iJRASET
International Journal For Research in Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 14 **Issue:** VIII **Month of publication:** August 2026

DOI: https://doi.org/10.22214/ijraset.2026.84649

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue VIII Aug 2026- Available at www.ijraset.com

E-Waste & Non-E-Waste Classification Using Deep Learning

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***Abstract:* In recent years there is an exponential growth of consumer electronics which has led to a massive increase in electronic waste (e-waste), posing a serious environmental and health challenges due to improper disposal of toxic components such as Lead, Mercury and cadmium. Manual segregation of e-waste is not efficient and safe for the workers. This Paper presents a report on low cost, deep Learning based project implemented for e-waste segregation system capable of classifying and sorting electronic waste into distinct categories such as sensors, wires, LEDs and non e-waste.**

The system utilizes a Raspberry Pi-4 integrated with a Pi camera to capture images of electronics waste. A convolutional Neural Network (CNN) trained using MobileNet performs real time classification, while a Raspberry Pi controlled conveyer belt moves to direct the waste in to the appropriate category. This combination of AI and embedded systems minimizes human involvement, improves segregation accuracy and provides a scalable model that can be extended for large scale recycling centers. The prototype demonstrates the feasibility of using computer vision and deep learning for sustainable e-waste management, supporting environmental protection and resource recovery

Keywords: e-waste, segregation, Deep Learning Model

I. INTRODUCTION

E-waste is increasing at an alarming rate, driven by consumer electronics turnover and limited recycling infrastructure. India is among the top e-waste-generating nations, producing millions of tons annually. Most recycling occurs in informal sectors, where workers manually dismantle electronics without proper protective equipment, leading to toxic exposure and environmental pollution. Existing recycling systems are either fully manual or partially mechanized but lack intelligent sorting capabilities. Manual segregation is inefficient and subjective, while advanced industrial automation systems are expensive and inaccessible to small-scale recycling units. Hence, there is a pressing need for an affordable, intelligent, and semi-automated segregation system that can efficiently classify e-waste components for safe and sustainable recycling. This project addresses that gap by providing a deep learning–based system capable of accurate, real-time waste classification and mechanical sorting using accessible, low-cost hardware.

II. REVIEW OF LITERATURE

A. Existing Solutions

Several researchers have proposed automation-based waste management systems leveraging image processing, IoT, and AI.Singh et al. [1] developed a smart waste management system using computer vision to classify municipal waste into recyclable and non-recyclable categories. Their system employed simple machine learning algorithms but lacked specialization for e-waste. Patil et al. [2] proposed an AI-based waste classification model using CNN and achieved over 90% accuracy on the TrashNet dataset, demonstrating deep learning's potential for visual waste sorting. Kumar and Reddy [3] implemented an Arduino-based segregation model integrating IR sensors and servo motors for automated bin switching, though their system used predefined thresholds instead of AI classification. Rashid et al. [4] created an image-based metal detection system using edge and color features, but its accuracy decreased for complex backgrounds. More advanced works such as Islam et al.[5] introduced dual-stream transformer networks for e-waste classification, which improved accuracy but required high computational resources unsuitable for low-power embedded systems. These prior studies collectively show that while intelligent waste segregation is feasible, few solutions focus specifically on e-waste, and most rely on high-end hardware, making them difficult to implement at smaller scales.

B. Limitations Of Existing Solutions

Despite significant research progress, existing e-waste classification systems face notable limitations:

1) Dependence on high-performance GPUs and cloud resources, unsuitable for low-cost hardware like Raspberry Pi.
2) Limited focus on hazardous electronic components; most models are trained on generic household waste datasets.

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3) Lack of mechanical integration — many systems classify images but do not automate the sorting process.
4) Poor adaptability to lighting variations and irregular waste shapes.
5) High cost and complexity make industrial-level systems inaccessible for educational or small recycling setups.

These challenges motivate the development of a **cost-effective, hardware-integrated, and deep learning–driven prototype**, capable of real-time operation on low-power devices.

II. PROPOSED SYSTEM DESIGN

The proposed system combines **image-based classification** and **servo-based segregation** into a single intelligent framework. It is divided into hardware and software modules, each handling a specific stage of the workflow.

