, reasoning, knowledge retrieval, and action execution in a closed-loop system. Furthermore, limited work has been done on integrating predictive fault detection with agentic reasoning in cloud environments.

To address these gaps, this paper proposes the ARCH framework, which integrates LLM-based agentic reasoning with RAG-driven contextual knowledge in a layered architecture. The proposed approach enables both reactive and predictive fault detection, along with autonomous remediation, thereby advancing the state of self-healing cloud systems.

III. PROPOSED ARCH ARCHITECTURE

This section presents the proposed ARCH (Autonomous Reasoning and Contextual Healing) framework, designed to enable intelligent, agent-driven, and predictive self-healing in cloud environments. The architecture integrates Large Language Models (LLMs) with Retrieval-Augmented Generation (RAG) to provide context-aware reasoning and autonomous fault remediation. The system is organized into a layered structure that supports modularity, scalability, and continuous feedback.

The overall architecture of the ARCH framework is illustrated in Fig. 1. It consists of four primary layers—Perception, Cognition, Knowledge, and Action—connected through a closed-loop feedback mechanism to ensure continuous monitoring and adaptive response.

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A. Architecture Overview

The ARCH framework follows a hierarchical layered design, where each layer performs a specific function while interacting with other components to achieve end-to-end automation.

The Perception layer is responsible for collecting telemetry data such as logs, metrics, and traces from cloud systems. This layer acts as the input interface, continuously monitoring system behavior and detecting anomalies.

The Cognition layer serves as the core reasoning engine of the framework. It utilizes LLM-based agentic reasoning to interpret telemetry data, generate hypotheses, and determine appropriate corrective actions. The reasoning process follows structured techniques such as Chain-of-Thought and ReAct, enabling step-by-step analysis of complex failure scenarios.

The Knowledge layer incorporates Retrieval-Augmented Generation (RAG) to enhance contextual understanding. It retrieves relevant historical incidents, system logs, and documentation from a knowledge base, allowing the system to make informed decisions based on past experiences.

The Action layer is responsible for executing remediation tasks through cloud APIs and orchestration tools. It ensures that corrective actions are applied efficiently and safely to restore system stability.

B. Layered Functional Components

1) Perception Layer: This layer continuously collects and processes telemetry data from distributed cloud components. It performs data preprocessing, filtering, and anomaly triggering, forming the foundation for subsequent analysis.
2) Cognition Layer (Agentic Reasoning Engine): The cognition layer implements LLM-driven reasoning to analyze system states and identify root causes. The internal reasoning workflow, illustrated in Fig. 3, follows a cycle of Thought → Action → Observation → Refined Thought, enabling adaptive and iterative decision-making.
3) Knowledge Layer (RAG Integration): This layer retrieves contextually relevant information from historical datasets and knowledge repositories. By grounding the reasoning process in factual data, it reduces hallucinations and improves decision accuracy.
4) Action Layer: The action layer executes remediation strategies such as service restart, resource scaling, or configuration updates. Validation mechanisms and safety guardrails are applied before execution to prevent unintended actions.

C. Predictive and Reactive Self-Healing Loop

The ARCH framework operates through a continuous feedback loop, as illustrated in Fig. 2. The process begins with telemetry data collection, followed by reasoning and knowledge retrieval. The system then executes remediation actions and evaluates system state through feedback.

In addition to reactive fault handling, the framework supports predictive fault detection by analyzing historical telemetry patterns. This enables the system to anticipate potential failures and take proactive measures, thereby improving system reliability and reducing downtime.

The integration of predictive and reactive capabilities makes the ARCH framework a comprehensive solution for intelligent cloud self-healing.

IV. RESULTS AND DISCUSSION

This section presents the experimental evaluation of the proposed ARCH framework. The performance is analyzed using quantitative metrics, including Mean Time to Repair (MTTR), Autonomous Success Rate (ASR), precision, recall, and overall system efficiency. The results are compared with baseline approaches such as traditional AIOps and deep learning-based models.

