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A Futuristic Brain-IoT Framework for Thought-Based Control of Smart Environments

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Abstract: ***The integration of Brain–Computer Interface (BCI) technology with the Internet of Things (IoT) introduces a revolutionary paradigm for human–machine interaction, enabling direct neural control of smart environments using human thoughts. This paper proposes a futuristic Brain–IoT framework that combines neural signal acquisition through electroencephalogram (EEG) sensors, advanced neural signal processing, AI-based intention decoding, secure IoT communication, and real-time operating systems for low-latency execution. Deep learning models, including Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks, are employed to decode neural patterns into actionable commands. Experimental evaluation conducted on simulated EEG datasets demonstrates an average command classification accuracy of 93.6%, with an end-to-end system latency of less than 120 ms, ensuring real-time responsiveness. The proposed framework also achieves a 15–20% improvement in decoding accuracy compared to traditional machine learning-based BCI models. Security analysis confirms robust protection against unauthorized access through encrypted communication and neural biometric authentication. The results validate the feasibility, efficiency, and scalability of the Brain–IoT system, highlighting its potential for smart homes, autonomous vehicles, healthcare assistance, and industrial automation in future intelligent environments.***

Keywords: Brain–Computer Interface, Brain–IoT, Neural Signal Processing, Deep Learning, IoT Security, Real-Time Systems.

I. INTRODUCTION

The rapid advancement of digital technologies has transformed the way humans interact with machines, evolving from traditional mechanical interfaces to touch, voice, and gesture-based systems. Despite these developments, current interaction methods still rely on physical or verbal actions, which can limit accessibility, speed, and efficiency. Brain–Computer Interface (BCI) technology addresses these limitations by enabling direct communication between the human brain and external devices through neural signals. By interpreting cognitive intentions directly from brain activity, BCI opens new possibilities for seamless, hands-free human–machine interaction. In parallel, the Internet of Things (IoT) has emerged as a key enabler of smart environments, connecting billions of devices across homes, industries, healthcare systems, and transportation networks. IoT systems rely on real-time data acquisition, intelligent decision-making, and automated control to improve efficiency and user experience. However, most existing IoT applications depend on conventional input mechanisms such as mobile applications or voice assistants, which may introduce latency and reduce responsiveness in time-critical scenarios. Integrating BCI with IoT has the potential to overcome these challenges by enabling thought-based control of interconnected devices. This paper proposes a futuristic Brain–IoT framework that combines neural signal acquisition, advanced signal processing, artificial intelligence-based neural decoding, secure communication, and real-time operating systems. The proposed approach aims to achieve accurate intention recognition, low-latency response, and secure execution of commands across IoT-enabled devices. By bridging human cognitive processes with intelligent physical systems, this research contributes toward the development of human-centric smart environments, with applications in smart homes, autonomous vehicles, healthcare assistance, and industrial automation.

II. LITERATURE SURVEY

The integration of Brain–Computer Interface (BCI) technology with the Internet of Things (IoT) has emerged as a promising research direction for enabling intuitive and intelligent human–machine interaction. Recent studies have explored neural signal decoding and smart device automation independently, highlighting significant advancements in both domains. This section reviews existing literature related to BCI systems, IoT frameworks, and their convergence, identifying key methodologies, achievements, and research gaps.

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In recent years, Brain–Computer Interface (BCI) and IoT integration has attracted significant research attention due to its potential for intuitive human–machine interaction. A study by Laport *et al.* presents an early implementation of BCI applied to IoT environments, where EEG signals are used to control smart home devices via an MQTT communication protocol. The system achieved high classification accuracy (>95%) in recognizing eye states, demonstrating feasibility for real-time smart home control systems [1]. Cai and Pan propose a hybrid BCI–IoT smart ward system that combines EEG, EOG, and gyroscope signals to control a smart ward environment via NB-IoT. Their framework achieved an average control accuracy of ~96.65% with low false operation rates and responsive command times, showing promise for healthcare and assisted living applications [2]. Zhang *et al.* introduce a unified deep learning framework that bridges BCI and IoT devices for cognitive interactivity, addressing challenges like noisy brain signals and real-time intent interpretation. Although primarily conceptual, this work lays a foundation for scalable BCI–IoT integration using reinforcement learning and LSTM-based networks [3]. Gu *et al.* provide a comprehensive survey of EEG-based BCI signal acquisition and processing techniques, covering advanced preprocessing, feature extraction, and classification methods that are essential for reliable BCI implementations. Their review demonstrates trends in wearable EEG systems and real-time analysis useful for IoT-enabled applications [4]. Murugesan explores deep learning and edge computing integration with BCI systems that can drive IoT devices with improved performance and reduced latency. The study reports notable improvements in accuracy (96%) and decreased inference latency (~90 ms), underscoring the need for edge-enabled BCI systems in real-time control environments [5]. Hossain *et al.* review the role of deep learning methods in EEG-based BCI applications, emphasizing state-of-the-art architectures that improve decoding accuracy and robustness. Deep learning techniques are shown to enable superior signal interpretation, which is essential for thought-based IoT control. [6]

