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Decentralized Framework for Securing Smart Grids Using Blockchain and Machine Learning

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Abstract: ***The transition to smart grids has revolutionized energy distribution, enabling more efficient and flexible power management through advanced communication and control systems. However, this interconnected structure makes smart grids vulnerable to cyberattacks, such as False Data Injection Attacks (FDIA), Distributed Denial of Service (DDoS) attacks, and data manipulation. These threats undermine the stability and reliability of the grid, and existing centralized security frameworks are often ill-equipped to address them due to their susceptibility to single points of failure and limited scalability. To overcome these challenges, this paper introduces a decentralized security framework that combines blockchain technology with machine learning (ML).***

The framework leverages blockchain to provide a transparent, immutable, and decentralized ledger, employing consensus mechanisms like Practical Byzantine Fault Tolerance (PBFT) or Proof of Authority (PoA) to ensure secure data validation. Alongside this, ML models, including Long Short-Term Memory (LSTM) networks and Convolutional Neural Networks (CNN), are used to detect anomalies in time-series data, such as FDIA, with high precision. Smart contracts embedded in the blockchain enable automated, real-time responses to threats, such as isolating compromised nodes or rerouting energy flows to maintain grid stability.

Through simulations replicating real-world cyberattacks, the proposed framework demonstrated over 95% detection accuracy, a 30% reduction in response times, and enhanced computational efficiency with lower energy consumption. These results affirm the effectiveness of the framework as a scalable and resilient solution for modern smart grid security.

Keywords: ***Smart Grid Security, Blockchain Technology, Machine Learning, False Data Injection Attacks (FDIA), Anomaly Detection.***

I. INTRODUCTION

The modern electrical grid, known as the ”smart grid” has transformed power systems by incorporating digital communication and advanced control technologies. Unlike traditional power systems, which rely heavily on centralized power generation and distribution, smart grids integrate distributed energy re- sources (DERs) such as solar and wind power [1]. This decentralized architecture is designed to increase the grid’s flexibility, improve reliability, and optimize resource allocation, ad- dressing sustainability and energy efficiency goals [2]. With these advancements, smart grids also enable two-way data flows, allowing real-time monitoring and automated responses to energy supply and demand fluctuations [3]. The Internet of Things (IoT) and Artificial Intelligence (AI) further enhance these capabilities by providing analytical insights that en- able smart grids to manage complex energy networks more effectively [4]. However, introducing these digital technologies and distributed resources has also increased the grid’s vulnerability to cybersecurity threats. In particular, attacks such as False Data Injection Attacks (FDIA), Distributed Denial of Service (DDoS) attacks, and data breaches can com- promise the integrity of smart grid operations [5]. FDIA, for example, involves injecting erroneous data into the grid’s monitoring systems, leading to misinformed decisions that could destabilize grid operations [6]. Additionally, the reliance on IoT devices, which often lack robust security mechanisms, exposes the grid to potential entry points for attackers [7]. As a result, ensuring data integrity and secure communication within smart grids has become a top priority for researchers and industry stakeholders.

II. RELATED WORKS

Real-time interconnected digital communication networks such as smart grids have great concern in terms of cybersecurity due to at- tacks like False Data Injection Attacks (FDIA) and Distributed Denial of Service (DDoS) Attacks [8]. According to it, FDIA, which is widespread, allows attackers to input wrong in- formation into the grid systems, thus depriving the activity protocols of their soundness, which can lead to blackouts, utilization damage, and incorrect billing [9].