A. Quantitative Performance Analysis

To evaluate the fault detection capability of the system, standard classification metrics such as precision and recall are considered.

Precision = TP / (TP + FP)

Recall = TP / (TP + FN)

These metrics provide insights into the accuracy and completeness of fault detection. High precision indicates fewer false positives, while high recall reflects the system's ability to identify most of the actual faults.

The comparative performance of the ARCH framework against baseline models is presented in Table II.

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Table II. Performance Comparison of AIOps, Deep Learning, and ARCH Framework

Model	MTTR (min)	ASR (%)	Efficiency (η)
AIOps	45.6	65.2	62.5%
Deep Learning	38.4	74.8	70.1%
ARCH Framework	8.2	89.5	88.4%

The results indicate that the ARCH framework outperforms baseline approaches in terms of both detection accuracy and recovery efficiency. A significant reduction in MTTR and improvement in autonomous success rate can be observed.
As illustrated in Fig. 4, the proposed framework significantly reduces the Mean Time to Repair (MTTR) compared to traditional AIOps and deep learning-based models.

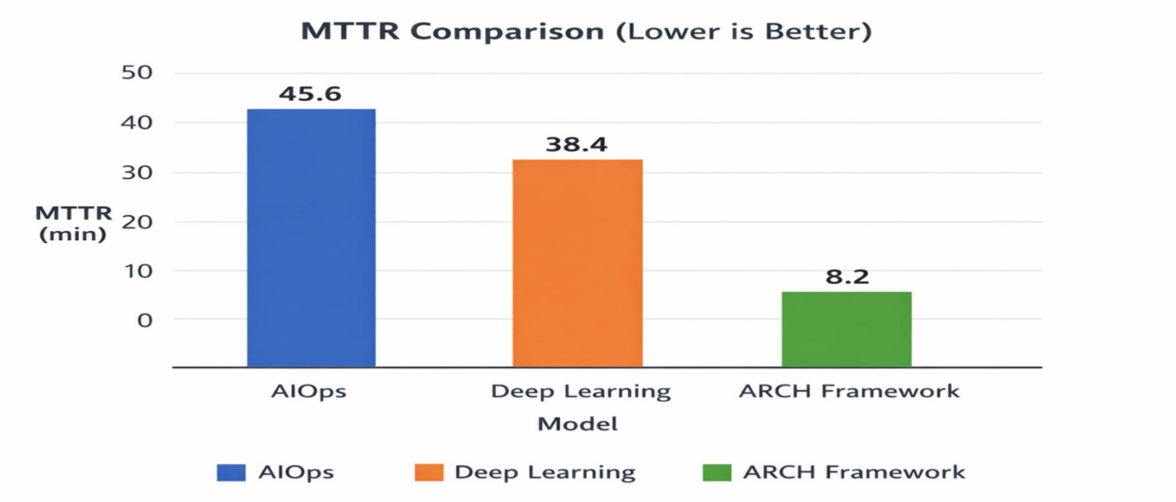

Fig. 4. MTTR Comparison across different approaches.

In addition to MTTR, the Autonomous Success Rate (ASR) is evaluated to measure the effectiveness of automated fault resolution. The ARCH framework achieves a higher success rate, as shown in Fig. 5.

