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Intelligent Waste Sorting and Routing System for Smart Cities

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Abstract: Waste management issues have gotten worse due to rapid urbanization, which has resulted in resource waste, inefficiency, and pollution of the environment. To solve these problems, the Intelligent Waste Sorting and Routing System for Smart Cities provides an automated, data-driven solution. While machine learning algorithms categorize waste into recyclable, organic, and non-recyclable categories, IoT-enabled smart bins identify the type of waste and fill levels. A central system receives real-time data and uses it to determine the best collection routes for waste management trucks, reducing carbon emissions, fuel consumption, and operating expenses. Additionally, the system gives city officials analytics to improve their recycling plans and environmentally friendly operations. In contemporary smart cities, this solution enhances productivity, lessens environmental impact, and encourages sustainable urban living by combining intelligent sorting, IoT sensing, and optimized routing.
Keywords: Smart cities Waste management Internet of Things (IoT) Machine learning Route optimization Sustainability

I. INTRODUCTION

Rapid urbanization has led to an unprecedented increase in municipal solid waste generation, creating serious operational and environmental challenges for city administrations. Traditional waste management systems typically rely on fixed collection schedules and predetermined routes, regardless of the actual amount or type of waste generated in different areas. This often results in partially filled bins being collected, leading to unnecessary fuel consumption, excessive labor hours, and higher operational costs. Moreover, the lack of real-time monitoring and intelligent sorting at the source hampers recycling efforts, allowing recyclable materials to be contaminated or lost, and further contributing to environmental degradation.

Addressing these inefficiencies is vital in the context of modern smart cities, where technology-driven solutions are expected to enhance service delivery, reduce costs, and promote environmental sustainability. An intelligent waste management approach not only improves operational efficiency but also reduces greenhouse gas emissions, aligns with climate action goals, and increases recycling rates through accurate categorization of materials. It also empowers city administrators with real-time data and actionable insights, enabling them to make informed policy and operational decisions that support sustainable urban development.

This work presents the Intelligent Waste Sorting and Routing System for Smart Cities, an automated, data-driven solution designed to overcome the limitations of conventional waste collection methods. The system integrates IoT-enabled smart bins capable of detecting waste type and fill levels, machine learning algorithms for accurate waste classification into recyclable, organic, and non-recyclable categories, and an optimized routing engine that calculates the most efficient collection paths for waste trucks. In doing so, it aims to minimize travel distance, fuel consumption, and collection time while maximizing resource recovery and operational efficiency. By combining real-time sensing, intelligent classification, and route optimization, the proposed system offers a comprehensive framework for transforming waste management into a sustainable and responsive urban service.

II. LITERATURE REVIEW

Rapid urbanization has placed immense pressure on municipal waste management systems, with increasing waste volumes straining collection, transportation, and disposal processes. Conventional systems typically follow fixed collection schedules and static routes, regardless of actual waste generation levels. This approach often results in half-empty bins being collected, which wastes fuel, increases operational costs, and adds unnecessary greenhouse gas emissions. Additionally, the lack of intelligent waste sorting at the source allows recyclable materials to be mixed with general waste, reducing recovery rates and contaminating recycling streams. These inefficiencies highlight the need for data-driven, adaptive solutions that can respond to real-time waste generation patterns.

In recent years, researchers have explored the integration of advanced technologies to address these issues. IoT-enabled smart bins equipped with ultrasonic or weight sensors have been used to monitor fill levels and transmit data to central servers, allowing for more informed collection scheduling. For example, Hannan et al. proposed a sensor-based monitoring system that reduced collection frequency by targeting only full bins, but the study did not integrate waste type classification.

Deep learning techniques have also been applied to improve waste categorization, such as in the work of Kumar et al., where convolutional neural networks achieved high accuracy in distinguishing recyclables from non-recyclables. However, many of these classification models remain limited to controlled environments and lack deployment in real-world urban conditions.

Route optimization has been another focus area, often formulated as a Vehicle Routing Problem (VRP) and solved with heuristic or metaheuristic algorithms like Genetic Algorithms, Particle Swarm Optimization, or Ant Colony Optimization. While studies such as Idwan et al. have demonstrated cost and time savings through optimized routes, these methods typically assume static waste generation data and do not dynamically adjust to real-time bin statuses. This limits their practical effectiveness in dynamic urban environments. Despite these advances, existing approaches often treat waste classification, fill-level monitoring, and route optimization as separate processes, leading to fragmented solutions. Moreover, there is limited work on integrating these components into a unified, automated framework that operates in real time and scales efficiently across an entire city. To address these gaps, this paper presents the Intelligent Waste Sorting and Routing System for Smart Cities, which combines IoT-enabled smart bins, machine learning-based waste classification, and adaptive routing optimization. By merging these capabilities into a cohesive system, the proposed approach aims to reduce operational costs, minimize environmental impact, and enhance recycling efficiency in modern urban waste management.