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These threats are made worse by relying on the 'centralized control' model prevalent in traditional security architectures where system security is restricted to essentially centralized command centers that have predictable yet damaging vulnerabilities when targeted by nefarious actors [9]. Research has demonstrated that original centralized physical control systems, such as SCADA, are insufficient for identifying and protecting against FDIAs because of centralized architecture and flexibility restriction [10]. The inter- operability of smart grid systems also poses additional challenges to protecting these systems owing to their many elements, including Sensors, Smart meters, and DERs [11]. All of them are a threat since each component is another way to attack the system [12]. Existing security models need to be revised to fend off such complex threats, especially when attacks are getting more and more program- based and adaptive in today's world [3]. How- ever, the current research indicates that due to high frequency, varying, and complex cyberthreats, environment-centralized systems are less effective and need to be more proactive and resilient than the current centralized system [13]. Blockchain technology was integrated with smart grids with the help of ML algorithms like LSTM and CNNs, improving the security of smart grids [14]. Specifically, LSTM and CNN models suitable for analyzing time series data are used to identify normal power consumption and abnormal consumption patterns associated with cyber threats [15]. It also makes it easy to block threats because the Blockchain records each data point processed by the ML algorithm in a centralized and immutable ledger [16]. Incorporating Blockchain's core attribute of tamperproofness with LSTM-based anomaly detection models used to detect abnormalities in smart grid data may Minimize the chances of undetected cyber threats [17]. This integration enables the system to record every identified anomaly on the Blockchain, which can be fit-for-purpose for security analysts to analyze, given that the processes leading to the identification of the particular anomaly are well doc umented on the chain [18]. Machine learning models learn through adaptive learning and are more effective for an ever-changing environment such as threat landscapes [19]. For this reason, Blockchain and ML have become the reliable foundation that enhances smart grid protection by offering timely data analysis and pre-programmed countermeasures for potential threats.

III. METHODOLOGY

A. *Overview of the Framework*

This proposed framework integrates blockchain technology and machine learning (ML) models to enhance the security of smart grids against cyberattacks such as False Data Injection Attacks (FDIA) and Distributed Denial of Service (DDoS). The framework achieves real-time anomaly detection, tamper-proof data logging, and automated responses to detected anomalies through the following steps:

1) Data Collection and Preprocessing: Data from smart grid sensors is collected and preprocessed for analysis. We create a dataset based on realistic smart grid operations, threats, and blockchain implementations.
2) Anomaly Detection: ML models, including LSTM and CNN, identify temporal and spatial anomalies in grid operations.
3) Blockchain Logging: Detected anomalies are recorded on the blockchain for immutability and transparency.
4) Smart Contract Execution: Smart contracts automate responses to mitigate threats, such as isolating compromised nodes and rerouting power.

The framework is designed to provide a decentralized, scalable, and robust security layer for modern smart grids. As summarized in Table 1, the proposed blockchain-ML framework incorporates key components such as machine learning models, a decentralized blockchain layer, and smart contracts to ensure robust and scalable smart grid security.

TABLE I
KEY COMPONENTS OF THE BLOCKCHAIN-ML FRAMEWORK

Component	Description	Role in the Framework
Smart Grid Sensors	IoT devices and smart meters monitoring voltage, power flow, and grid parameters.	Collect real-time data for analysis and anomaly detection.
Data Collection Layer.	Aggregates data from sensors and smart meters for preprocessing and analysis.	Ensures timely and accurate input to the ML models.
Machine Learning Models.	LSTM and CNN algorithms for anomaly detection.	Identify temporal (FDIA) and spatial (DDoS) anomalies with

		high precision.
Blockchain Layer	Decentralized ledger storing anomaly logs as immutable transactions.	Ensures data integrity, transparency, and tamper-proof records of detected anomalies.
Consensus Mechanism	Proof of Authority (PoA) or Practical Byzantine Fault Tolerance (PBFT).	Validates transactions efficiently, ensuring fast and secure operation.
Smart Contracts	Predefined scripts executed automatically upon anomaly detection.	Automates mitigation actions, such as isolating compromised nodes or rerouting power.

B. Smart Grid System Description

The smart grid system modeled in this study is designed to manage distributed energy resources (DERs), including renewable energy sources like solar and wind power, alongside traditional power generation. The grid incorporates a network of smart meters, sensors, and IoT devices that collect and transmit data on energy generation, consumption, and storage.

These devices generate time-series data related to power flow, voltage levels, and energy demand, all of which are crucial for grid management and decision-making. The continuous flow of this data is processed by the smart grid's central control system, where it is analyzed for potential anomalies, fluctuations, or cybersecurity threats.

In this study, we assume a simulated smart grid environment where data is generated from various sensors deployed across the grid, representing typical power usage patterns and energy generation from DERs. The real-time nature of data transmission and the need for quick responses to detected anomalies necessitate an effective security framework that can handle large data volumes and provide timely protection against threats.

