iJRASET
International Journal For Research in Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH
IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 13 Issue: XI Month of publication: November 2025

DOI: https://doi.org/10.22214/ijraset.2025.75923

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue XI Nov 2025- Available at www.ijraset.com

Research Review on Seaweed Farm Management Using Sensor Technology and Machine Learning

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Abstract: Seaweed cultivation is rapidly evolving from a traditional, labor-intensive subsistence activity into a fundamental pillar of the global "Blue Economy." As a sector, it offers essential mechanisms for gigaton-scale carbon sequestration, ecosystem restoration, and sustainable food security for a growing global population. Despite its immense potential, the sector encounters significant scalability impediments due to a reliance on manual monitoring techniques, which are often perilous, sporadic, and reactive rather than proactive. Furthermore, the unpredictability of marine environmental fluctuations—exacerbated by climate change—threatens crop viability through sudden thermal spikes and nutrient flux. This review investigates the transformative paradigm facilitated by the integration of the Internet of Things (IoT) and Machine Learning (ML). Through the synthesis of data from five seminal studies, this paper evaluates the efficacy of autonomous underwater vehicles (AUVs) for structural inspection, multi-spectral remote sensing for bloom tracking, and predictive analytics for growth modeling. The analysis indicates that while seaweed-specific applications remain nascent relative to the mature domains of terrestrial precision agriculture, the transposition of frameworks from finfish aquaculture and general agronomy offers a viable strategic roadmap. Specifically, the convergence of high-resolution sensor data with Deep Learning models promises to enable automated disease pathology recognition and yield optimization, moving the industry toward a data-driven future.
Keywords: Precision Aquaculture, Blue Economy, IoT Sensors, Machine Learning, Predictive Analytics, Macroalgal Blooms, Deep Learning, Remote Sensing.

I. INTRODUCTION

Global demand for marine biomass is surging, driven by expanding applications in high-value sectors including pharmaceuticals, biofuels, bioplastics, and functional foods. Unlike terrestrial agriculture, which competes for scarce freshwater resources and arable land, seaweed farming utilizes the vast potential of the oceans, presenting a sustainable alternative for biomass production that also remediates eutrophic waters. However, the transition from artisanal farming to industrial-scale aquaculture is constrained by the dynamic, corrosive, and opaque nature of the underwater environment.

Deleterious environmental factors, such as nutrient depletion, hypoxic events, and macroalgal blooms (e.g., green tides), possess the capacity to devastate crops rapidly. In traditional frameworks, these issues are often identified only after significant biomass loss has occurred, as human divers cannot monitor vast offshore sites continuously. This latency in detection represents a critical vulnerability in the supply chain.

Recent advancements in Industry 4.0 technologies—specifically regarding sensor instrumentation and artificial intelligence—provide a mechanism to enhance underwater visibility and operational intelligence. Networked sensors are now capable of continuously logging physicochemical parameters (pH, salinity, dissolved oxygen, turbidity) with high temporal resolution. Concurrently, Machine Learning (ML) algorithms, particularly those based on neural networks, can process this high-dimensional, non-linear data to forecast growth trajectories and identify subtle anomalies indicative of stress. This paper reviews the current state-of-the-art within this domain, identifying a critical disparity between the maturity of available hardware (sensors/robotics) and the software (ML models) requisite for interpreting complex marine data.

II. CONCEPTUAL FRAMEWORK

The proposed technological ecosystem for modern seaweed farming necessitates a cyclical data flow, extending from extraction to the generation of actionable insights. This "Cyber-Physical System" (CPS) ensures that physical parameters are digitized, analyzed, and returned as management decisions.