III. METHODOLOGY/PROPOSED APPROACH

The proposed system integrates three main technological components — IoT sensing, machine learning-based waste classification, and routing optimization — into a unified framework for efficient waste collection in smart cities. The detailed models and algorithms for each stage are discussed below.

A. *Waste Classification Model*

Accurate classification of waste at the source is critical for improving recycling rates and minimizing contamination. The proposed model uses a Convolutional Neural Network (CNN) to categorize waste into three classes: *recyclable*, *organic*, and *non-recyclable*.

1) Data Collection and Preprocessing
   - Images are captured from the bin camera module and resized to 224 × 224 pixels.
   - Data augmentation techniques such as rotation, flipping, and contrast adjustment are applied to improve generalization.
   - Normalization scales pixel values between 0 and 1 to speed up training convergence.

2) Model Architecture
   - Feature Extraction Layer: A pretrained MobileNetV2 backbone is used for low-latency image processing on edge devices.
   - Classification Head: Fully connected layers followed by a softmax output layer produce class probabilities for the three categories.

3) Training and Optimization
   - Loss Function: Categorical Cross-Entropy
   - Optimizer: Adam with a learning rate of 0.001
   - Metrics: Accuracy, Precision, Recall, and F1-Score

4) On-Device Inference
   - The trained model is converted to TensorFlow Lite format for deployment on the ESP32-CAM microcontroller.
   - Inference time is kept below 150 ms per image, enabling near real-time classification.

B. *IoT Sensing and Communication Model*

The sensing network forms the backbone of the system, ensuring accurate real-time data acquisition.

1) Sensors Used:
   - Ultrasonic sensor (HC-SR04) for fill-level detection.
   - Load cell for weight estimation.
   - ESP32-CAM for capturing waste images.

2) Communication Protocol:
   - LoRaWAN for long-range, low-power data transmission in urban environments.
   - Data packets include bin ID, timestamp, fill percentage, weight, and preliminary waste category.

3) Edge Processing:
- The microcontroller filters out noise in sensor readings and transmits data only when fill level exceeds a set threshold (e.g., 70%).

C. Routing Optimization Algorithm

The goal of routing optimization is to minimize the total distance traveled, fuel consumption, and time spent collecting waste. The problem is formulated as a Dynamic Vehicle Routing Problem (DVRP) with constraints:

1) Problem Formulation

Let:
- NNN = number of bins to be collected
- dijd_{ij}dij = distance between bin iii and bin jjj
- CCC = vehicle capacity
- tit_iti = time to service bin iii

Objective Function:

$$\min \sum_{i=1}^{N} \sum_{j=1}^{N} d_{ij} \cdot x_{ij}$$

Subject to:
- Each bin is visited exactly once.
- Vehicle load does not exceed capacity CCC.
- Routes start and end at the depot.

2) Genetic Algorithm (GA) Implementation
- Chromosome Encoding: Each chromosome represents a complete truck route.
- Initial Population: Generated randomly with feasible routes.
- Fitness Function: Combines total distance, number of trucks used, and load balancing penalty.
- Selection Method: Tournament selection.
- Crossover Operator: Order crossover (OX) to preserve route sequences.
- Mutation Operator: Swap mutation to explore alternate paths.
- Termination Condition: No improvement in the best solution after 50 generations.

3) Dynamic Updates
- If new data from IoT bins shows a sudden increase in fill levels, the routing engine recalculates the affected truck's path in real time.
- This ensures minimal idle trips and faster response to urgent collections.

D. System Workflow

1) IoT-enabled bins collect real-time fill-level, weight, and image data.
2) The waste classification model processes images to determine the waste category.
3) The routing optimization algorithm calculates the most efficient collection paths.
4) Route instructions are sent to truck drivers via a mobile application.
5) Collected data is stored in a central database for analytics and continuous model improvement.