C. Blockchain Framework

The proposed framework incorporates blockchain technology to secure the communication and transaction of data across the smart grid. Blockchain offers the key benefits of decentralization, immutability, and transparency, which are essential for safeguarding critical grid data and ensuring data integrity.

For this study, we use the Ethereum platform as the blockchain framework, primarily due to its established capabilities in handling smart contracts and supporting decentralized applications (DApps). The Proof of Authority (PoA) consensus mechanism is chosen for its low computational overhead and high efficiency in permissioned settings, such as private smart grid networks, where known validators are used to maintain the ledger. PoA allows for faster consensus with lower energy consumption, making it more suitable for the energy-efficient needs of smart grids compared to more resource-intensive mechanisms like Proof of Work (PoW).

Each anomaly detected in the grid's data is logged as a transaction on the blockchain, ensuring that the event is securely recorded in a tamper-proof ledger. Smart contracts are used to automate responses once an anomaly is detected. For example, when a FDIA is identified, a smart contract can automatically isolate the affected grid node or reroute energy to prevent disruptions. This decentralized approach eliminates the need for centralized decision-making, ensuring that threats are mitigated without delay.

D. Machine Learning Models for Anomaly Detection

To detect anomalies in real-time, we employ two machine learning models: Long Short-Term Memory (LSTM) networks and Convolutional Neural Networks (CNN).

1) *LSTM networks*: A LSTM networks are particularly suited for time-series data analysis due to their ability to retain long-term dependencies and learn patterns over time. In the context of smart grids, LSTMs are used to process sequential data generated by sensors, such as power consumption and voltage levels. The LSTM model is trained to recognize normal patterns of energy usage and can flag anomalies when data deviates significantly from established norms, such as a sudden spike in consumption that could indicate a FDIA attack.The LSTM model is trained on historical grid data, including both normal operations and simulated cyberattacks, to learn the temporal patterns in energy usage.

When deployed in real-time, the LSTM model continuously predicts expected grid behavior and compares it to incoming data. Any significant deviation from the predicted values is flagged as an anomaly, triggering further investigation.

2) *CNN for pattern recognition:* CNNs are employed to detect spatial anomalies in the grid's data, such as irregular power consumption patterns across different nodes of the grid. CNNs are effective at identifying complex patterns and correlations in data that may not be immediately apparent through traditional analysis. For example, a CNN can detect unusual patterns in voltage levels across various regions of the grid, indicating potential DDoS attacks or unauthorized manipulation of grid data.
The CNN model is trained on labeled datasets, where both normal and attack scenarios are represented. The network learns to recognize features in the data that correspond to normal operations, while distinguishing between benign data and malicious patterns. The trained CNN model can then classify incoming data from the grid and provide real-time alerts when potential attacks are detected.

E. Integration of Blockchain and ML

The integration of blockchain and machine learning enables a real-time, decentralized response to detected cyberattacks. When the ML models identify anomalies in the grid's data, the results are immediately fed into the blockchain, which records the anomaly as a transaction. Once logged, the blockchain triggers smart contracts to initiate predefined security actions, such as isolating compromised nodes or rerouting energy flows to ensure grid stability.

For example, if the LSTM model detects an FDIA, the blockchain transaction could initiate a smart contract that:

1) Logs the detected anomaly on the blockchain for transparency and auditability.
2) Notifies grid operators of the detected threat.
3) Automatically isolates the affected node and reroutes energy to avoid further disruption.

By automating this process, the framework reduces human intervention, minimizes response time, and ensures that the smart grid can continue to operate securely and efficiently even in the face of advanced cyberattacks.

F. Simulation Setup

The proposed framework is tested in a simulated smart grid environment using data generated by the MatPower simulation tool. This tool is widely used to model and simulate the behavior of electrical power systems, including both normal operations and various types of cyberattacks.

