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AI-Based River Cleaning Robot for Plastic Waste: Design, Development, and Implementation

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Abstract: Plastic waste contamination of rivers and other water bodies has become a pressing global environmental challenge. Conventional waste management techniques, which often rely on manual labour, are inefficient and struggle to handle the vast scale of pollution. This study introduces an AI-powered river-cleaning robot designed to autonomously identify, collect, and manage floating plastic waste to address this issue. The system enhances detection and waste retrieval efficiency by incorporating Artificial Intelligence (AI), the Internet of Things (IoT), and computer vision. The robot utilizes advanced technologies such as Convolutional Neural Networks (CNN) and the YOLO (You Only Look Once) algorithm for real-time waste identification, while a conveyor belt mechanism facilitates efficient collection. Additionally, IoT-enabled monitoring ensures real-time data transmission and performance tracking. The robot uses a dual-energy system, combining a rechargeable battery with solar power to enhance sustainability. This innovative approach aims to minimize reliance on manual labour, improve the effectiveness of waste removal, and promote environmentally responsible waste management. Experimental evaluations confirm the system's high accuracy in detecting and collecting plastic debris, demonstrating its potential as a scalable and efficient solution for river pollution control.
Keywords: AI, IoT, River Cleaning Robot, Plastic Waste Management, Computer Vision, Sustainability

I. INTRODUCTION

Water is essential for all life forms, yet it faces increasing threats due to overexploitation and pollution. The availability of clean drinking water is rapidly diminishing as urbanisation, industrial expansion, and human activities contribute to widespread contamination. Plastic pollution is among the most significant threats to aquatic ecosystems, resulting from improper waste disposal. The accumulation of plastic waste in rivers disrupts marine biodiversity, degrades water quality, and poses serious health risks to humans as shown in Fig. 1. Traditional river-cleaning methods, which rely heavily on manual labour, are inefficient and time-consuming and expose workers to hazardous conditions [1].

With advancements in technology, artificial intelligence (AI), the Internet of Things (IoT), and autonomous robotics are emerging as innovative solutions to this pressing issue.

Fig. 1 The floating wastes in oceans, coastal areas, and inland waters

This study introduces an AI-powered river-cleaning robot to detect, collect, and manage plastic waste in water bodies [2]. By leveraging AI-driven image processing, IoT-enabled monitoring, and robotic automation, this system minimises human intervention, improves waste collection efficiency, and enhances the overall effectiveness of river-cleaning operations as shown in Fig. 2. [3]

Fig. 2 Examples of cleaning water surfaces manually

Global conservation organisations' reports highlight pollution's devastating impact on aquatic ecosystems. For instance, WWF Myanmar has documented the threat faced by Irrawaddy River Dolphins due to pollutants from pesticides, mining, and dam construction. Similarly, WWF Malaysia has identified river pollution as a critical environmental concern, with declining water quality as an alarming indicator of ecological degradation [4][5]. The sources of river pollution are diverse, encompassing domestic and industrial sewage, waste from livestock farms, manufacturing discharge, and mining activities. In 2021, authorities in Malaysia classified several rivers as "dead" due to extreme pollution, which led to dangerously low dissolved oxygen levels, endangering aquatic life and biodiversity. These alarming trends emphasis the urgent need for innovative and efficient river-cleaning solutions to restore the health of these vital ecosystems [6][7]. Research efforts have explored various river-cleaning technologies to combat pollution. A developed Ro-Boat, an autonomous river-cleaning robot equipped with computer vision algorithms and kinematic analysis to detect and sort pollutants in real-time [8]. A river-cleaning machine that utilises a conveyor system to lift and remove waste from water bodies [9]. A semi-automatic mechanical drainage cleaner, enhancing waste removal while maintaining efficient water flow [10]. Additionally, an automatic sewage-cleaning system, incorporating remote-controlled motors to prevent waste from spreading and mitigate associated health risks. A developed a river waste-cleaning machine featuring DC motors, propellers, and conveyor mechanisms for efficient waste collection. Collectively, these studies underscore the potential of mechanical and autonomous systems in tackling the growing challenge of river pollution. Although significant advancements have been made in addressing river pollution, there remains an urgent need for a more efficient, scalable, and comprehensive solution. This study focuses on designing and simulating an advanced waste collection system with the potential for real-world implementation. The proposed system is engineered to remove various types of debris, including floating litter, trash, logs, and discarded tyres from rivers, lakes, and other water bodies [11]. The system enables real-time monitoring and control by incorporating Internet of Things (IoT) technology, significantly improving operational efficiency and adaptability. The primary objective is to develop a river-cleaning machine that mitigates current pollution challenges and plays a crucial role in restoring and preserving inland waterways. This ensures their sustainability for future generations. The structure of this paper is as follows: Section 1 provides an introduction, Section 2 details the system description, Section 3 presents the results, and Section 4 concludes the study.