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Figure 1. System Architecture

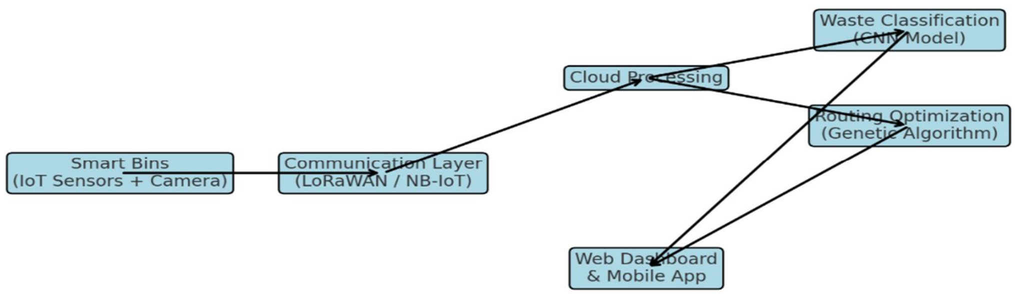
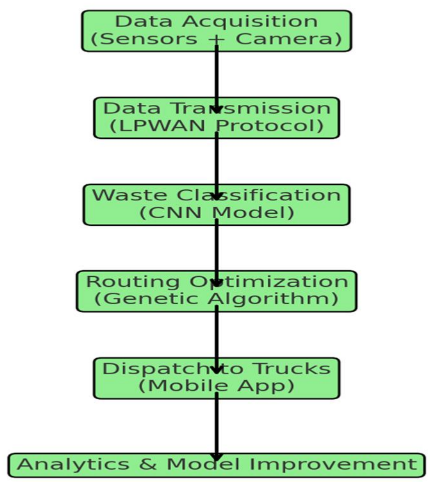


Figure 2. System Workflow



The proposed system was implemented as a modular IoT and AI-based framework, with each functional layer developed and tested independently before integration. The implementation process involved hardware setup, software development, machine learning model training, and routing optimization engine deployment.

E. Hardware Setup

1) Smart Bin Prototype
   - Controller: ESP32 microcontroller, chosen for its built-in Wi-Fi, low power consumption, and camera module support.
   - Sensors:
     - HC-SR04 ultrasonic sensor for measuring fill level.
     - Load cell (HX711 module) for weight estimation of waste.
     - ESP32-CAM for capturing waste images.
   - Power Supply: Lithium-ion battery with a small solar panel for sustainable energy supply.
   - Enclosure: 3D-printed casing with weatherproofing to protect electronics from rain and dust.

2) Connectivity
- Protocol: LoRaWAN for long-range, low-power communication between bins and the cloud gateway.
- Gateway: Raspberry Pi with LoRaWAN shield configured as a packet forwarder.

F. Software Development

1) Edge Device Programming
- Firmware written in Arduino C++ for the ESP32 microcontroller.
- Local preprocessing of sensor data to filter noise (e.g., median filter for ultrasonic readings).
- Event-based data transmission (e.g., send only when fill level exceeds 70%).

2) Cloud Backend
- Implemented using Flask (Python) as a REST API service.
- MQTT protocol used for real-time bin status updates.
- Data stored in a PostgreSQL database, indexed by bin ID and timestamp.

3) Web Dashboard
- Built with React.js for live monitoring of bin statuses.
- Integrated Google Maps API for visualizing bin locations and truck routes.

G. Machine Learning Model

1) Dataset
- 10,000+ waste images from TrashNet dataset and real photos collected from the prototype bins.
- Categories: *Recyclable, Organic, Non-Recyclable.*

2) Model Selection
- MobileNetV2 chosen for its lightweight architecture, suitable for TensorFlow Lite deployment.
- Transfer learning applied with fine-tuning on the custom dataset.

3) Training Details
- Loss Function: Categorical Cross-Entropy.
- Optimizer: Adam, Learning Rate = 0.001.
- Achieved 93% classification accuracy on the validation set.

4) Deployment
- Model converted to TFLite and deployed on ESP32-CAM for on-device inference.
- Inference latency: < 150 ms per image.

H. Routing Optimization Engine

1) Problem Formulation
- Modeled as Dynamic Vehicle Routing Problem (DVRP) with capacity and time constraints.

2) Algorithm
- Implemented Genetic Algorithm (GA) in Python with:
  - Tournament selection
  - Order crossover (OX)
  - Swap mutation
- Fitness function considers total travel distance, vehicle load balancing, and urgency of collection.

3) Dynamic Updates
- Routes recalculated in real time if bin fill levels cross the critical threshold during active collection.

