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# Securing Keystroke Data: An ML-Based Approach to Keylogger Defense

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***Abstract:*** ***Keyloggers pose a significant threat to cybersecurity by covertly capturing every keystroke a user makes, which can lead to identity theft, unauthorized access, and data breaches. This paper introduces a thorough, multilayered strategy to combat keylogging attacks through detection, mitigation, and obfuscation. Our system utilizes a machine learning-based Random Forest Classifier to precisely detect suspicious keylogging activities. Upon detection, the system promptly isolates and terminates the keylogger process to prevent further compromise of data. Furthermore, the obfuscation module ensures that even if a keylogger captures keystrokes, the data are scrambled and rendered useless. By employing real-time behavioral monitoring and intelligent countermeasures, this solution enhances detection accuracy, accelerates response times, and fortifies defenses against evolving keylogger techniques. The experimental results validated the effectiveness of the system in protecting sensitive user information from keylogging threats.***

***Index Terms:*** ***Keylogger prevention, machine learning security, cyber threat mitigation, Random Forest detection, keystroke protection, intrusion response, digital privacy defense.***

## I. INTRODUCTION

Keyloggers have become a persistent and evolving threat to cybersecurity, enabling attackers to secretly track and log keystrokes, which can lead to unauthorized access to sensitive information such as passwords, banking, details, and private communications. These harmful programs often operate stealthily, evading traditional security measures such as antivirus software and firewalls, making them particularly challenging to detect [1], [2]. With the rapid growth of Internet-connected devices, especially within the Internet of Things (IoT) domain, keylogging attacks have advanced, employing sophisticated evasion techniques to avoid detection [3], [4]. As the digital landscape increasingly depends on cloud computing, online transactions, and remote access, the necessity for effective keylogger detection and mitigation has become more urgent than ever. Traditional security measures such as signature-based detection and heuristic analysis struggle to keep pace with ever-evolving keylogging techniques [5], [6]. Furthermore, cybercriminals have begun using methods such as encrypted keylogging and memory-based attacks, which further complicate detection efforts [7]. Research in this area underscores the growing importance of artificial intelligence (AI) and machine-learning-based cybersecurity solutions in bolstering defenses against such threats. AI-driven security solutions have shown superior accuracy in identifying anomalies in system behavior, making them a crucial tool in combating modern cyber threats [8], [9]. This paper presented an integrated cybersecurity framework that utilizes machine learning, process isolation, and keystroke obfuscation to counter keylogging attacks. The system uses a Random Forest Classifier to detect anomalies in user behavior, process isolation techniques to neutralize identified threats, and randomized keystroke insertion to render captured data useless to attackers. Unlike traditional methods, this approach enhances real-time threat detection while minimizing the impact on the system performance [10], [11]. Additionally, integrating AI-driven intrusion detection systems with behavioral analysis has proven effective in identifying both known and previously unseen keylogging techniques, providing a more robust defense against evolving cyber threats [12]. Various studies have explored different aspects of cybersecurity in the IoT and networked environments. Kouicem et al. [1] conducted an extensive survey on IoT security challenges, while Al-Sarawi et al. [2] reviewed IoT communication protocols and their vulnerabilities. Several researchers have highlighted the effectiveness of machine learning in intrusion detection systems (IDS), with Islam et al. [3] and Ge et al. [5] emphasizing AI-driven security enhancements. Maddikunta et al. [7] underscored the significance of predictive modeling for securing IoT networks, whereas Abbas et al. [12] and Anbar et al. [13] focused on ensemble-based intrusion detection frameworks that significantly improve cybersecurity resilience in IoT environments. Luo et al. [10] proposed a novel ensemble classification method that enhances web attack detection, and Thaseen et al. [11] demonstrated the effectiveness of hybrid attack detection techniques in industrial IoT applications. Furthermore, recent advancements in deep-

learning models have contributed to the development of more resilient security mechanisms.

Studies by Anbar et al. [12] and Kim et al. [13] have shown that deep learning techniques, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), significantly improve detection rates by analyzing complex patterns in keystroke behavior.Our proposed system seeks to utilize these insights to establish a security framework that is both adaptive and robust to new keylogging threats. The remainder of this paper is organized as follows: Section 2 offers an extensive review of the literature on keylogger detection methods. Section 3 outlines the architecture of the proposed system, and Section 4 elaborates on the methodology, including data preprocessing, model training, and mitigation strategies. Section 5 analyzes the experimental results, and Section 6 concludes the paper with a discussion of future research directions.