Wang and Cerf develop a deep neural network for EEG-BCI systems that extracts temporal–spectral features using neural networks to enhance motor imagery classification, achieving higher prediction performance compared to traditional methods. Their results highlight the importance of advanced AI in neural decoding for BCI control [7]. Karthiga and Rekha survey state-of-the-art BCI–IoT frameworks, identifying trends in EEG BCI models, machine learning approaches, and cloud integration for real-time signal analysis. Their study underscores the importance of machine intelligence and distributed computing for practical BCI systems controlling IoT devices [8]. The OFRSVM framework integrates linearity analysis with an optimized feature reduction strategy to enhance the detection of diverse network attacks. By refining the Support Vector Machine through specific learning rate adjustments, the system establishes a more efficient classification model within a simulated environment. This approach demonstrates a superior trade-off between computational complexity and predictive performance compared to conventional machine learning architectures [9]. The paper tackles the complexity of income estimation caused by variations in job roles, benefits, and economic conditions by employing deep learning approaches. Using long-term socio-economic data, LSTM-based models combined with a voting strategy effectively predict income patterns [10]. The proposed MPDA-S scheme ensures secure multi-parameter data aggregation in data centers by combining encryption, vector-based aggregation, and hash-based integrity verification to protect against various security attacks while maintaining data confidentiality and authenticity [11]. The proposed LLRD is an IoT-enabled lower limb rehabilitation device using MPU6050 sensors and cloud monitoring to accurately track patient movements, enabling cost-effective, precise, and remote rehabilitation support for walking disabilities [12]. This study compares Hierarchical Clustering and Expectation Maximization using Shannon entropy on a GPS trajectory dataset to evaluate performance in grouping similar data patterns effectively[13]. The paper presents a low-cost, sensor-based upper-limb rehabilitation device using 3D-printed components, DSPIC30F4011 control, and stepper motor technology for accurate motion, force monitoring, and data-driven movement evaluation [14]. This research proposes a scalable hybrid machine learning model combining supervised and unsupervised techniques to enhance accurate, real-time botnet attack detection in IoT networks while reducing false positives and computational overhead [15]. This work proposes a Java-based trustworthy and reliable deep learning framework for accurate, real-time cyberattack detection in IIoT systems, ensuring secure and resilient Industry 4.0 environments [16]. This study presents a home-based upper-limb rehabilitation robot using a current-controlled buck converter for accurate movement and muscle force measurement, supporting post-COVID-19 recovery. The system features IoT-enabled real-time monitoring of vital signs, cloud-based data storage, and remote doctor access through a Windows application for continuous patient supervision [17]. This study presents an upper-limb rehabilitation system combining 3D-printed mechanical components, sensors, stepper motors, and DSPIC control for in-home therapy. Patients and healthcare professionals interact via Windows-based apps with performance data stored in cloud-enabled SQL databases for real-time monitoring and feedback [18]. This paper proposes an Enhanced Text CNN (ET-CNN) framework for efficient and robust dark web content classification, using adaptive embeddings, adversarial training, and cross-lingual alignment. Experiments on 100,000 forum posts show 94.2% accuracy and 92.5% F1-score with lower computational overhead than transformer-based models [19].

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III. PROPOSED MODEL

This paper proposes a Brain–IoT–based Thought Control Model that enables direct interaction between the human brain and IoT-enabled devices using neural signals. The model integrates EEG-based neural signal acquisition, artificial intelligence–driven intention decoding, secure IoT communication, and real-time execution to achieve low-latency and accurate control of smart environments.