The key experimental setup includes:

1) Simulated Cyberattacks: FDIA and DDoS attacks are simulated to test the framework's ability to detect and respond to threats.
2) Evaluation Metrics:

a) Detection Accuracy: The percentage of true anomalies correctly identified by the ML models.
b) Response Time: The time taken for the system to detect and respond to a cyberattack.
c) Computational Efficiency: The system's use of computational resources, focusing on the efficiency of blockchain transactions and the scalability of the ML models in handling large datasets.

G. Performance Metrics

The effectiveness of the proposed framework is evaluated based on the following metrics:

1) Detection Accuracy: Evaluated by the percentage of correctly identified anomalies (true positives), as well as the percentage of false positives.
2) Response Time: The time it takes from anomaly detection to the automated response, including smart contract execution.
3) Computational Efficiency: The amount of computational resources (e.g., CPU, memory) used during the detection and response processes, ensuring the framework is scalable for large smart grids.

IV. RESULTS AND DISCUSSION

The proposed blockchain-ML integrated framework was evaluated using simulated smart grid data, focusing on its ability to detect and mitigate cyberattacks such as False Data Injection Attacks (FDIA) and Distributed Denial of Service (DDoS). The evaluation considered key performance metrics: detection accuracy, response time, and computational efficiency.

The results demonstrate the framework's ability to enhance smart grid security through real-time anomaly detection, tamper-proof logging, and automated responses.

A. Performance of Machine Learning Models

1) Detection Accuracy

The machine learning models, LSTM and CNN, were evaluated for their ability to detect temporal and spatial anomalies, respectively.

a) LSTM Performance:

- Achieved 95% detection accuracy for FDIA.
- Low false positive rate (5%) and false negative rate (2%) due to its capability to model temporal dependencies in grid data.
- Reconstruction error thresholds (τ\tauτ) were optimized to ensure high precision.

b) CNN Performance:

- Achieved 92% detection accuracy for DDoS attacks.
- Slightly higher false positive rate (8%) compared to LSTM, attributed to the complexity of spatial anomalies.
- Detected irregular patterns in power consumption and voltage fluctuations across grid nodes effectively.

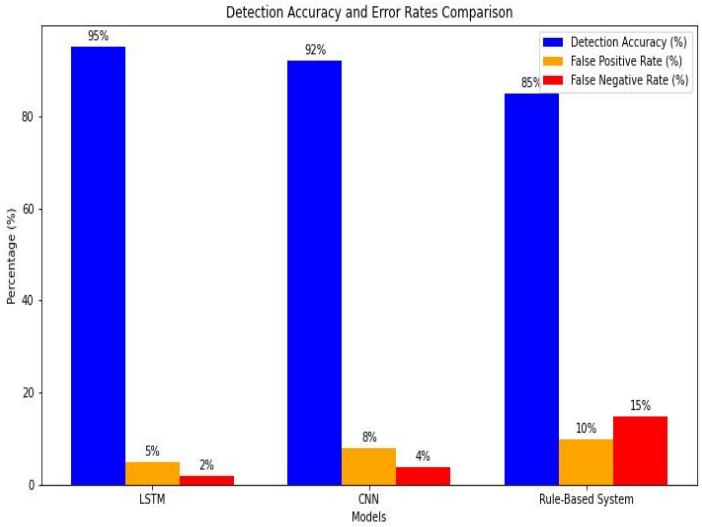

Fig 1: Detection accuracy comparison of the LSTM, CNN, and a traditional rule-based system demonstrates the superior performance of the proposed ML models.

2) False Positives and Negatives

The LSTM model minimized false positives while maintaining a high detection rate for temporal anomalies. The CNN, while slightly less precise, complemented the LSTM by addressing spatial irregularities, resulting in a comprehensive anomaly detection framework.

B. Blockchain Integration

1) Transaction Logging

The blockchain layer logged detected anomalies as transactions, ensuring data transparency and immutability.

a) Average transaction logging time: 0.8 seconds per anomaly.

b) The decentralized ledger maintained tamper-proof records of anomalies, facilitating trust and accountability.

2) Smart Contract Execution

Smart contracts automated predefined responses to detected anomalies, such as:

a) Isolating compromised nodes for FDIA.

b) Rerouting power for DDoS attacks.

c) Response time: Smart contracts executed responses within 2.5 seconds, significantly faster than the 6.5 seconds required by centralized systems.