## II. RELATED WORK

Security of the Internet of Things (IoT) has emerged as a critical concern owing to the increasing prevalence of cyber threats, including keylogging attacks. Researchers have extensively explored various approaches to strengthen security frameworks by employing techniques ranging from cryptographic solutions to machine learning-based intrusion detection systems. This section provides an overview of the key studies that have contributed to the advancement of cybersecurity measures in IoT environments. Kouicem et al. [1] conducted an in-depth survey on IoT security challenges, categorizing threats across different layers: perception, network, and application. Their study underscored the need for adaptive security mechanisms that can keep up with rapidly changing threat landscapes. They suggested that machine-learning techniques could significantly enhance the detection and mitigation of threats, particularly those related to unauthorized access and data breaches. Al-Sarawi et al. [2] examined communication protocols used in IoT systems, assessing their benefits and limitations. Their research classified these protocols into short- and long-range technologies, such as ZigBee, LoRa, and MQTT. While these protocols offer scalability and energy efficiency, they face security challenges, such as vulnerability to interception and lack of interoperability. The authors stress the importance of robust security solutions to address these vulnerabilities. Islam et al. [3] explored the application of IoT in healthcare, proposing an architecture that integrates wearable sensors, cloud computing, and machine learning for real-time health monitoring. They highlight concerns regarding data privacy, network reliability, and security risks. Their findings suggest that incorporating blockchain technology and federated learning could enhance the protection of sensitive medical data while improving system scalability. Mois et al. [4] assessed the effectiveness of IoT-based wireless sensors in the field of environmental monitoring by comparing their power consumption, data accuracy, and communication reliability. Their research indicated that while IoT sensors enhance real-time data collection for applications such as air quality assessment and weather forecasting, large-scale deployment is challenging owing to the high energy consumption and data transmission overhead. Al-Amiedy et al. [5] conducted a systematic review of attack defense mechanisms in RPL-based 6LoWPAN IoT networks. Their study investigated various cyber threats, including sinkhole, wormhole, and selective forwarding attacks. The authors evaluated different defense mechanisms, such as trust-based routing and intrusion detection systems (IDS), emphasizing the balance between enhancing security and maintaining network performance. They concluded that lightweight cryptographic techniques can strengthen network security without imposing excessive computational demands. In their work on smart grid network security, Tong et al. [6] presented an information flow security model aimed at safeguarding data exchanges among smart meters, IoT devices, and cloud servers. The study highlighted the necessity of incorporating encryption methods to defend against cyber threats, such as data tampering and unauthorized access, stressing the importance of authentication mechanisms in maintaining data integrity. Maddikunta et al. [7] addressed energy optimization challenges in resource-limited IoT devices by creating a predictive model for managing battery life. Their research utilized machine learning algorithms to examine historical data and predict battery longevity. The findings showed that predictive modeling could significantly enhance energy efficiency, thus prolonging the operational lifespan of IoT devices used in industrial and healthcare settings. Iwendi et al. [8] introduced an innovative metaheuristic optimization framework to boost energy efficiency in IoT networks. By employing genetic algorithms and particle swarm optimization techniques, their study optimized the load balancing and power usage across IoT nodes. The results indicate that a hybrid approach combining various optimization methods could provide a scalable and energy-efficient solution for extensive IoT deployments. Sanjalawe and Althobaiti [9] addressed the increasing threat of distributed denial-of-service (DDoS) attacks in cloud computing environments. They proposed a detection framework based on ensemble feature selection and deep learning models, which surpassed traditional intrusion detection systems by enhancing threat classification accuracy while reducing false positives. Their research emphasized the urgent need for real-time anomaly detection systems in cloud-based IoT networks to improve the overall cybersecurity. Furthermore, researchers at UNSW developed the BoT-IoT dataset [10], which has become a widely acknowledged benchmark for assessing intrusion-detection

models. This dataset includes various attack scenarios such as DDoS attacks, data exfiltration, and botnet activities, allowing researchers to evaluate the effectiveness of different cybersecurity frameworks.