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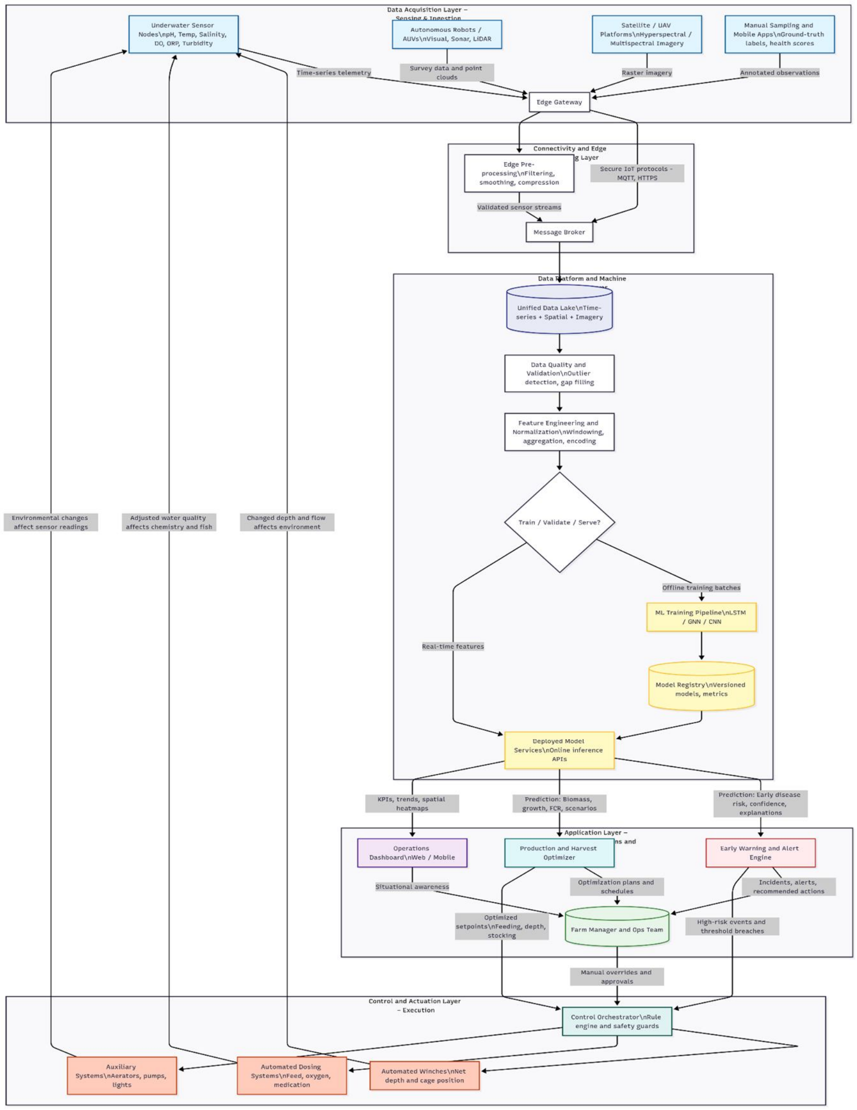

Fig 2.1: IoT Architecture for Seaweed Aquaculture

1) *Layer 1 Data Acquisition – Sensing & Ingestion:* The foundational layer consists of heterogeneous data sources responsible for digitizing the marine environment. This includes Underwater Sensor Nodes that continuously log physicochemical parameters (pH, temperature, dissolved oxygen, turbidity) crucial for detecting hypoxic events. Autonomous Underwater Vehicles (AUVs) supplement this with high-resolution visual and sonar surveys to inspect structural integrity and biomass density. Concurrently, Satellite/UAV Platforms provide macro-scale raster imagery for bloom tracking, while Manual Sampling ensures ground-truth validation for algorithm training.
2) *Layer 2 Connectivity & Edge Processing:* Given the bandwidth constraints of offshore environments, this layer serves as a critical bridge. The Edge Gateway aggregates raw telemetry and performs Edge Pre-processing—filtering noise, compressing large files, and smoothing time-series data—before transmission. Validated streams are then routed via secure protocols (MQTT, HTTPS) to a Message Broker, ensuring reliable data delivery even during intermittent connectivity.
3) *Layer 3 Data Platform & Machine Learning:* This layer functions as the intelligence core. All incoming data streams are unified into a Data Lake, where Data Quality modules perform outlier detection and gap filling. The pipeline then splits into two paths: an Offline Training Pipeline where historical batches train deep learning models (CNNs, LSTMs), and an Online Inference Path where deployed models analyze real-time features. A Model Registry manages version control, ensuring only the most accurate models are in production.