A. *Block Diagram of the proposed project*

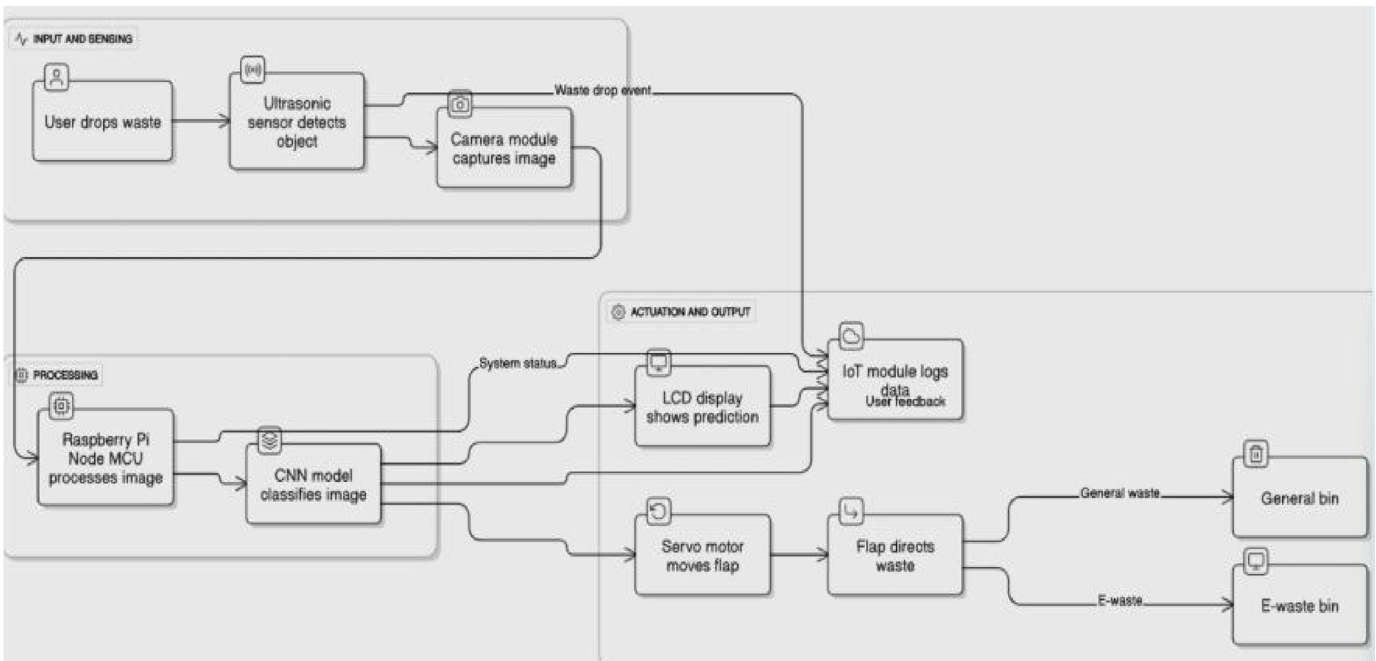

Fig 3.1 Design with block diagram

B. *System flow*

1) Waste object is placed under the Raspberry Pi Camera.
2) Image of the object is captured and preprocessed using MobileNet to remove background noise, enhance edges, and normalize brightness.
3) The CNN model running on the Raspberry Pi classifies the object into categories such as e-waste & non e-waste.
4) The classification result is used by the Raspberry Pi to directly control Dc motor and servo motor.
5) DC motor rotates to move the item forward.
6) Waste object is directed automatically to the assigned container.

C. *System Description*

1) *Image Acquisition Module*

The image acquisition module is responsible for capturing high-quality images of incoming waste items. A high-definition Raspberry Pi Camera is mounted directly above the sorting area, providing a top-down perspective that ensures complete visibility of each object. High-resolution imaging preserves fine details such as texture, color gradients, and surface irregularities, which are essential for distinguishing visually similar materials like plastic, glass, metal, and PCBs. The camera's frame rate and resolution are carefully balanced to support real-time operation while maintaining sufficient detail for reliable classification.