II. SYSTEM DESCRIPTION

The river-cleaning robot is designed to function efficiently in stagnant and flowing water bodies, including lakes, ponds, and rivers. It integrates computer vision, robotic manipulation, and IoT-based monitoring to operate autonomously. The system utilises a dual power source comprising rechargeable batteries and solar energy to ensure uninterrupted functionality, even in remote locations. This AI-powered river-cleaning system is a comprehensive solution for detecting, collecting, and segregating plastic waste from aquatic environments. By leveraging advanced machine learning algorithms, IoT technologies, and robust hardware, the robot enhances efficiency and scalability in waste management operations. The following sections outline the system's key hardware components and algorithmic framework, followed by a workflow diagram [12]. The AI-powered river-cleaning robot is designed to operate effectively in stagnant and flowing water bodies, such as lakes, ponds, and rivers. It integrates advanced computer vision, robotic manipulation, and IoT-based monitoring to function autonomously, minimising human intervention.

To ensure uninterrupted performance, even in remote locations, the system is powered by a dual-energy source, combining rechargeable batteries with solar energy for sustainable operation [13]. This intelligent system is developed to efficiently detect, collect, and segregate plastic waste, leveraging AI-driven algorithms, IoT technology, and robust hardware components [14]. Into hardware, At the heart of the system lies the Raspberry Pi 4 Model B, which serves as the central processing unit, running AI-based object detection, navigation, and waste segregation algorithms. Equipped with a quad-core ARM Cortex-A72 processor, GPU support for computer vision tasks, and built-in Wi-Fi and Bluetooth connectivity, it processes sensor data, controls actuators, and ensures seamless communication with external systems. The vision system comprises a high-resolution (8–12 MP) camera, which captures real-time images for waste detection and classification. Utilising AI models such as Convolutional Neural Networks (CNNs), YOLO, and Mask R-CNN, the camera accurately identifies and differentiates plastic waste, providing critical visual input for navigation and collection. The robot is equipped with multiple sensors to navigate efficiently and avoid obstacles. Ultrasonic sensors (HC-SR04) measure distances to detect objects and ensure smooth movement, while infrared (IR) sensors prevent accidental falls by identifying edges or potential hazards. Plastic identification sensors employ infrared spectroscopy to distinguish recyclable plastics from other waste materials, and environmental sensors (DHT11) monitor temperature and humidity to optimise operational efficiency. A GPS module (NEO-6M) also tracks the robot's location and logs its movement for performance analysis and data collection. For mobility, the system relies on DC and servo motors, controlled by an L298N motor driver, which interfaces with the Raspberry Pi to regulate speed and direction. The robotic arm, powered by MG996R servo motors, enables precise waste collection, while a 2-DOF or 3-DOF mechanical gripper securely holds debris during retrieval. To facilitate long-range communication and data transmission, the robot is equipped with Wi-Fi and Bluetooth modules for cloud-based monitoring on platforms such as Blynk or Thing speak. In remote locations, LoRa or Zigbee modules ensure reliable, low-power communication.

Energy management is a crucial aspect of the system, designed for sustained operation. The Li-ion or Li-Po batteries provide sufficient power for motors, sensors, and the central processing unit. In contrast, a power management module regulates energy distribution to maintain stable voltage levels. Solar panels can be integrated as an alternative power source to extend operational time and enhance sustainability. The frame and chassis, constructed from lightweight yet durable materials such as aluminum or polycarbonate, provide structural stability while ensuring the robot remains buoyant and maneuverable.

Additional features include speakers and buzzers, which alert users to system status updates, such as a full waste container, and LED indicators that display essential operational statuses like power activation and object detection. The waste collection container securely stores collected plastic waste until it can be properly disposed of. By integrating these advanced components, the AI-based river-cleaning robot offers a scalable, autonomous, and environmentally sustainable solution to tackle plastic pollution in water bodies.