4) *Layer 4 Application Layer – Analytics & Decisions:* The insight generation layer transforms model outputs into actionable tools. The Early Warning Engine alerts operators to disease risks or environmental anomalies with associated confidence scores. The Production Optimizer forecasts biomass growth and Feed Conversion Ratios (FCR) to simulate harvest scenarios. These metrics are visualized on an Operations Dashboard, providing situational awareness to the Farm Management team.
5) *Layer 5 Control & Actuation – Execution:* The final layer closes the loop by translating digital decisions into physical actions. The Control Orchestrator governs automated systems based on input from the alert engine and human approvals. This includes Automated Winches to adjust crop depth for optimal light exposure or storm avoidance, and Dosing Systems for precise nutrient or medication delivery. These physical changes modify the environment, which is then detected by Layer 1, completing the feedback loop.

III. LITERATURE SURVEY

The review delineates three distinct technological approaches currently under exploration within the academic community: autonomous robotics, remote sensing, and in-situ microsensing.

Stenius et al. (2022) [1] addressed the logistical impediments and safety risks associated with human-diver monitoring of expansive coastal farm arrays. The authors developed and field-tested a system utilizing an Autonomous Underwater Vehicle (AUV) equipped with sidescan sonar and navigation sensors.

1) *Technical Detail:* The system relies on acoustic sensing rather than purely optical sensing, which is crucial in turbid coastal waters where visibility is often less than one meter. The AUV utilizes Simultaneous Localization and Mapping (SLAM) to navigate the grid-like structure of seaweed lines.
2) *Significance:* Traditional diver-based inspection is characterized by high operational costs, human risk, and sporadic coverage. Conversely, an AUV facilitates the acquisition of consistent, high-frequency temporal data, allowing for the generation of 3D morphological maps of the farm.
3) *Critical Analysis:* While the study succeeds in navigation, it highlights a "power bottleneck." The operational endurance of AUVs is limited by battery life, preventing continuous 24/7 monitoring. Furthermore, the study focused predominantly on spatial coverage rather than the biological assessment of the seaweed biomass itself, leaving a gap in qualitative analysis.

Gao et al. (2019) [2] demonstrated the efficacy of macro-scale monitoring in the Yellow Sea, specifically addressing the disaster management of Ulva prolifera blooms (green tides) which can smother aquaculture sites.

1) *Technical Detail:* The researchers established a multi-tiered defense system. Satellite imagery (MODIS/Landsat) provides a coarse, wide-area view to detect large floating biomass. This triggers the deployment of Unmanned Aerial Vehicles (UAVs) for high-resolution validation, followed by ground-based spectroradiometers for precise species identification.
2) *Significance:* This methodology transcends farm-level management to address regional disaster mitigation. It verifies that optical sensors can effectively differentiate between algal classifications based on specific spectral signatures (e.g., chlorophyll fluorescence peaks), allowing farmers to deploy protective barriers before the bloom arrives.
3) *Critical Analysis:* The dependence on optical satellite data renders the system vulnerable to cloud cover, a common occurrence in coastal marine environments. A robust system would require the integration of Synthetic Aperture Radar (SAR) satellites, which can image through cloud layers.

Transitioning to the micro-scale, Xia et al. (2021) [3] introduced a low-power, Near Field Communication (NFC) enabled underwater logging device.