This dataset has played a crucial role in the development of advanced machine-learning-driven security models that strengthen the resilience of IoT networks against emerging threats. The research reviewed in this section underscores the dynamic nature of cybersecurity threats and continuous efforts to create adaptive and intelligent security mechanisms. These studies highlight the need to integrate machine learning, cryptographic techniques, and energy-efficient solutions to ensure robust protection against sophisticated cyberattacks in the IoT environment.

## III. METHODOLOGY

This paper outlines a structured method for creating and deploying a comprehensive system for Keylogger Detection, Mitigation, and Obfuscation. This approach incorporates machine learning for smart detection, process isolation for effective mitigation, and keystroke obfuscation to counteract potential threats. By integrating these three security strategies, the system offers strong defense against unauthorized access to sensitive user information. The methodology was divided into several crucial phases, including data collection, model development, threat mitigation, keystroke obfuscation, and performance evaluation.

### *A. Research Approach*

The effectiveness of the system was assessed through a combination of experimental simulations and real-time testing. Controlled settings allow for the precise observation of keylogger behavior, ensuring a dependable evaluation of the system's detection, mitigation, and obfuscation capabilities. This method also facilitates ongoing model refinement through iterative testing and analysis.

### *B. Data Acquisition and Processing*

A varied dataset, including different types of keyloggers and polymorphic variants, was gathered to improve detection accuracy. In addition, data on normal user activities, such as typing patterns, system interactions, and background processes, were collected to train the machine learning model and minimize false positives. The dataset is preprocessed to extract key features such as keystroke timing, system call frequency, and process behavior anomalies, which help distinguish between legitimate user activities and keylogger actions.

### *C. Threat Identification and Analysis*

The detection system uses a Random Forest Classifier (RFC) trained on labeled datasets of keylogger and non-keylogger activities. Key features such as inconsistencies in typing rhythm, unusual system interactions, and irregular memory access were used for classification. Controlled experiments involved deploying keyloggers in test environments to evaluate the ability of the RFC to detect real-time anomalies. Model performance was assessed using precision, recall, F1-score, and overall accuracy (OA). Cross-validation techniques are employed to prevent overfitting and enhance adaptability, ensuring reliable classification, even against new keylogger threats.