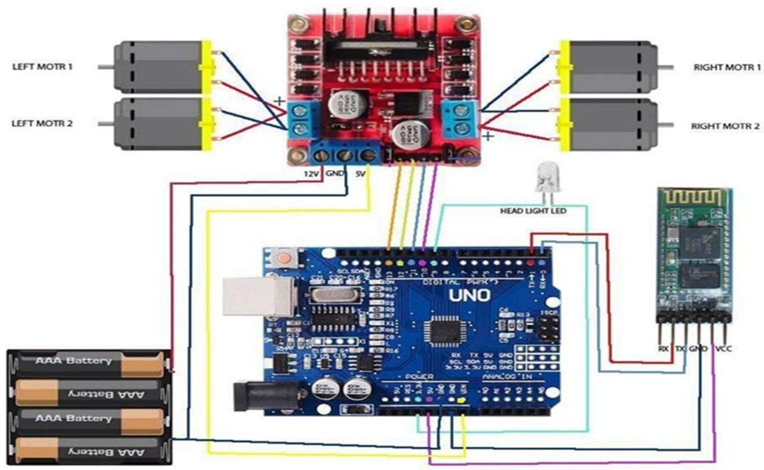

Fig. 3 Arduino Connection

A. Hardware Components

The hardware architecture of the AI-based river-cleaning robot is designed to ensure efficient operation, precise waste detection, and seamless communication. The Raspberry Pi 4 Model B is at the system's core, which acts as the primary processing unit, executing AI algorithms responsible for object detection, navigation, and waste segregation. Equipped with a quad-core ARM Cortex-A72 processor, GPU support for computer vision tasks, and built-in Wi-Fi and Bluetooth connectivity, it efficiently processes data from multiple sensors and control actuators. It facilitates communication with external systems, as shown in Fig. 3.

The vision system is a crucial component, consisting of a high-resolution (8–12 MP) camera that captures real-time images to identify and classify plastic waste. It works with AI models such as Convolutional Neural Networks (CNNs), YOLO, and Mask R-CNN, ensuring precise detection and classification of waste materials. This visual input is fundamental for the robot's navigation and collection mechanisms [15].

For safe and efficient movement, the system integrates a variety of sensors. Ultrasonic sensors (HC-SR04) measure distances to detect obstacles and prevent collisions, while infrared (IR) sensors identify edges and potential hazards to avoid accidental falls. Plastic identification sensors employ infrared spectroscopy to distinguish recyclable plastics from other waste materials, ensuring proper segregation. Environmental sensors (DHT11) also monitor temperature and humidity levels to optimise the robot's operational performance. A GPS module (NEO-6M) tracks the robot's location, allowing it to log its movement path and analyse the areas covered during waste collection [16].

The locomotion system relies on DC and servo motors, which an L298N motor driver controls to regulate speed and direction. This ensures smooth movement across the water surface. The manipulation system includes a robotic arm powered by MG996R servo motors, allowing precise movement for waste collection. A 2-DOF or 3-DOF mechanical gripper securely holds collected debris, preventing it from slipping back into the water.

The robot is equipped with Wi-Fi and Bluetooth modules to enable real-time monitoring and data transmission, allowing seamless integration with cloud-based platforms like Blynk or Thingspeak for remote monitoring. For operations in remote areas, LoRa or Zigbee modules provide long-range, low-power communication, ensuring connectivity even in challenging environments.

Efficient power management is essential for extended operation. The system is powered by Li-ion or Li-Po batteries, which supply energy to the motors, sensors, and processing unit. A power management module regulates energy distribution, ensuring stable voltage levels to optimise performance. Additionally, solar panels can be incorporated as an alternative energy source, further enhancing the robot's sustainability and operational longevity [17].

The frame and chassis are constructed from lightweight yet durable materials such as aluminum or polycarbonate, providing structural stability and ensuring the robot remains buoyant and maneuverable in aquatic environments. Additional features include speakers and buzzers, which alert users to important system updates such as a full waste container, and LED indicators, which display operational statuses like power activation and object detection. The waste collection container securely stores gathered plastic until properly disposed of, contributing to effective waste management.