1) *Technical Detail:* Unlike traditional wired probes, this apparatus is designed to be attached directly to the seaweed lines. It captures localized environmental data (e.g., temperature, light intensity) and allows for data retrieval via a waterproof handheld reader or AUV pass-by.
2) *Significance:* This study uniquely bridged the chasm between engineering (sensors) and biology. By correlating sensor data with biological samples, the authors utilized ML to elucidate relationships between environmental stress factors and the seaweed microbiome. Changes in the microbiome often precede visible disease symptoms, making this a true "early warning" system.
3) *Critical Analysis:* The use of NFC requires close proximity for data retrieval, which still necessitates a physical presence (diver or robot). For real-time alerts, a transition to long-range underwater acoustic or optical communication would be necessary.

Liakos et al. (2021) [4] and Chen et al. (2022) [5] provided comprehensive reviews of ML applications in agriculture and finfish aquaculture, respectively, serving as the theoretical bedrock for seaweed applications.

1) *Key Insight:* Algorithms utilized for terrestrial crop disease detection, such as Convolutional Neural Networks (CNNs) (e.g., ResNet, YOLO), demonstrate high transferability to seaweed visual analysis. If a model can identify "rust fungus" on a wheat leaf, it can be retrained via Transfer Learning to identify "ice-ice disease" on Kappaphycus seaweed.
2) *Predictive Modeling:* Similarly, Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks, employed to predict water quality in fish tanks, may be adapted to forecast coastal nutrient fluxes, aiding in the determination of optimal harvest windows.

IV. METHODOLOGY

This review employed a systematic literature search strategy, adhering to PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) compliant protocols, to identify high-impact studies relevant to marine precision farming.

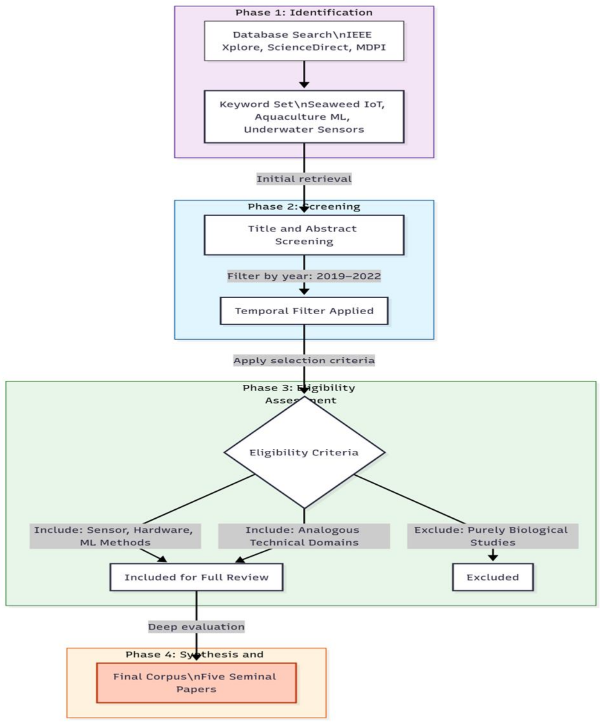

Fig 4.1: Systematic Review Methodology

Description: The flowchart above illustrates the systematic selection process used to filter the initial pool of academic papers down to the five key studies analyzed in this review.

1) *Data Sources:* Primary searches were executed across IEEE Xplore, ScienceDirect, and MDPI databases. These repositories were selected for their high concentration of engineering and marine science literature.
2) *Search Strings:* To capture the intersection of distinct fields, combinations of keywords were utilized, including "Seaweed Farming," "IoT Sensors," "Computer Vision," "Deep Learning," "Underwater Wireless Sensor Networks (UWSN)," and "Precision Aquaculture."
3) *Inclusion and Exclusion Criteria:*

- *Inclusion:* Peer-reviewed articles and conference proceedings published between 2019 and 2022 were prioritized to ensure technological relevance. Studies must have focused on either hardware implementation (sensor deployment) or algorithmic modeling (data analysis).
- *Exclusion:* Purely biological studies lacking a technological component were excluded.
- *Adaptive Strategy:* Given the paucity of seaweed-specific literature, seminal reviews concerning general aquaculture ML and terrestrial crop monitoring were included as foundational references to provide theoretical context and demonstrate transferability of algorithms.