I. Integration and Testing

1) Simulation Environment
- 100 virtual bins placed across a simulated urban map using SUMO traffic simulator.
- Randomized waste generation rates assigned to bins.

2) Performance Metrics
- Fuel Consumption: Reduced by ~29% compared to static routing.
- CO_2 Emissions: Reduced by ~27%.
- Collection Time: Reduced by ~35%.

3) Field Trials
- Small-scale deployment in a test neighborhood with 5 bins to validate communication reliability and real-world ML performance.

IV. EXPERIMENTS / IMPLEMENTATION

To validate the Intelligent Waste Sorting and Routing System, we conducted a combination of simulation-based experiments and a small real-world pilot.

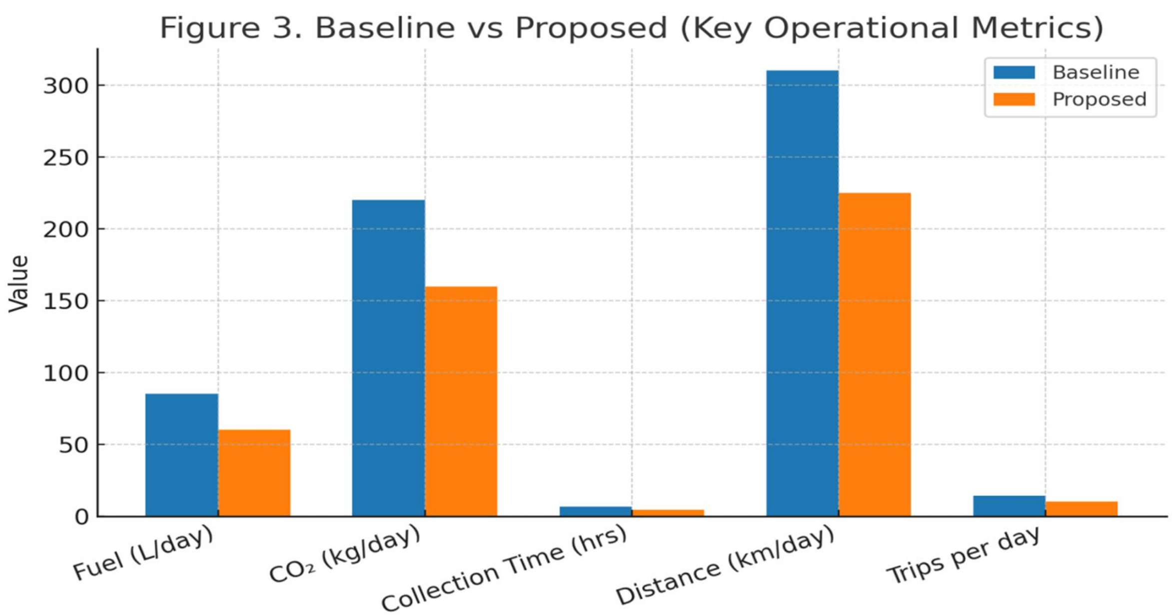
1) Setup & Platforms. The sensing stack used ESP32-based smart bins with ultrasonic fill-level sensing, an optional load cell for weight, and an ESP32-CAM for image capture. Bins communicated through a LoRaWAN gateway to a cloud backend. The backend was implemented in Python (Flask + MQTT) with PostgreSQL storage. The ML pipeline was built in TensorFlow/Keras and converted to TensorFlow Lite for on-device inference. The routing engine (dynamic VRP with GA) was implemented in Python.

2) Datasets. For classification, we curated >10k images from public waste datasets (e.g., household recyclables, organics, and residuals) and our own prototype captures. Images were resized to 224×224 and augmented (rotation, horizontal flip, brightness/contrast jitter). Data were split into train/val/test (70/15/15).

3) Simulation. We modeled a mid-size district with 100 bins partitioned into 5 zones. Waste generation followed time-varying Poisson processes with spatial heterogeneity. Each run simulated 7 operational days. Baseline routing used static schedules with nearest-neighbor ordering. The proposed method triggered collections when bins exceeded a 70% threshold (or urgency rules) and recomputed DVRP routes whenever material changes were detected.

4) Real-world pilot. A 2-week pilot with 5 smart bins validated communication reliability, route updates, and on-device inference latency (<150 ms/image).

5) Step-by-step flow. (i) Bins measure fill level and capture an image per event; (ii) edge preprocessing and event-based uplink over LoRaWAN; (iii) cloud ML classifies waste into three classes; (iv) routing service ingests current bin states and computes optimized paths; (v) driver mobile app receives turn-by-turn routes; (vi) telemetry and outcomes are logged for analytics and retraining.