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2) Preprocessing Module

Captured images are pre-processed to match the specific input requirements of the MobileNetV2 model. Images are resized to exact 224x224 pixel dimensions to ensure uniformity. Instead of utilizing computationally heavy OpenCV background segmentation or Canny edge detection filters, the system relies on Keras's native preprocess_input function, which mathematically normalizes the image pixel values to a standard [-1, 1] range. By relying on the model's robustly trained ability to isolate objects from the plain cardboard background natively, these streamlined steps reduce computational overhead, reduce input variance, and dramatically improve the inference speed on constrained hardware such as the Raspberry Pi.

3) Deep Learning Classification Module

A lightweight MobileNetV2 Convolutional Neural Network (CNN) trained with TensorFlow/Keras is used to evaluate the waste. Rather than outputting a simple binary prediction, the model utilizes a multi-class softmax layer to classify objects precisely across 12 distinct material categories (such as diodes, PCBs, glass, or plastic). The model performs multi-class classification at the waste category level, where all electronic components are grouped under a unified ‘e-waste’ class. A secondary Python inference script then dynamically maps this specific prediction into the broader "e-waste" or "non e-waste" master categories. The model can be optimized with TensorFlow Lite for deployment on the Raspberry Pi, allowing efficient inference without compromising accuracy. The CNN extracts hierarchical features from input images, identifying patterns and textures unique to each material type. Accurate classification at this stage is critical, as it directly determines the efficiency of the subsequent sorting mechanism, and optimization ensures real-time performance on edge devices.

III. SYSTEM DESIGN

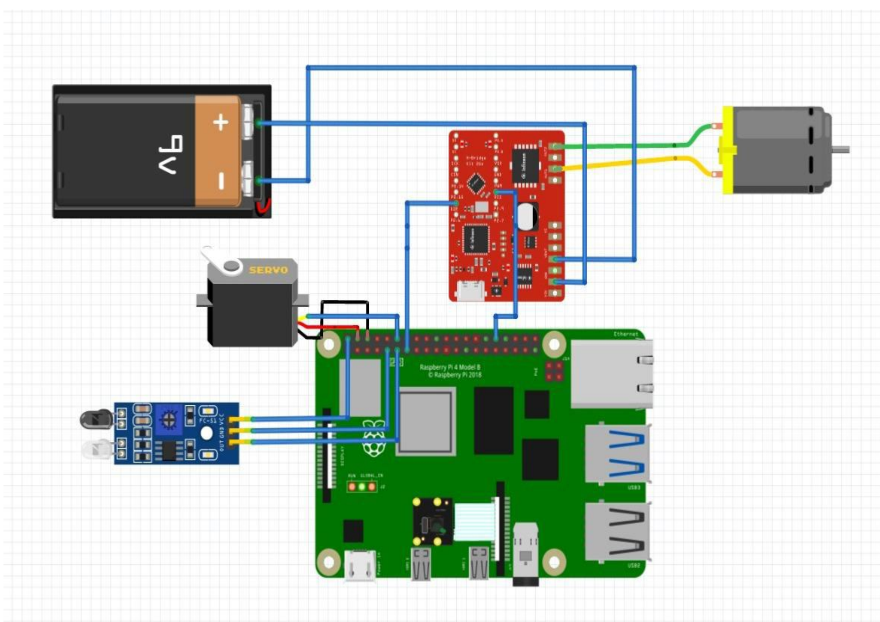

Fig 4.1 Circuit Diagram

The circuit of the proposed system revolves around the Raspberry Pi 4b, which acts as the central processing unit coordinating image acquisition, classification, and bin actuation. The design integrates two main functionalities: high-accuracy visual waste classification and automated sorting into corresponding bins.

1) Raspberry PI Interface

At the heart of the circuit is the Raspberry Pi 4b, chosen for its high processing capabilities, multiple GPIO pins, and support for CSI camera input. It interfaces directly with the camera module, Dc motor, and the servo motor. Signal lines are connected using appropriate level shifting and filtering circuits where necessary to ensure stable data acquisition, reliable servo control, and safe operation of connected components.