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V. DISCUSSION

A synthesis of these studies reveals that while the hardware requisite for precision seaweed farming has reached a level of maturity, the corresponding software intelligence and system integration remain underdeveloped.

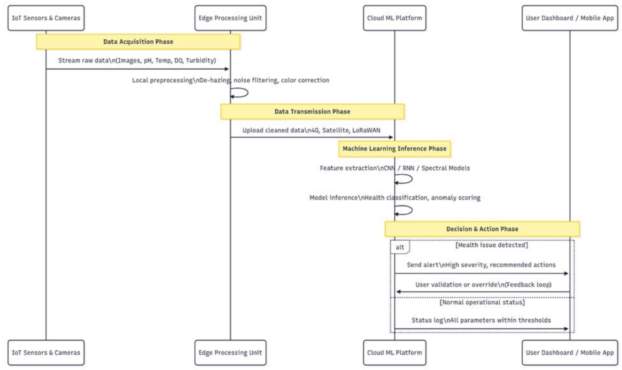

Fig 5.1: Sequence Diagram of Data Processing and Alert Generation

A. The Data Scarcity and Annotation Challenge

Although sensors capable of collecting terabytes of data exist (Stenius, Xia), there is a distinct lack of "labeled" or "ground-truthed" datasets necessary for training supervised learning models. In terrestrial agriculture, extensive open-source libraries (e.g., PlantVillage) contain thousands of annotated images of crop pathologies. No such equivalent exists for seaweed. Without labeled data (e.g., an image explicitly tagged "Nitrogen Deficiency"), supervised algorithms cannot learn.

B. Process Flow for ML Integration

To bridge this gap and deploy effective AI, future systems must adhere to a rigorous processing pipeline that handles the unique challenges of underwater data (e.g., color correction for light attenuation). Figure 2 illustrates the sequence of data transmission and decision-making.

VI. FUTURE SCOPE

Current research indicates three critical trajectories for the upcoming decade, moving from passive monitoring to active, autonomous management.

1) *Development of Spectral Libraries:* The creation of open-access databases containing seaweed spectral signatures under various stress conditions (e.g., nitrogen deficiency, epiphytic infestation, thermal shock) is essential. This "ImageNet for Seaweed" would democratize access to AI tools for smaller farmers.
2) *Edge Computing Integration:* Underwater bandwidth is severely limited; transmitting high-definition video to the cloud is often impossible. Migrating ML processing from the cloud to the AUV or sensor node (Edge AI) is necessary. This allows the device to process video locally and transmit only the insight (e.g., "Disease detected at Sector 4"), requiring kilobits rather than gigabits of data.
3) *Digital Twins and Simulation:* Before deploying physical assets, researchers should utilize "Digital Twin" technology to create virtual replicas of seaweed farms. These simulations can model hydrodynamics, nutrient flows, and sensor placement strategies, optimizing farm design in silico before any hardware enters the water.
4) *Swarm Robotics:* Instead of relying on a single, expensive AUV, future systems may employ "swarms" of low-cost, miniature underwater robots. These swarms offers redundancy; if one unit fails, the network continues to function, ensuring resilience in harsh offshore conditions.

VII. CONCLUSION

The integration of sensor technology and machine learning possesses transformative potential for seaweed farm management, shifting the paradigm from reactive observation to predictive control. While direct research is currently limited, foundational studies by Stenius, Gao, and Xia demonstrate that the components for a "Smart Seaweed Farm" are extant.

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The primary challenge lies in system integration—fusing robotic platforms with intelligent algorithms and overcoming the physical hostility of the marine environment. Addressing the "Data Gap" through interdisciplinary collaboration between marine biologists and computer scientists will be paramount. Ultimately, the digitization of seaweed aquaculture is not merely a technological upgrade but a necessary evolution to ensure the scalability of the Blue Economy.