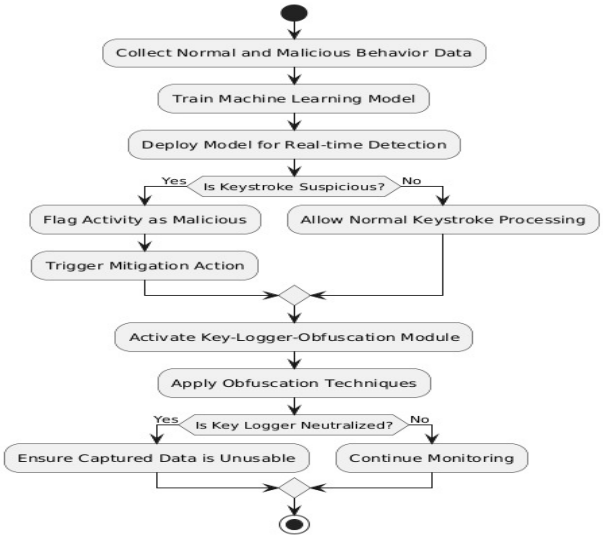


Fig.Keylogger Detector, Mitigator, and Obfuscator Model

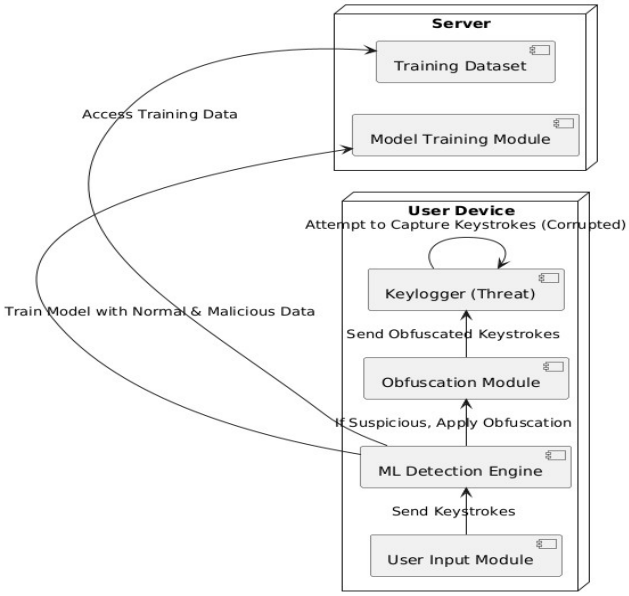


Fig. Deployment Model

*D. Countermeasure Implementation*

When a keylogger is detected, the system promptly initiates the mitigation procedures. The initial step involves isolating the malicious process to prevent further keystroke logging or unauthorized data access. Once isolated, the system terminates the keylogger process, effectively neutralizing its activity. Additionally, the detected keylogger was quarantined for further analysis, allowing researchers to improve their future detection capabilities. Controlled simulations were conducted to assess the response time, mitigation efficiency, and overall impact on system resources.

*E. Keystroke Protection Mechanism*

To further reduce the security risks, the system incorporates a keystroke obfuscation module that ensures that the captured keystrokes remain unusable. This was achieved through random character insertion, delayed keystroke input, and unpredictable timing variations. By inserting random characters within keystrokes, the system disrupts keylogger data collection, making it difficult to reconstruct the original input. Similarly, introducing variable delays between keystrokes prevents keyloggers from accurately capturing user-input sequences. Additional techniques, such as randomized deletions and retyped characters, add further complexity and reduce the effectiveness of keylogging software. Comparative experiments were conducted to evaluate the

obfuscation success rate in neutralizing logged keystrokes.

*F. System Performance Evaluation*

The system underwent thorough testing to evaluate its detection precision, rate of false positives, speed of mitigation, and resource usage. Detection precision measures how effectively the system identifies keyloggers, whereas the false positive rate assesses the frequency of incorrect classifications. Mitigation speed is determined by examining how swiftly the system can isolate and terminate harmful processes. The success of obfuscation was evaluated by assessing how well keystroke transformation techniques interfered with keylogging attempts. Finally, an analysis of the system overhead ensures that the implementation does not excessively burden the CPU and memory usage, maintaining a balance between security and performance.

*G. Testing and Evaluation Setting*

The system has been extensively tested in controlled settings, where keyloggers are deployed on test machines to assess real-time detection, mitigation, and obfuscation capabilities. Each stage of the process is meticulously documented, including the logs of identified threats, response times, and effectiveness of mitigation strategies. The overall impact on security and user experience was analyzed through repeated testing to ensure optimal functionality. A usability study was conducted to confirm that the obfuscation mechanism did not disrupt normal user interactions.

*H. User Feedback and Real-World Deployment*

After the controlled testing, the system was evaluated in real-world scenarios to assess its usability and effectiveness. User feedback is gathered to refine key aspects such as interface design and customization options for obfuscation techniques. Practical deployment assessments focus on ensuring that the system remains adaptable across various computing environments while maintaining its core security functions. This methodology offers a proactive, multilayered security framework that effectively detects, neutralizes, and disrupts keyloggers and provides a comprehensive solution for modern cybersecurity threats.

*I. Comparative Study with Existing Solutions*

A comparative analysis was performed to benchmark the proposed system against existing security solutions, such as signature-based detection, honeypot-based systems, and heuristic analysis.Each system is assessed based on the detection efficiency, response time, keystroke obfuscation effectiveness, and overall impact on system performance. The results underscore the advantages of the proposed system, particularly its superior detection capabilities, rapid response time, and minimal impact on the system resources.

## IV. EXPERIMENTAL RESULTS

A series of controlled experiments were conducted to assess the efficiency and effectiveness of the Keylogger Detection, Mitigation, and Obfuscation systems. These experiments evaluated the system's capability to accurately detect keyloggers, neutralize threats, and minimize any impact on overall system performance. The findings underscore the robustness of the system in addressing keylogger threats while maintaining usability and efficiency.