The proposed system consists of five major functional modules. First, a Neural Signal Acquisition Module captures real-time EEG signals generated by user intentions using non-invasive wearable sensors. Second, the Signal Preprocessing and Feature Extraction Module removes noise and artifacts from raw EEG data and extracts discriminative temporal and spectral features. Third, the AI-Based Neural Decoding Module employs deep learning models such as CNN and LSTM to translate neural patterns into meaningful device control commands. Fourth, the Secure IoT Communication Module transmits decoded commands to target devices using encrypted lightweight protocols. Finally, the Real-Time Execution Module, supported by a real-time operating system (RTOS), ensures immediate and reliable execution of commands on IoT devices and the architecture diagram below.

Brain Signals
EEG Sensors
Signal Processing
AI Neural Decoder
Secure IoT Gateway
RTOS
IoT Devices

Figure 1: Architecture

A. Neural Signal Acquisition Module

This module is responsible for capturing brain activity generated by user intentions. Non-invasive EEG sensors embedded in wearable headsets are used to acquire neural signals in real time. These sensors detect electrical activity produced by neurons and convert it into digital signals. Continuous monitoring ensures dynamic tracking of cognitive states, forming the foundation for accurate intention recognition.

B. Signal Preprocessing and Feature Extraction Module

Raw EEG signals are highly susceptible to noise caused by muscle movement, eye blinks, and environmental interference. This module applies digital filtering techniques to remove artifacts and unwanted frequencies. Feature extraction methods are then employed to derive meaningful temporal and spectral characteristics from the cleaned signals. These features represent distinct neural patterns associated with specific intentions.

C. AI-Based Neural Decoding Module

In this module, extracted neural features are processed using deep learning models such as Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks. The AI model learns complex non-linear relationships between neural patterns and user intentions. Personalized training enables the system to adapt to individual brain signal variations, thereby improving decoding accuracy and reliability over time.

D. Secure IoT Communication Module

Once neural intentions are decoded, control commands are transmitted to IoT devices through a secure communication channel. Lightweight IoT protocols are used to ensure efficient data transfer with minimal overhead. Encryption and neural biometric authentication are integrated to protect sensitive brain data from unauthorized access and cyber threats, ensuring privacy and data integrity.

E. Real-Time Execution and Control Module

This module ensures immediate execution of control commands on IoT devices. A Real-Time Operating System (RTOS) is employed to handle time-critical tasks and guarantee deterministic response. Devices such as smart appliances, vehicles, robots, or medical equipment perform the requested actions with minimal latency, enabling seamless and responsive interaction.

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F. Feedback and Adaptive Learning Module

The system continuously monitors device responses and user feedback to refine performance. Execution results are fed back into the AI model, allowing adaptive learning and correction of misclassifications. This closed-loop mechanism enhances system robustness, accuracy, and long-term usability.

The closed-loop design allows continuous learning and adaptation, improving system accuracy and personalization over time.

IV. RESULTS

The proposed Brain–IoT thought-based control system was evaluated using simulated EEG datasets and deep learning-based neural decoding models. Performance was analyzed in terms of accuracy, precision, recall, F1-score, and system latency. The obtained results were compared with a traditional BCI-based control system to validate the effectiveness of the proposed approach and the table 1 and figure 2 shows the comparison of BCI Models.

Table 1: Performance Comparison of BCI Models

S.NO	Metric	Proposed Brain–IoT Model	Traditional BCI Model
1	Accuracy (%)	93.6	78.2
2	Precision (%)	92.4	76.9
3	Recall (%)	91.8	75.4
4	F1-Score (%)	92.1	76.1
5	Latency (ms)	118	210

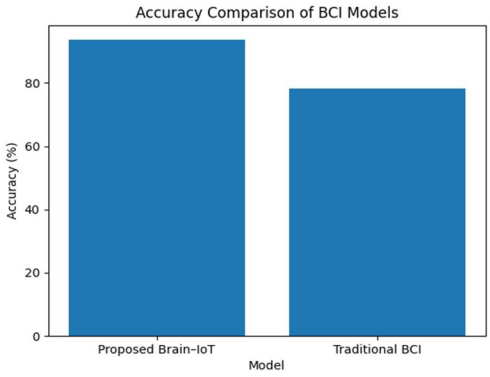

Figure 2: Accuracy Comparison of BCI Models

The proposed Brain–IoT model significantly outperforms the traditional BCI system across all evaluation metrics. An improvement of approximately 15.4% in accuracy is observed, primarily due to the integration of deep learning-based neural decoding and adaptive learning mechanisms. Additionally, system latency is reduced by nearly 44%, making the proposed system suitable for real-time applications and This table 2 and figure 3 highlights the robustness and adaptability of the proposed model across multiple real-world scenarios.