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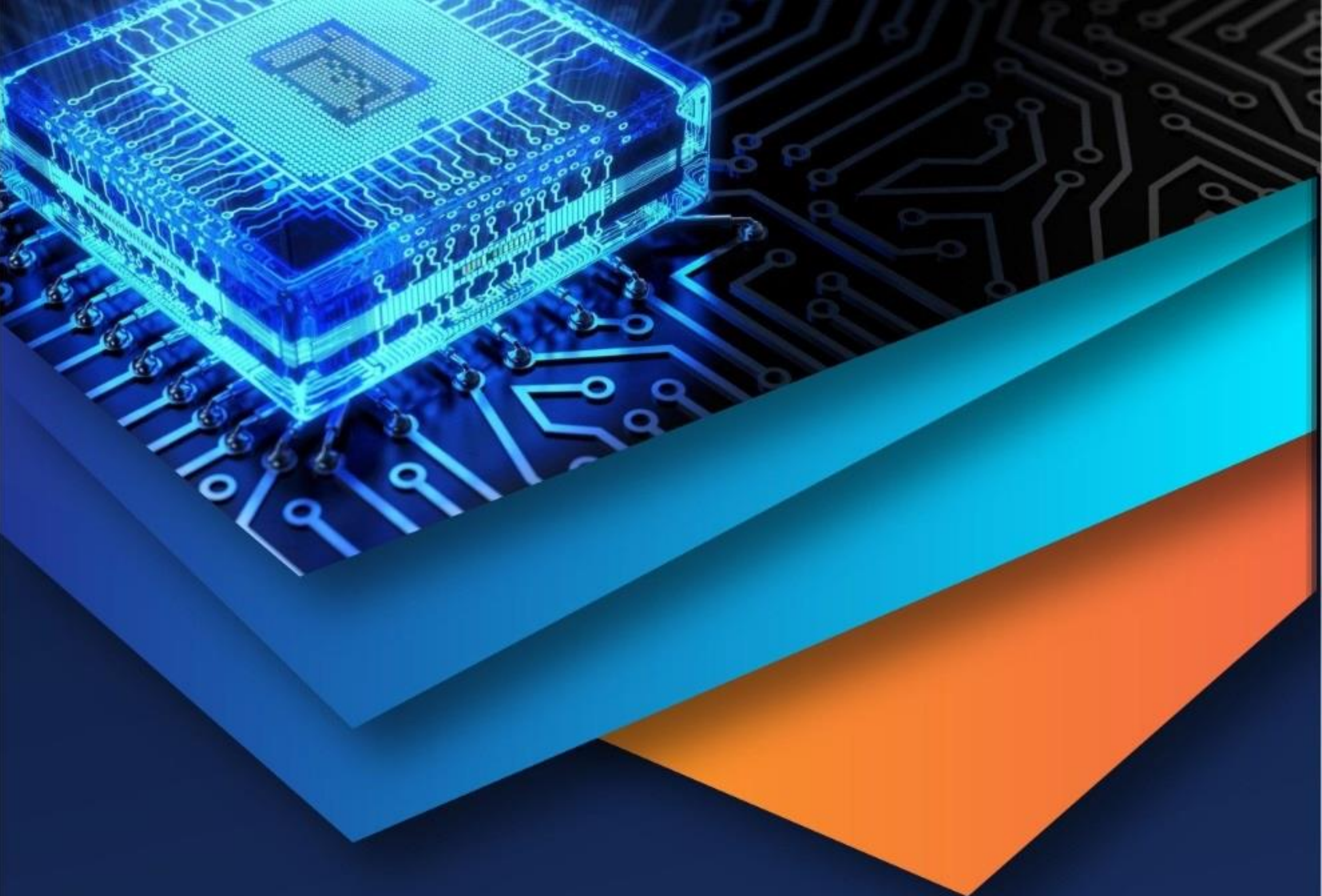

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