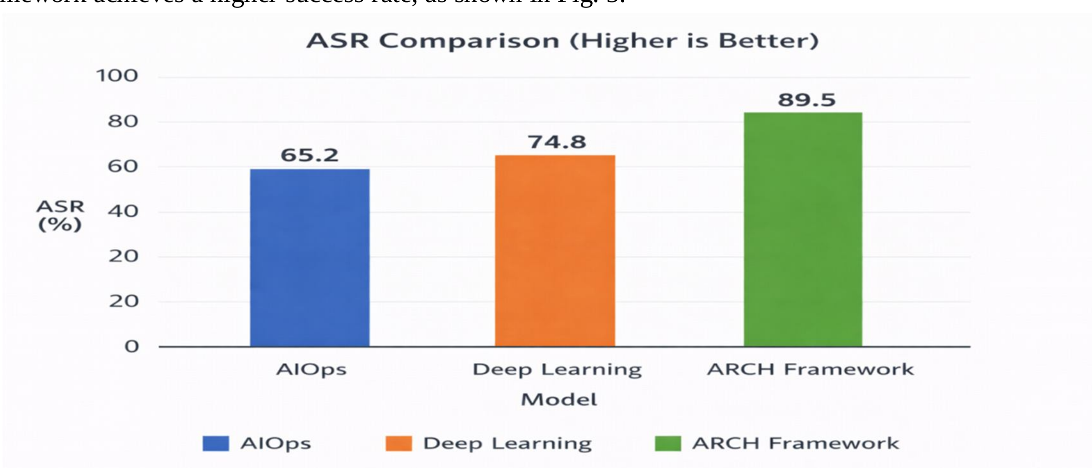

Fig. 5. Autonomous Success Rate (ASR) comparison.

B. Efficiency Analysis

To further analyze system performance, the self-healing efficiency (η) is considered:

$$n = \frac{[\sum T\ manul - T\ auto)]}{n * T\ manual}$$

This metric captures the relative improvement in recovery time achieved through automation.
As depicted in Fig. 6, the ARCH framework demonstrates significantly higher efficiency compared to baseline approaches.

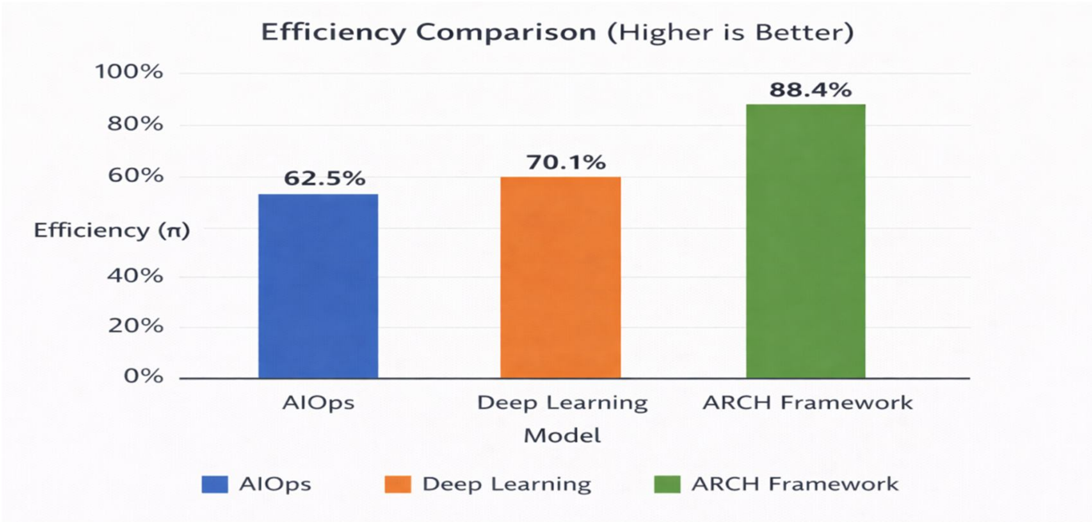

Fig. 6. Self-Healing Efficiency (η) comparison.

C. Discussion

The experimental results clearly demonstrate that the ARCH framework outperforms conventional approaches across multiple performance metrics. The integration of LLM-based reasoning enables the system to analyze complex fault scenarios effectively, while the RAG-based knowledge retrieval enhances contextual understanding.

One of the key advantages of the proposed approach is its ability to support both reactive and predictive fault detection. By leveraging historical telemetry data, the system can anticipate potential failures and reduce downtime.

However, the system introduces certain trade-offs, including increased computational overhead and potential latency due to LLM-based reasoning. Despite these challenges, the overall improvements in accuracy, automation, and efficiency make the ARCH framework a promising solution for intelligent cloud operations.