B. Algorithm Components

The AI-powered river-cleaning robot relies on sophisticated algorithmic components to detect, collect, and manage plastic waste efficiently. These algorithms enhance the robot's accuracy, mobility, and decision-making capabilities, ensuring optimal performance in various aquatic environments. For object detection and recognition, the system leverages Convolutional Neural Networks (CNNs) to analyse visual data and classify plastic waste accurately. The YOLO (You Only Look Once) model processes images rapidly while maintaining precision to enable real-time detection. Additionally, Mask R-CNN is employed, including segmentation, allowing the system to identify and differentiate irregularly shaped plastic waste accurately. Regarding navigation and localisation, the robot utilises Simultaneous Localization and Mapping (SLAM) to create a real-time map of its surroundings while tracking its exact position. An A algorithm determines the optimal path to efficiently reach detected waste, ensuring minimal energy consumption and effective route planning. For more complex terrains, Rapidly Exploring Random Trees (RRT) assists in generating feasible paths while avoiding obstacles. For robotic manipulation, the system incorporates Inverse Kinematics (IK) to control the robotic arm precisely, ensuring accurate collection of waste materials [18]. Additionally, force control algorithms dynamically adjust the grip strength, allowing the system to handle lightweight and fragile waste without damaging it. Once the waste is collected, it undergoes segmentation and classification to facilitate proper disposal. K-Means Clustering segregates waste into different categories, such as plastic and non-plastic. Support Vector Machines (SVM) further refine the classification process, distinguishing between specific material types. To improve computational efficiency, Principal Component Analysis (PCA) reduces data dimensions while retaining essential features, ensuring faster and more efficient processing. The robot continuously improves its performance through learning and optimisation techniques. Reinforcement Learning (RL) allows it to adapt cleaning strategies over time by learning from trial and error. Meanwhile, Genetic Algorithms optimise path planning and resource allocation, ensuring that waste collection is conducted most efficiently. Effective energy management is critical to the system's sustainability. Dynamic Power Management adjusts power distribution based on task requirements, optimising battery efficiency. Additionally, heuristic optimisation algorithms prioritizes areas with a higher density of plastic waste, minimising unnecessary movement and energy consumption.

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For communication and IoT integration, the system employs Message Queuing Telemetry Transport (MQTT), a lightweight protocol that enables real-time communication between the robot and a remote-control system. Edge AI algorithms enable on-device decision-making to enhance performance further, reducing reliance on cloud processing and minimizing latency. Finally, to accurately identify different types of plastic, the robot uses spectroscopic analysis, which examines light absorption patterns to differentiate between materials such as PET and HDPE. Neural networks for classification refine this process by analyzing visual or spectral data to predict the type of plastic waste collected [19].

C. System Working

The AI-based river-cleaning robot follows a structured workflow to efficiently detect, collect, and manage plastic waste in water bodies. The process begins with initialization, where the robot is powered on, and all sensors, cameras, and communication modules are activated. The GPS module records the starting location, allowing for precise navigation and tracking. Once initialized, The robot proceeds with environment mapping using Simultaneous Localization and Mapping (SLAM) to analyse its surroundings and determine its position relative to obstacles and waste. This step ensures effective navigation and enhances the robot's ability to operate autonomously. The next stage involves waste detection, where the onboard camera captures real-time images. These images are processed using Convolutional Neural Networks (CNNs), YOLO, or Mask R-CNN, enabling the system to identify and classify plastic waste accurately. Once detected, the robot determines the most efficient path to reach the waste using the A or RRT algorithm*.

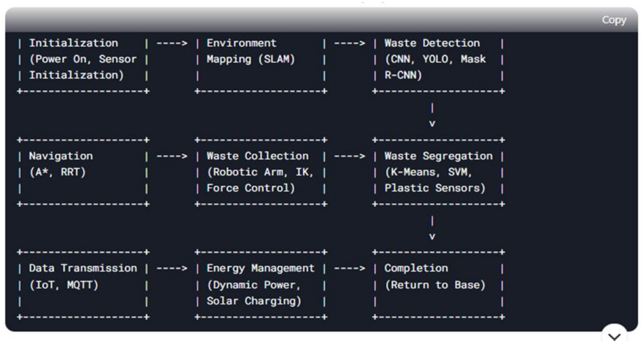

Fig. 4 Flow Chart for the steps involved in the operation of AI-based river cleaning robot