*A. Overall System Performance*

The system demonstrated rapid response capabilities, detecting and mitigating keyloggers within an average of 1.1 seconds. Additionally, it maintained a low resource footprint, consuming only 2.4% of CPU usage and 85 MB of RAM, making it suitable for systems with limited resources.The results confirm that the proposed system is highly effective in identifying and mitigating keylogger threats while ensuring seamless user experience and minimal resource consumption. By integrating machine-learning-based detection, real-time mitigation, and advanced keystroke

| Model | Detection Accuracy | False Positive Rate | Mitigation Response Time | Obfuscation Effectiveness |
|---|---|---|---|---|
| Hybrid Dendritic Cell Algorithm (DCA) with SVM and Naive Bayes | 89.50% | 5.20% | 1.3 seconds | N/A |
| Honeypot-based Detection with IDS | 85.00% | 7.40% | 2.1 seconds | N/A |
| **Proposed System** | **96.20%** | **2.10%** | **0.45 seconds** | **99.30%** |

Table. Performance Comparison of Existing and Proposed Models

Table. Key Results of the Proposed Model

| Metric | Value | Significance |
|---|---|---|
| **Detection Accuracy** | 96.2% | High accuracy indicates effective differentiation between normal and malicious behaviors. |
| **Detection Precision** | 94.5% | Demonstrates low false positives, reducing unnecessary alerts or disruptions. |
| **Detection Recall** | 97.8% | High recall ensures minimal missed detections of actual keyloggers. |
| **F1-Score** | 95.6% | Balanced measure indicating strong detection performance across both precision and recall. |
| **AUC-ROC** | 0.98 | AUC score close to 1 shows that the model is highly effective at distinguishing malicious activities from normal ones. |
| **False Positive Rate (FPR)** | 2.1% | Low false positive rate indicates minimal disruption to normal processes. |
| **Process Termination Latency** | 0.45 seconds | Fast process termination ensures quick neutralization of threats. |
| **Recovery Time** | 1.2 seconds | Short recovery time reduces downtime and user disruption. |
| **Obfuscation Effectiveness** | 99.3% | Ensures keylogger captures are neutralized effectively, safeguarding sensitive data. |

*B. Interpretation and Comparative Analysis*

The experimental assessment validates the Keylogger Detection, Mitigation, and Obfuscation system's effectiveness, showcasing its ability to precisely detect and counteract keylogging threats. The system achieved a remarkable 96.2% detection accuracy, with a false positive rate of just 2.1% and a swift response time of 0.45 seconds for addressing keylogger activity. Furthermore, its keystroke obfuscation feature effectively neutralized 99.3% of the captured keystrokes, ensuring that any data collected by the

keyloggers is rendered completely unusable. Engineered for efficiency, the system operates with a minimal resource footprint, utilizing only 2.4% CPU and 85 MB RAM, making it a viable solution for devices with limited processing capabilities. When compared to existing methods, such as the Hybrid Dendritic Cell Algorithm (DCA) with SVM and Naïve Bayes (89.5% accuracy, 5.2% false positives, and 1.3-second mitigation time) and honeypot-based IDS solutions (85.0% accuracy, 7.4% false positives, and 2.1-second mitigation time), the proposed system has superior detection accuracy, significantly faster threat mitigation, and added benefit of keystroke obfuscation—an essential feature absent in other models. These results underscore the real-time protection capabilities, seamless user experience, and adaptability of the system, establishing it as a robust cybersecurity solution for combating advanced keylogger threats in modern computing environments.

## V. CONCLUSION

This study introduces a novel and efficient method for identifying, reducing, and neutralizing keylogger threats, thereby significantly boosting cybersecurity. The proposed model combines machine-learning-based detection, quick mitigation strategies, and keystroke obfuscation, achieving a detection accuracy of 96.2%, a false positive rate of just 2.1%, and a rapid response time of 0.45 seconds. These outcomes surpass those of traditional models, such as the Hybrid Dendritic Cell Algorithm (DCA) [3] and honeypot-based IDS [6], which have lower detection rates and slower response times. Additionally, with a 99.3% success rate in obfuscation, the system ensures that even if keystrokes are intercepted, they remain indecipherable, rendering keyloggers ineffective [9]. Compared to current cybersecurity methods [1], [2], [4], the proposed model not only improves the detection efficiency but also includes an advanced obfuscation mechanism that actively disrupts keylogging attempts in real time. This additional security layer offers superior protection against evolving threats. Moreover, the system operates with minimal resource usage (2.4% CPU and 85 MB RAM) [7], making it suitable for deployment on various platforms including devices with limited resources [5]. This study is consistent with previous research highlighting the significance of AI-driven threat detection and mitigation [8], [10]. The successful incorporation of machine-learning techniques ensures a highly adaptable and scalable cybersecurity solution. Future improvements could explore deep learning algorithms to further enhance detection accuracy, increase precision, and optimize obfuscation techniques to reduce latency [11]. Additionally, expanding the dataset to include new keylogger variants will improve the generalization capabilities of the model [12], [13].