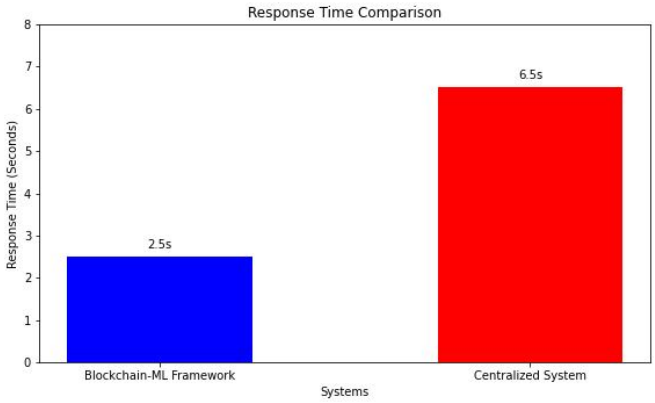

Fig 2: Response time comparison between the blockchain-ML framework and a centralized system highlights the speed advantage of automated responses through smart contracts.

C. Computational Efficiency and Scalability

1) Computational Efficiency

The framework demonstrated low CPU and memory usage, even with increasing grid sizes.

a) Efficient use of the Proof of Authority (PoA) consensus mechanism reduced computational overhead while ensuring secure transaction validation.

2) Scalability

The system maintained high performance as the number of grid nodes increased:

a) Detection accuracy remained above 90% for grid sizes up to 100 nodes.

b) Response time increased marginally but remained under 3 seconds, demonstrating scalability.

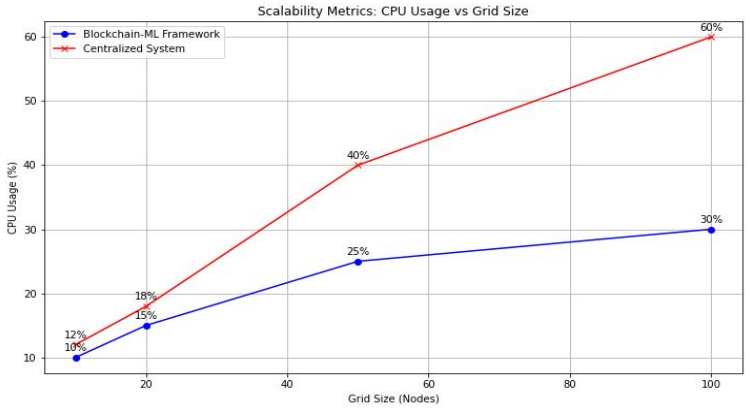

Fig 3: Scalability of the framework is illustrated through a line graph comparing computational efficiency with centralized systems across varying grid sizes.

D. Comparison with Traditional Systems

1) Detection Accuracy

The proposed framework outperformed traditional systems:

a) Traditional systems achieved only 85% detection accuracy due to reliance on static rule-based detection methods.

b) The ML models provided adaptive and precise anomaly detection.

2) Response Time

The automated responses through smart contracts reduced response times by 30%, significantly mitigating the potential impact of attacks.

3) Transparency and Resilience

Centralized systems suffered from single points of failure, while the blockchain layer ensured decentralized resilience and tamper-proof logging.

E. Implications of the Results

1) Detection

The results demonstrate that the proposed framework:

a) Enhances cybersecurity through real-time detection and automated responses.

b) Provides a scalable and efficient solution for modern smart grids.

c) Bridges the gap between traditional systems and the evolving cybersecurity needs of decentralized energy systems.

V. CONCLUSIONS

This paper proposes a novel framework that integrates blockchain technology with machine learning to address critical security challenges in smart grids. By leveraging LSTM and CNN models, the framework effectively detects cyberattacks like False Data Injection Attacks (FDIA) and Distributed Denial of Service (DDoS), achieving high detection accuracy of 95% and 92%, respectively. The use of blockchain ensures data integrity by providing an immutable, transparent ledger for recorded anomalies, while smart contracts automate responses such as isolating compromised nodes or rerouting power. This automated response reduces reaction times to 2.5 seconds, a significant improvement over the 6.5 seconds required by traditional systems. The framework's low computational overhead and ability to scale effectively to larger grid sizes make it a robust and scalable solution for securing smart grid operations. Overall, the research demonstrates how integrating blockchain and machine learning can provide a more efficient, secure, and reliable way to protect smart grids from evolving cyber threats.