V. CHALLENGES AND FUTURE RESEARCH DIRECTIONS

While the proposed ARCH framework demonstrates significant improvements in autonomous cloud self-healing, several challenges remain that must be addressed for large-scale and real-world deployment.

A. Challenges

1) LLM Hallucination: Large Language Models (LLMs) may occasionally generate inaccurate or misleading outputs, commonly referred to as hallucinations. In cloud operations, such incorrect reasoning may lead to inappropriate remediation actions, potentially affecting system stability. Although the integration of Retrieval-Augmented Generation (RAG) helps reduce this issue, it cannot fully eliminate it.
2) Latency and Computational Overhead: The use of LLM-based reasoning introduces additional latency due to context processing, inference, and response generation. This can impact performance in time-sensitive environments. Moreover, continuous reasoning cycles and large-scale data processing increase computational resource requirements.
3) Context Window Limitations: LLMs operate within a fixed context window, which restricts the amount of telemetry data that can be processed simultaneously. In large-scale cloud systems, this limitation may affect the completeness of analysis and decision-making.
4) Security and Trust Issues: Autonomous execution of remediation actions raises security concerns. Incorrect or malicious actions may impact critical infrastructure. Additionally, the use of external APIs for LLMs introduces potential risks related to data privacy, confidentiality, and compliance.
5) Real-Time Constraints: Although the ARCH framework improves fault resolution efficiency, its applicability in real-time scenarios is limited due to the inherent delay in reasoning and validation processes.

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B. Future Research Directions

Future work can focus on enhancing the efficiency, reliability, and scalability of the ARCH framework.

1) Lightweight and Optimized Models: Developing lightweight LLMs and optimizing inference mechanisms can reduce latency and computational cost, making the system more suitable for real-time applications.
2) Advanced Guardrails and Validation: Incorporating robust validation mechanisms and safety guardrails can improve system reliability by ensuring that only verified and safe actions are executed.
3) Hybrid AIOps Architectures: Combining LLM-based reasoning with traditional rule-based and machine learning approaches can provide a balanced trade-off between speed and intelligence.
4) Enhanced RAG Strategies: Improving retrieval techniques and expanding knowledge bases can enhance contextual understanding and reduce dependency on model-generated reasoning.
5) Real-World Deployment and Evaluation: Future research should focus on deploying the ARCH framework in real cloud environments to evaluate its performance, scalability, and robustness under practical conditions.

VI. CONCLUSION

In this paper, an intelligent and autonomous self-healing framework, ARCH (Autonomous Reasoning and Contextual Healing), has been proposed to address the challenges of fault detection and remediation in modern cloud environments. The framework integrates Large Language Models (LLMs) with Retrieval-Augmented Generation (RAG) to enable context-aware reasoning, adaptive decision-making, and automated recovery.

The proposed architecture adopts a layered design consisting of perception, cognition, knowledge, and action components, supported by a closed-loop feedback mechanism. This design allows continuous monitoring, accurate fault diagnosis, and efficient remediation with minimal human intervention. In addition, the incorporation of agentic reasoning strategies enhances the system’s ability to handle complex and dynamic failure scenarios.

Experimental evaluation demonstrates that the ARCH framework significantly improves system performance, achieving notable reductions in Mean Time to Repair (MTTR) and higher Autonomous Success Rate (ASR) compared to traditional approaches. The integration of predictive capabilities further strengthens system resilience by enabling proactive fault detection based on historical telemetry patterns.

Overall, the proposed approach highlights the potential of combining LLM-based reasoning with RAG-driven knowledge retrieval for building scalable and intelligent cloud self-healing systems. The results indicate that the ARCH framework can serve as a foundation for next-generation autonomous cloud operations.

Future work will focus on improving real-time performance, reducing computational overhead, and enhancing security mechanisms to ensure safe and reliable deployment in production environments.