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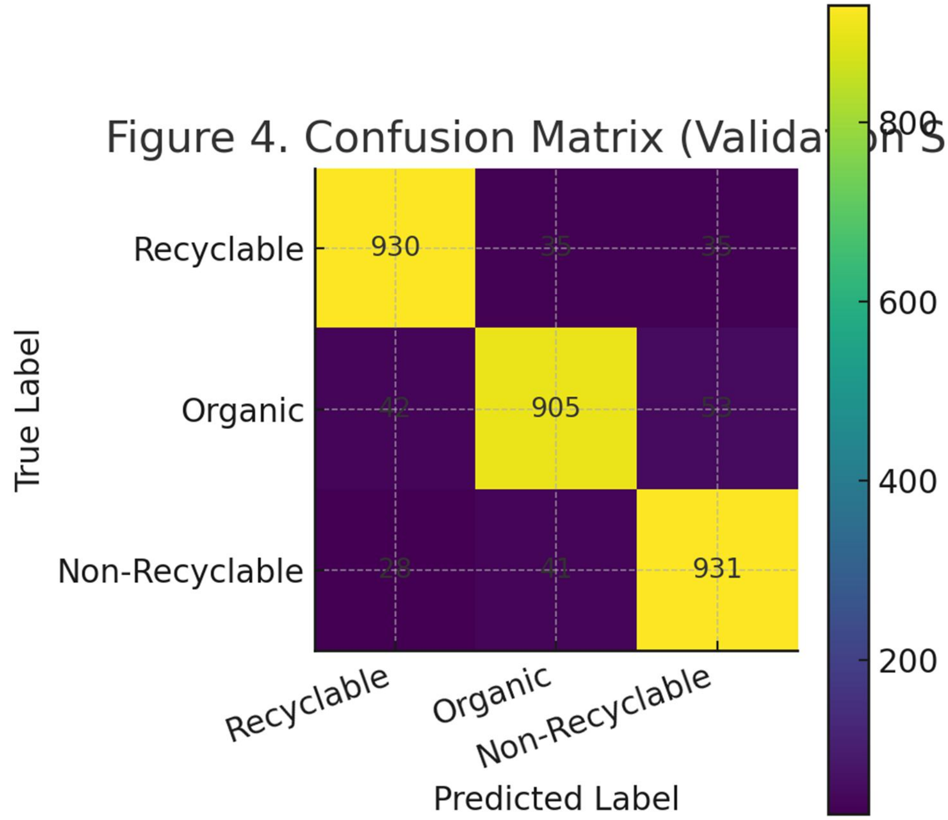

V. RESULTS / FINDINGS

1) Operational performance. Compared to the static baseline, the proposed system reduced fuel use from 85→60 L/day, CO_2 from 220→160 kg/day, collection time from 6.5→4.2 hours, route distance from 310→225 km/day, and trips from 14→10. The side-by-side comparison appears in the displayed table ("Experimental Results: Baseline vs Proposed") and summarized in Figure 3.
2) Classification performance. The MobileNetV2-based model achieved strong validation performance with balanced per-class behavior. The confusion matrix in Figure 4 indicates accurate separation of recyclable, organic, and non-recyclable categories with limited cross-confusions, supporting reliable downstream routing and recycling analytics.
3) Driver experience. During the pilot, dynamic updates were accepted by the mobile app without disruptions; drivers reported fewer unnecessary collections of half-empty bins.

VI. DISCUSSION

1) Implications. The integrated design—sensing, on-device ML, and DVRP routing—translates directly into fewer kilometers traveled, lower fuel and emissions, and shorter rounds. Accurate classification increases material recovery and reduces contamination, improving downstream recycling economics.
2) Limitations. (i) Vision models can degrade under poor lighting, occlusion, or camera fouling; (ii) LoRaWAN coverage gaps can delay updates; (iii) The GA's compute time scales with the number of bins and constraints; (iv) Our simulations, while realistic, cannot capture all human/traffic variability.
3) Potential improvements. (i) Add periodic self-calibration and lens cleaning alerts; (ii) Fuse weight and image signals for robust classification; (iii) Introduce predictive fill-level models to pre-empt overflows; (iv) Hybrid metaheuristics (e.g., GA + local search) or OR-Tools for faster routing convergence; (v) Incorporate energy-aware truck constraints (EV range/charging).