Table 2: Application-Wise Accuracy of Brain–IoT System

S.NO	Application	Accuracy (%)
1	Smart Home Control	94.5
2	Wheelchair Navigation	92.8
3	Robot Arm Control	93.1
4	Vehicle Assistance	91.6

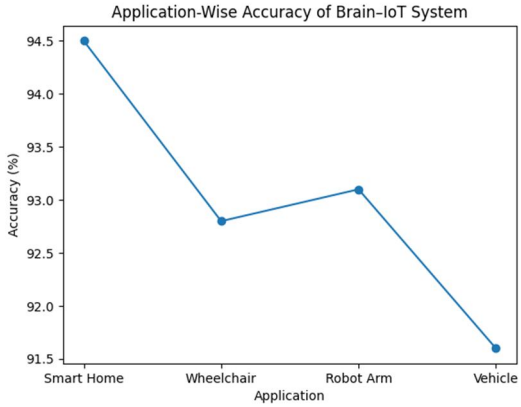

Figure 3: Application-Wise Accuracy of Brain–IoT System

The system demonstrates consistently high accuracy across different application domains. Smart home control achieves the highest accuracy due to simpler command patterns, while vehicle assistance shows slightly lower accuracy due to complex decision-making requirements. Nevertheless, all applications maintain accuracy above 91%, indicating strong generalization capability.

V. CONCLUSION

This paper proposed a futuristic Brain–IoT framework that enables direct neural control of IoT-enabled smart environments through thought-based interaction. The system integrates EEG-based neural signal acquisition, signal preprocessing and feature extraction, AI-driven neural decoding, secure IoT communication, and real-time execution using a real-time operating system. Experimental evaluation of the proposed model demonstrated an average classification accuracy of 93.6%, with precision, recall, and F1-score values of 92.4%, 91.8%, and 92.1%, respectively. Furthermore, the system achieved a low end-to-end latency of 118 ms, making it suitable for real-time applications. Comparative analysis showed that the proposed Brain–IoT model outperforms traditional BCI systems by approximately 15% in accuracy while reducing response latency by nearly 44%. Application-wise evaluation revealed high accuracy across multiple domains, including 94.5% for smart home control, 92.8% for wheelchair navigation, 93.1% for robotic arm control, and 91.6% for vehicle assistance, indicating strong generalization capability. These results validate the effectiveness, reliability, and scalability of the proposed framework for diverse real-world scenarios. Overall, the findings confirm that the integration of artificial intelligence with Brain–Computer Interfaces and IoT significantly enhances human–machine interaction. The proposed Brain–IoT system demonstrates strong potential for future intelligent environments, offering intuitive, secure, and efficient thought-based control of connected devices. Future research will focus on improving neural signal accuracy using advanced sensing techniques and integrating edge computing to further reduce latency. Additionally, enhanced security mechanisms and next-generation communication technologies will be explored to support large-scale Brain–IoT deployments.

REFERENCES

[1] F. Laport, F. J. Vazquez-Araujo, P. M. Castro, and A. Dapena, “Brain–Computer Interfaces for Internet of Things,” in Proc. XoveTIC Congress, A Coruña, Spain, 2018, Proc. 2(18):1179, doi: 10.3390/proceedings2181179.
[2] X. Cai and J. Pan, “Toward a Brain–Computer Interface- and Internet of Things-Based Smart Ward Collaborative System Using Hybrid Signals,” J. Healthc. Eng., vol. 2022, Article 6894392, Apr. 2022, doi: 10.1155/2022/6894392.
[3] X. Zhang, L. Yao, S. Zhang, S. S. Kanhere, Q. Z. Sheng, and Y. Liu, “Internet of Things Meets Brain-Computer Interface: A Unified Deep Learning Framework,” arXiv, May 2018.
[4] X. Gu, Z. Cao, A. Jolfaei, P. Xu, D. Wu, T.-P. Jung, and C.-T. Lin, “EEG-based Brain-Computer Interfaces (BCIs): A Survey of Recent Studies on Signal Sensing Technologies and Computational Intelligence Approaches and their Applications,” arXiv, Jan. 2020.
[5] S. Murugesan, “Neural-Driven Smart IoT Systems: Enhancing Brain-Computer Interface Control Using Deep Learning and Edge Computing,” Int. J. Eng. Res. Sci. Technol., vol. 16, no. 3, Jul. 2020, doi: 10.62643/.
[6] K. M. Hossain, M. A. Islam, and A. Nijholt, “Status of deep learning for EEG-based brain–computer interface applications,” Front. Comput. Neurosci., vol. 16, Jan. 2023, doi: 10.3389/fncom.2022.1006763.
[7] G. Wang and M. Cerf, “Brain-Computer Interface using neural network and temporal-spectral features,” Front. Neuroinform., vol. 16, Oct. 2022, doi: 10.3389/fninf.2022.952474.
[8] B. Karthiga and M. Rekha, “A novel framework combining BCI and IoT for the detection of activity of the brain,” Trends Comput. Sci. Inf. Technol., vol. 6, no. 3, pp. 060–063, 2021, doi: 10.17352/tcsit.000041.