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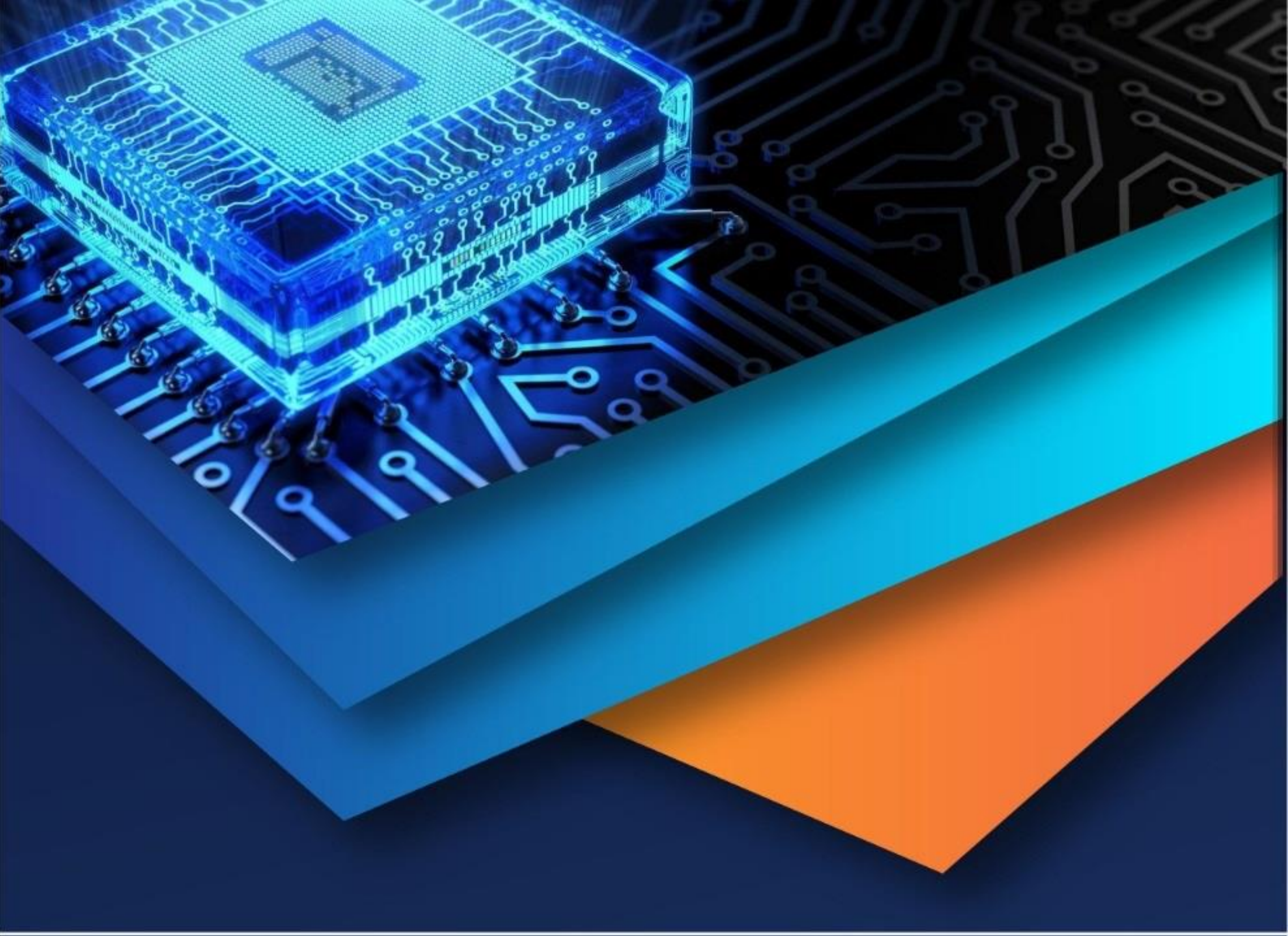

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