2) Image Acquisition (Pi Camera)

The Raspberry Pi Camera HQ is mounted above the sorting area to provide a top-down view of incoming waste objects. The camera connects to the Pi through the CSI interface. A regulated 3.3 V power supply is used for the camera.

Controlled LED lighting is added around the camera to maintain uniform illumination, critical for accurate classification by the CNN.

3) Preprocessing and Classification

The Pi receives raw images from the camera, which are processed locally using OpenCV for background removal, edge enhancement, and brightness normalization. The processed images are fed into a TensorFlow Lite–optimized CNN running on the Pi. The CNN outputs classification labels corresponding to material types, such as batteries, wires, sensors and resistors

4) Sorting Mechanism (Servo Motors)

The classification result from the CNN drives the Dc motor to rotate, moving the conveyor belt , the belt stops when the object is detected by the IR sensor, the Pi camera captures image and the SG90 servo motor which is connected to the flap directs the waste item to their dedicated bin**s.**

5) Monitoring and User Interface

A Python-based GUI provides real-time monitoring of the system. The interface displays the live camera feed, classification results. This module connects directly to the Pi and optionally to an HDMI display, enabling operators to verify performance and troubleshoot errors in real-time.

6) Power Supply

The system operates on a regulated 5 V DC supply, powering the Raspberry Pi, servo motors, LEDs, and camera. Voltage regulators and filtering capacitors ensure stable operation and protect sensitive components from spikes or noise, ensuring consistent performance of both the classification algorithm and the sorting mechanism.

A. The hardware setup is as shown in the figure below.

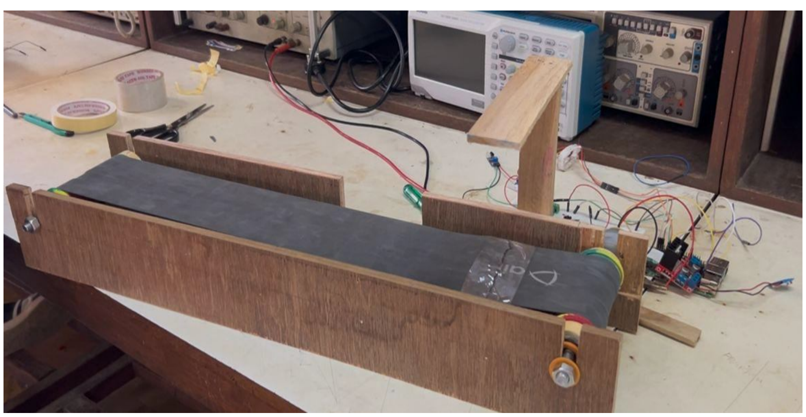

Fig 4.2 Conveyor Belt

It consists of a Raspberry Pi connected to a camera module, a servo motor, a DC motor with a motor driver, an IR sensor, and an external battery supply arranged on a breadboard. The Raspberry Pi acts as the central unit, coordinating all components. The camera is used to capture images, while the DC motor drives the conveyor mechanism and the servo motor is used for sorting the waste. The IR sensor helps in detecting the presence of objects. All components are interconnected using jumper wires, with power supplied through both the Raspberry Pi and an external battery. In addition, a conveyor belt structure was fabricated using a sturdy wooden frame, supported with ball bearings and screws to ensure smooth and stable movement. This mechanical setup allowed the objects to move efficiently under the camera for real-time detection and classification. The complete hardware system was assembled and tested successfully, and all connections were observed to be working as intended.