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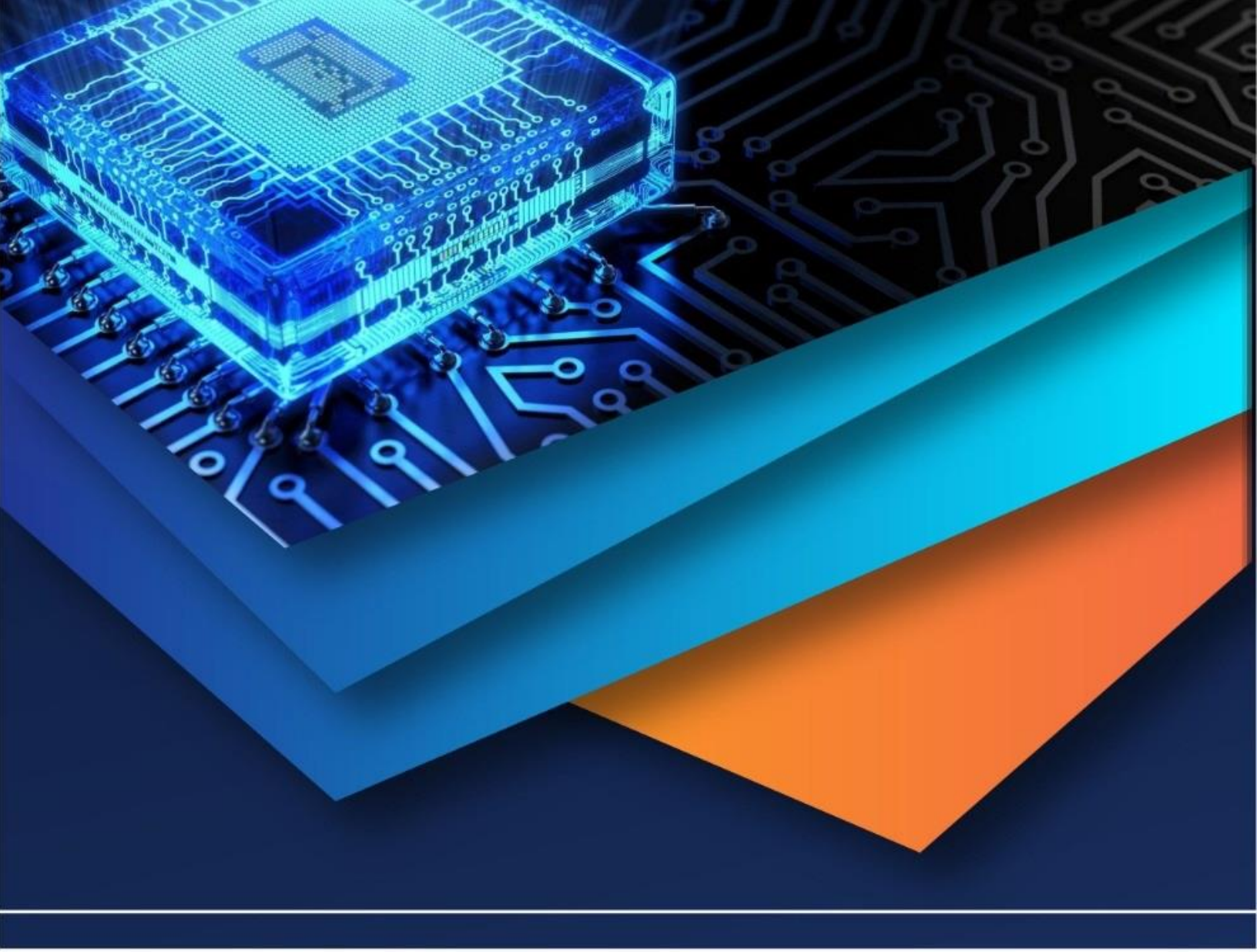

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