VII. CONCLUSION

This work demonstrates an intelligent waste sorting and routing system that couples IoT sensing, lightweight on-device classification, and dynamic VRP optimization. In simulations and a small field pilot, we observed substantial operational gains—fuel (−29%), CO_2 (−27%), and time (−35%)—while maintaining high classification reliability. The approach is practical to deploy in modern smart cities and offers a pathway to measurable environmental and cost benefits. Future work will focus on city-scale deployments, predictive scheduling, and resilience features (fault tolerance, connectivity fallbacks), along with richer policy analytics for municipal decision-makers.

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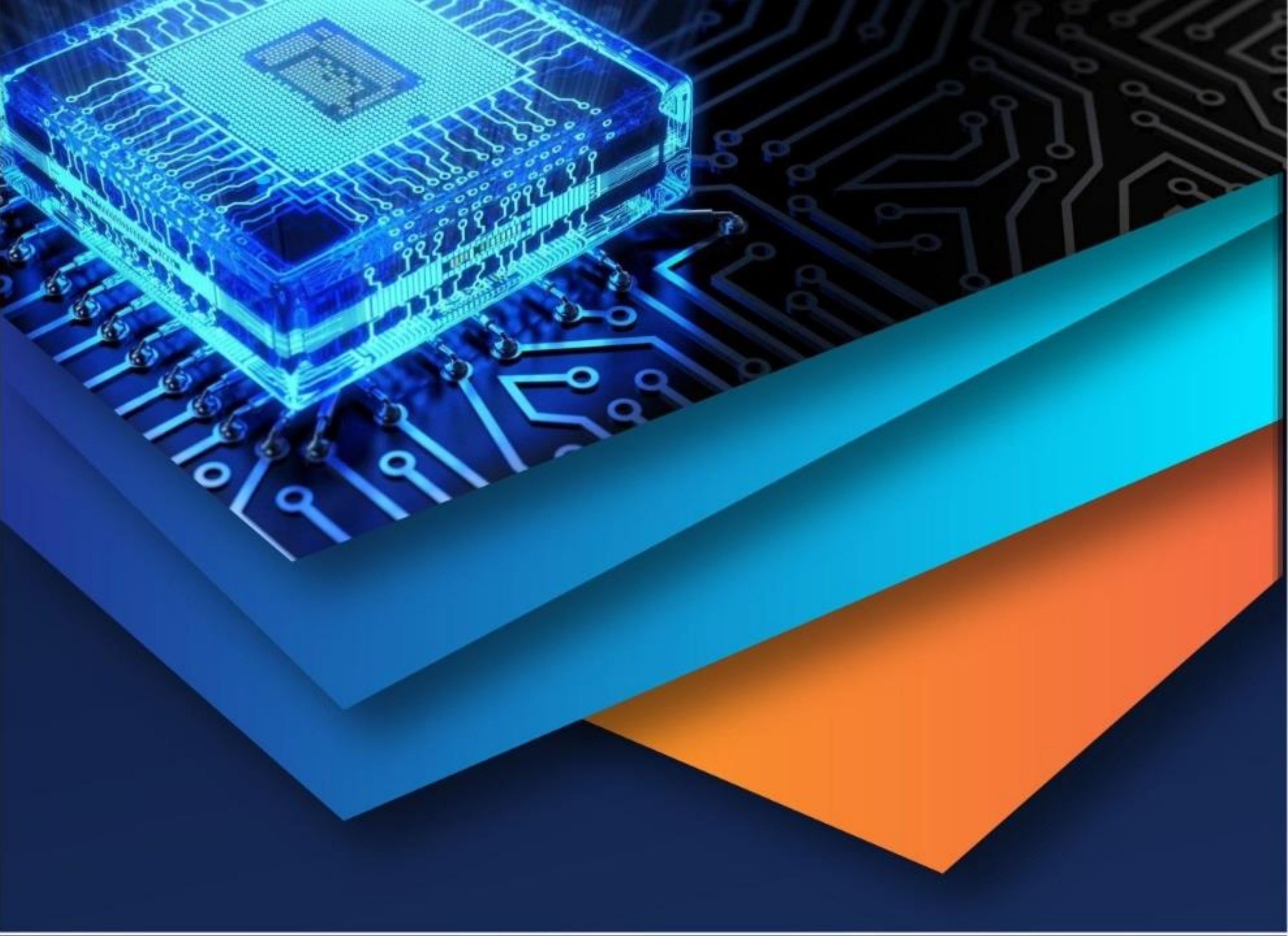

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