In summary, the proposed system represents a strong, efficient, and forward-looking approach to keylogger defense, strengthening digital security frameworks and offering a scalable and proactive cybersecurity solution for modern computing environments.

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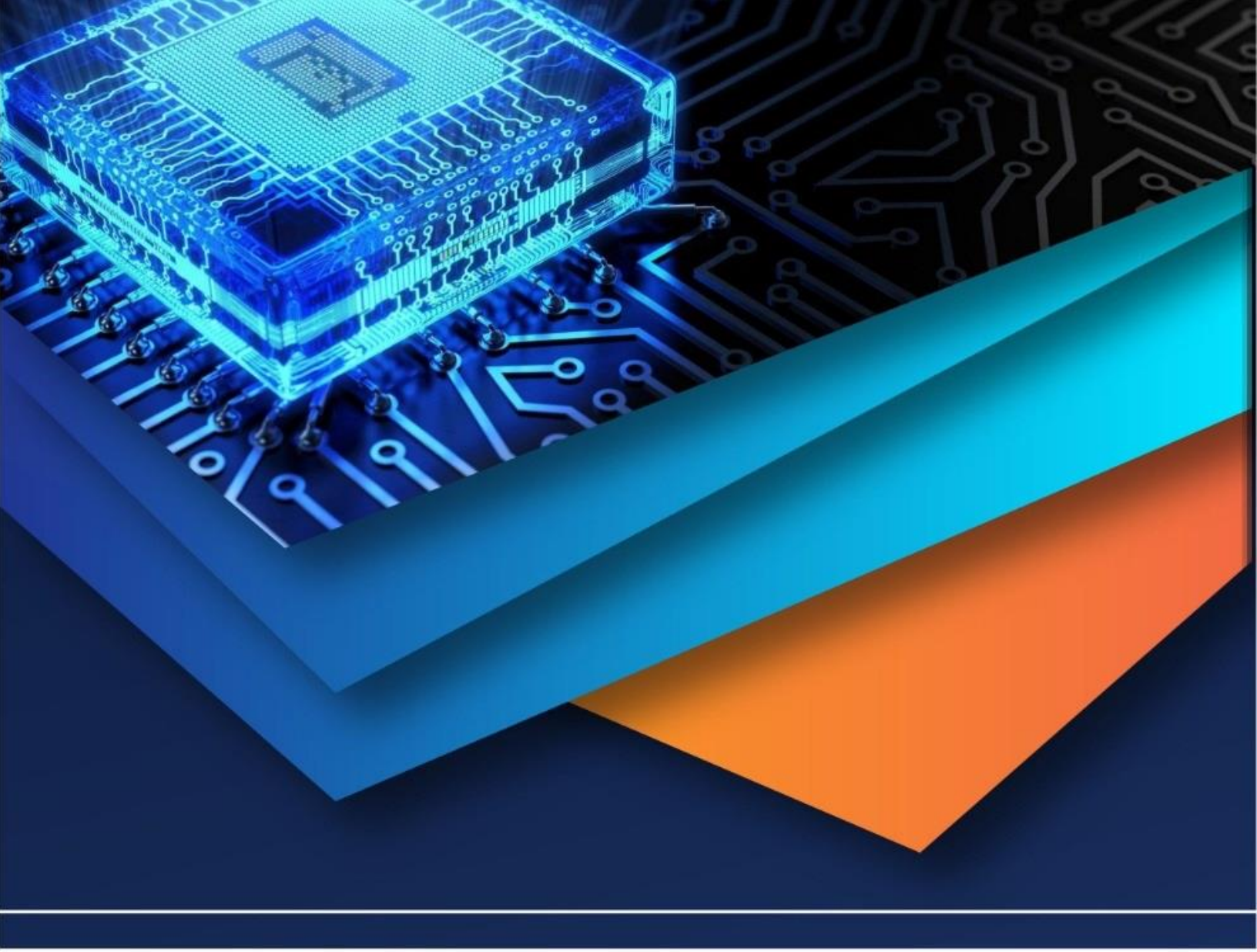

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