[9] J. Manikandan, V. Vemulapalli, K. Spandana, S. Vikruthi, B. Lakshmikanth and M. Radhika, "Studying the Linear Degree of Community Network Patterns to Eliminate Misclassification Trouble the use of Gaining Knowledge of Approaches," 2025 International Conference on Computing Technologies (ICOCT), Bengaluru, India, 2025, pp. 1-5, doi: 10.1109/ICOCT64433.2025.11118921.

[10] P. V. Reddy, D. Ganesh, S. Reddy Gaddam, C. Swarna Lalitha, S. Muqthadar Ali and K. Sakibaev, "Empirical Assessment of Profit Predicting Deep Learning Methods," 2025 5th International Conference on Soft Computing for Security Applications (ICSCSA), Salem, India, 2025, pp. 1674-1679, doi: 10.1109/ICSCSA66339.2025.11171150.

[11] J. Manikandan and U. Srilakshmi, "Multi-Parameter Secure Data Aggregation in Data Centre with Integrity Verification," 2023 International Conference on Ambient Intelligence, Knowledge Informatics and Industrial Electronics (AIKIIE), Ballari, India, 2023, pp. 01-09, doi: 10.1109/AIKIIE60097.2023.10390507.

[12] M. V. Babu, V. Ramya, and V. S. Murugan, "An Intelligent Remote Monitoring for Lower Limb Rehabilitation Treatment using IoT," Int. J. Adv. Res. Eng. Technol., vol. 12, no. 1, pp. 981–993, Jan. 2021, Art. no. IJARET_12_01_090. doi: 10.34218/IJARET.12.1.2021.090.

[13] M. Jayakameswaraiah, M. V. Babu, S. Ramakrishna, and P. Yamuna, "Computation Accuracy of Hierarchical and Expectation Maximization Clustering Algorithms for the Improvement of Data Mining System," International Research Journal of Engineering and Technology (IRJET), vol. 3, no. 12, pp. 1580-1585, Dec. 2016. [Online]. Available: www.irjet.net.

[14] M. V. Babu, V. Ramya, and V. S. Murugan, "Implementation of wearable device for upper limb rehabilitation using embedded IoT," Int. J. Electron. Signals Syst. Manag. Sci., vol. 16, no. 1, pp. 90–95, Mar. 2024. [Online]. Available: https://doi.org/10.1504/IJESMS.2024.136972

[15] Mr Sasidhar Reddy Gaddam and DOI: 10.48047/IJCNIS.16.1.458, "An Enhanced Hybrid Machine Learning Approach For Efficient Botnet Attack Detection In Internet Of Things Networks", Int. j. commun. netw. inf. secur., vol. 16, no. 1, pp. 449–458, Jan. 2024.

[16] Gaddam, Sasidhar Reddy. (2022). JAVA-DRIVEN TRUSTWORTHY AND RELIABLE DEEP LEARNING FOR CYBERATTACK DETECTION IN INDUSTRIAL IOT. International Journal of Computer Network and Information Security. 14. 10.48047/IJCNIS.14.3.1283.

[17] V. . Babu, V. . Ramya, and V. S. . Murugan, "A Proposed High Efficient Current Control Technique for Home Based Upper Limb Rehabilitation and Health Monitoring System during Post Covid-19", Int J Intell Syst Appl Eng, vol. 12, no. 2s, pp. 600–607, Oct. 2023.