During navigation, the robot moves toward the waste while avoiding obstacles with ultrasonic and infrared (IR) sensors, ensuring smooth and safe movement. Upon reaching the target, the waste collection phase begins. The robotic arm, guided by inverse kinematics, carefully picks up the detected waste. Force control algorithms adjust the grip strength dynamically to prevent damage to lightweight and fragile materials. Once the waste is collected, the robot proceeds with waste segregation, where K-Means Clustering or Support Vector Machines (SVM) categorize the collected materials. Additionally, plastic identification sensors further classify the waste based on composition, ensuring effective sorting for recycling or disposal [20]. The robot maintains real-time data transmission via IoT modules throughout the operation, continuously sending updates regarding waste collection status, location, and operational parameters to a cloud platform. This allows for remote monitoring and performance analysis, enhancing overall system efficiency [21]. To ensure uninterrupted functionality, the system incorporates energy management strategies. Dynamic power management optimizes energy consumption based on task requirements, while solar panels recharge the batteries during operation, extending the robot's runtime and promoting sustainability [22]. The process concludes with the completion phase, where the robot returns to a designated location once the waste collection container is full or the cleaning task has been completed. Following this structured workflow, the AI-based river-cleaning robot efficiently contributes to environmental conservation by autonomously managing plastic waste in aquatic ecosystems as shown in Fig. 4. [23, 24, 25]

III. RESULTS

A comparison between traditional river cleaning techniques and AI-driven approaches highlights remarkable progress in technology, efficiency, scalability, and sustainability. Conventional methods depend heavily on human labour, basic tools, and nets, which are time-consuming and restricted to small-scale tasks. These approaches are error-prone, frequently failing to detect smaller or submerged debris and face challenges in reaching remote or inaccessible areas. Moreover, manual intervention in traditional methods often disrupt ecosystems, and the absence of data collection mechanisms hinders the ability to monitor and enhance cleaning efforts. Although these methods have lower upfront costs, their reliance on continuous labour makes them less economical.

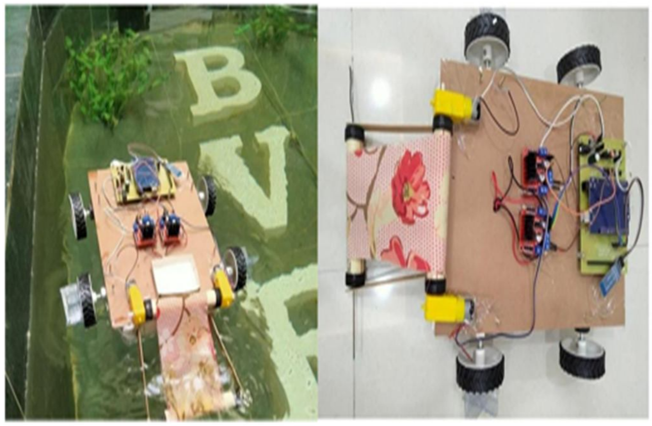

Fig. 5 Prototype of AI-based river cleaning robot

On the other hand, AI-based river cleaning systems utilize robotics, artificial intelligence, IoT sensors, and automation to deliver superior efficiency and scalability. These systems function autonomously with minimal human involvement, drastically reducing the time and workforce needed for cleaning tasks. Advanced vision systems can accurately detect real-time waste, capturing floating and submerged debris. Their autonomous navigation capabilities enable them to operate in challenging environments, making them ideal for large rivers and complex settings. Additionally, AI-driven methods are eco-friendly, employing targeted cleaning techniques that minimise ecological disruption. By incorporating renewable energy sources like solar power, they promote sustainability, while IoT integration facilitates real-time data collection and analysis, supporting informed decision-making and operational enhancements as shown in Fig. 5. Despite higher initial investments, the long-term reduction in operational expenses makes AI-based systems a more cost-efficient option for large-scale river cleaning initiatives. AI-based river cleaning solutions surpass traditional methods in nearly every dimension, providing a more effective, scalable, and sustainable approach to tackling plastic pollution in aquatic environments. Future efforts should refine these systems to improve their accuracy, energy efficiency, and adaptability for broader implementation.