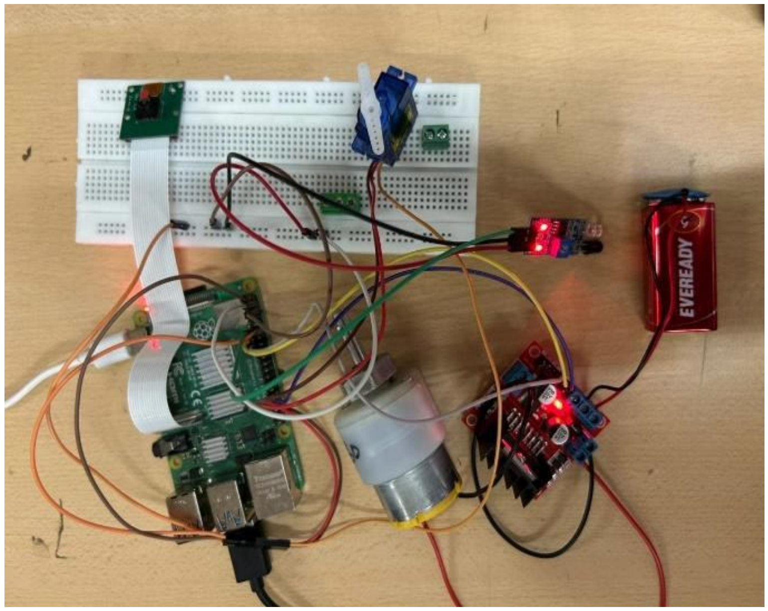

Fig 4.3 Raspberry Pi Connections

B. Software System Design

The software system of the automated waste-sorting project is responsible for image acquisition, preprocessing, classification using a CNN, and controlling the servo-based sorting mechanism. The design is modular, enabling each component to be tested independently and integrated seamlessly for real-time operation.

1) Image Acquisition

Images of waste items are captured using the **Raspberry Pi Camera**. The camera is configured to maintain a fixed resolution and frame rate, providing consistent input for the classification model. Controlled LED lighting ensures uniform illumination, reducing variability that could affect model accuracy.

2) Preprocessing Module

Captured images are preprocessed using OpenCV to standardize input before classification. Instead of relying on computationally heavy OpenCV background segmentation or contour detection, the system utilizes streamlined native framework steps:

Resizing: Resizes images to exactly 224x224 pixels to match the MobileNetV2 input dimensions.

Mathematical Normalization: Scales pixel values to a standard [-1, 1] range using Keras's native preprocess_input function.

These streamlined preprocessing steps are critical for reducing computational overhead, minimizing input variability, and significantly improving the CNN’s inference speed on real-time edge devices like the Raspberry Pi.

3) CNN Classification Module

A lightweight Convolutional Neural Network (CNN) is trained using TensorFlow/Keras on labeled images of waste materials (plastic, metal, PCB, glass). The CNN architecture includes:

a) Convolutional Layers: Extract feature maps highlighting textures, edges, and patterns unique to each material.
b) Pooling Layers: Reduce spatial dimensions while preserving important features.
c) Fully Connected Layers: Map extracted features to classification probabilities for each category. 30
d) Softmax Output Layer: Produces the probability distribution over all classes, with the highest probability determining the material type.

For deployment on the Raspberry Pi, the model is converted to TensorFlow Lite, enabling efficient inference with minimal latency while maintaining classification accuracy.

The model is trained using a two-phase transfer learning approach, where the pretrained backbone is initially frozen and later selectively fine-tuned to adapt to waste-specific features

4) Servo Control Integration

Once the CNN outputs the classification label, the Raspberry Pi directly sends **PWM signals** to the SG90 servo motors to rotate the corresponding bin into position. The servo control module ensures precise and smooth motion, preventing misplacement of waste items.

IV. RESULTS & DISCUSSIONS

The proposed system for E-Waste Classification using Deep Learning integrated with Raspberry Pi and Pi Camera was tested on multiple real-time images captured from the conveyor setup. The model successfully classified objects into E-waste and Non E-waste categories with high confidence scores.

1) Test Case 1: Non E-Waste (Cardboard)

- Input: Cardboard box placed on conveyor belt
- Prediction: *Non E-Waste*

Fig 5.1 Classification of non E-Waste

The model correctly identified the object as non e-waste, specifically cardboard. The high confidence (above 90%) indicates strong feature extraction by the model. Minor confusion with "metal" suggests slight similarity in texture or lighting conditions, but it does not affect final classification.