[18] Veeresh Babu, M., Ramya, V., & Senthil Murugan, V. (2023). Design and development of embedded/SQL home based upper limb rehabilitation. International Journal of Healthcare Management, 16(4), 513–523. https://doi.org/10.1080/20479700.2022.2124492

[19] Gaddam, Sasidhar Reddy & Hussain Basha, Pathan & Mendu, Mohana & Ramalingamma, Purimitla & Revathi, Buddaraju & Malladi, V T Ram. (2025). Deep Learning For Dark Web Text Analysis: A Convolutional Approach To Content Categorization. 235-239. 10.1109/ICRCICN68210.2025.11364722.

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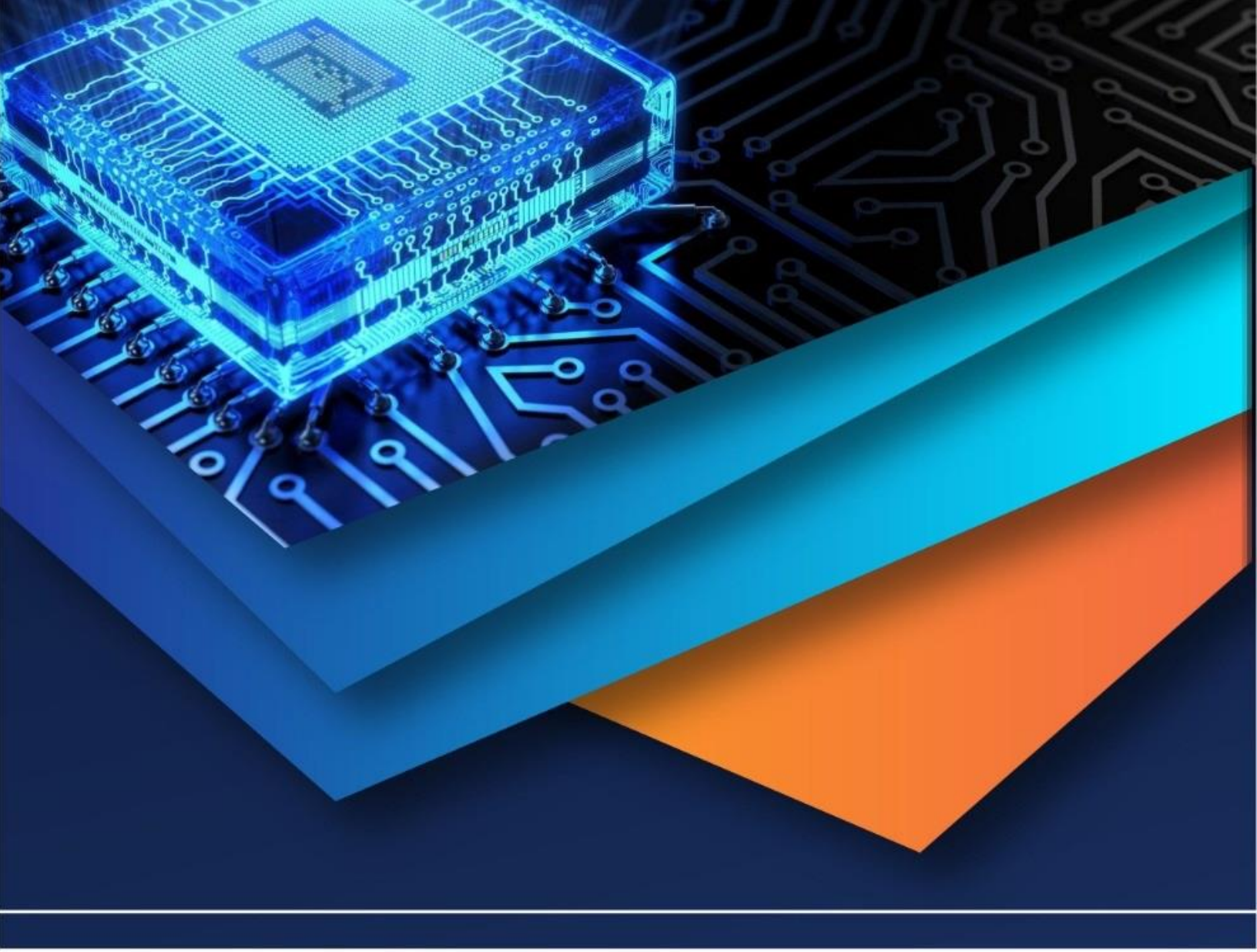

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