IV. CONCLUSION

This paper presents the design and development of an AI-based river-cleaning robot that integrates AI, IoT, and robotics technologies to autonomously detect, collect, and segregate plastic waste from water bodies. The proposed system offers a cost-effective, energy-efficient, and scalable solution for river cleaning, reducing the reliance on manual labour and minimising environmental impact. Experimental results demonstrate the robot's ability to efficiently clean water surfaces, with an average waste detection accuracy of 96%. Future work will focus on improving the robot's battery life, scalability, and real-world deployment.

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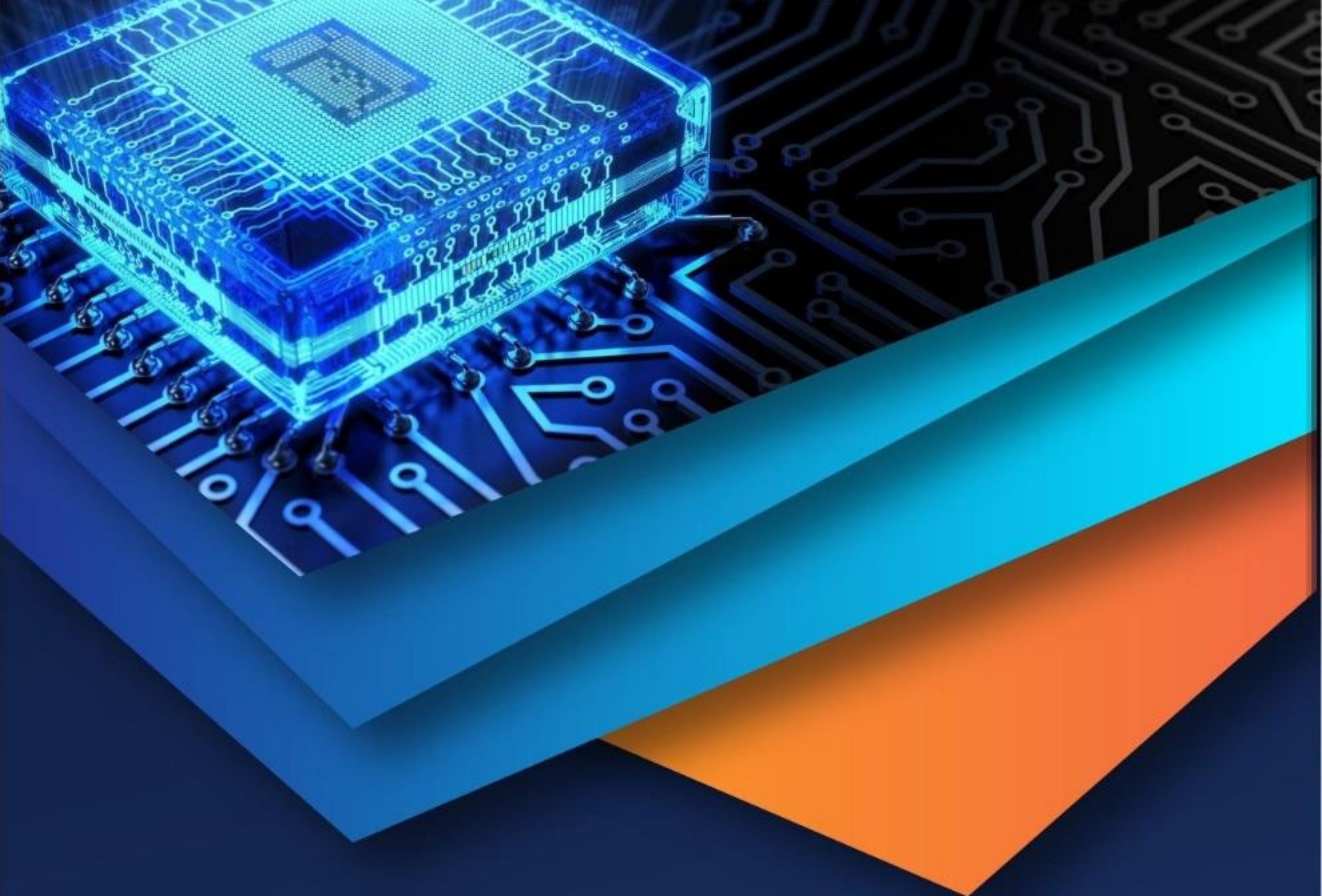

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