2) Test Case 2: E-Waste (LED Component)

- Input: Electronic LED component
- Prediction: E-Waste
- Confidence: 98.41%

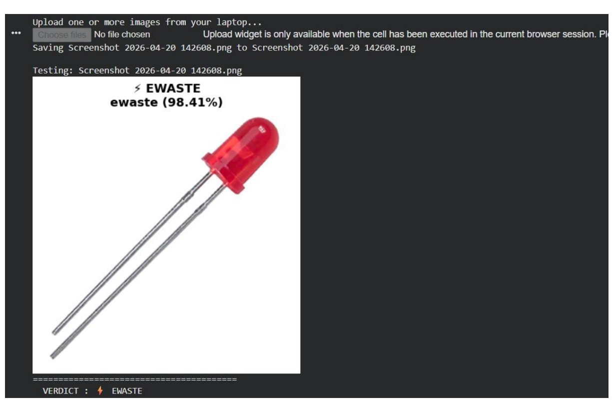

Fig 5.2 Classification of E-Waste

The model achieved very high accuracy in detecting electronic waste. The LED component has distinct features such as:

- Metal leads
- Plastic casing

These features are well learned by the model, resulting in near-perfect classification.

V. OBSERVATIONS

The terminal log captures the complete real-time operation of the e-waste sorting system running on the Raspberry Pi. The system initializes by setting the servo motor to its default Parallel position (70°), representing the "Allow Pass" state, confirming successful hardware initialization before entering AUTO mode.

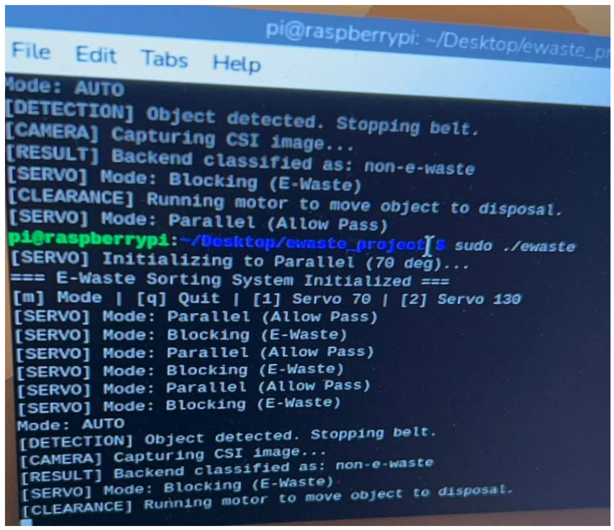

Fig 5.3 Terminal Output of Real-Time System

Upon object placement, the IR sensor triggers a [DETECTION] event and the conveyor belt stops. The Pi Camera immediately captures a CSI image, which is forwarded to the classification backend. Across both recorded cycles, the backend consistently returned a classification of non-e-waste, demonstrating stable and repeatable inference under real-world conditions.

Following each classification, the [CLEARANCE] module activates the DC motor to physically move the object toward the disposal area, after which the servo resets to Parallel (Allow Pass) in preparation for the next item. The clean repetition of the full detection → capture → classify → actuate → reset cycle across multiple runs confirms the reliability and consistency of the end-to-end pipeline.

A. *Key Findings*

1) IR-based detection successfully triggers image capture without manual intervention.
2) Classification inference runs reliably on-device with no crashes or timeouts observed.
3) Servo actuation and motor clearance execute sequentially as designed.
4) The system resets correctly between cycles, confirming loop stability in AUTO mode.

VI. CONCLUSION

The proposed system successfully demonstrates an efficient and low-cost approach to automated e-waste segregation by integrating deep learning with embedded hardware. By combining a Raspberry Pi, Pi Camera, and a trained CNN model, the system is capable of accurately identifying and classifying waste materials in real time. The classification results are effectively linked to hardware actions, enabling automatic sorting through the use of a servo motor and conveyor mechanism. A key achievement of this project is the successful design and integration of a conveyor belt system using a sturdy wooden frame, ball bearings, and a DC motor. This mechanical setup ensured smooth and continuous movement of objects under the camera, allowing reliable image capture and consistent classification. The synchronization between image processing and conveyor movement played a crucial role in achieving real-time operation.

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ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue VIII Aug 2026- Available at www.ijraset.com

The system performed well across multiple test cases, achieving high accuracy in distinguishing between e-waste and non e-waste materials. It reduces the need for manual sorting, thereby improving safety, efficiency, and consistency in waste management.
Overall, the project highlights the practical feasibility of using deep learning and embedded systems for smart recycling applications. It provides a scalable foundation that can be further enhanced for industrial use, contributing toward sustainable and environmentally responsible e-waste management solutions.

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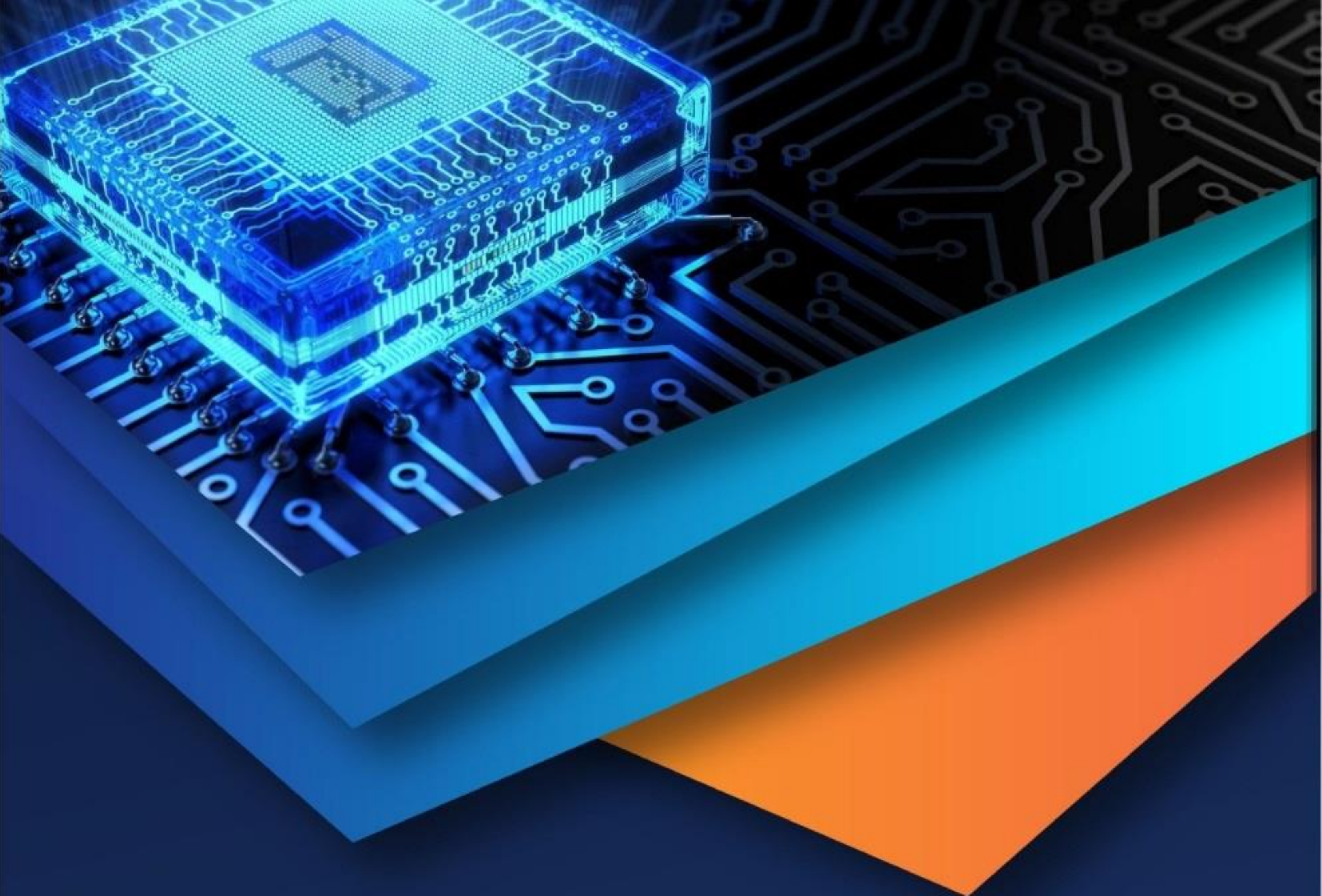

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