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AI Powered Smart Waste Segregation System Using IOT

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Abstract: ***Waste management is an environmental challenge because many people do not separate or dispose of waste correctly. This project introduces an AI-powered waste segregation system that uses IoT technology to automate the classification and collection of waste. The system uses a camera and an AI model to recognise waste categories and a motorised mechanism to move each piece of waste into the proper bin. IoT sensors keep track of how full each bin's sending real-time updates and alerts. The goal of this waste segregation system is to cut down on manual labour boost the efficiency of waste segregation encourage recycling and help create a more sustainable future, for waste management.***
Keywords: IOT, Sensor, Artificial Intelligence, Management, Waste, Dry, Wet, Metal, Segregation.

I. INTRODUCTION

Waste management is now an environmental issue. It grows because cities expand more people live together and both homes and businesses produce waste. When we do not separate waste at the source recyclable items get mixed with food scraps and other trash. This mix makes it harder to process the waste later. Traditional waste collection relies heavily on people sorting waste by hand. This method raises the amount of work needed and puts workers in unsafe conditions Automated waste segregation systems use sensors and mechanical parts to spot and sort materials. Yet each sensor usually gives details, about a single physical trait, not a full picture of an item. For instance an inductive sensor can find metallic objects while a moisture sensor tells about how wet something is. No single sensor can trustfully identify every waste category. Artificial Intelligence AI particularly computer vision offers an approach by interpreting the visual characteristics of waste items. Multimodal vision models can analyze captured images. Provide object and material descriptions. When combined with sensor measurements these predictions can support more informed classification decisions. The Internet of Things (IoT) makes waste management better by linking sensors, controllers and monitoring platforms together. When fill-level data and waste statistics are sent to a dashboard waste management operators can watch how bins are doing and know when they need to be collected. This paper introduces a waste segregation system that uses artificial intelligence. The system includes a camera, a cloud-based vision model, physical sensors, a motorized sorting device and IoT monitoring. The main controller used is an ESP32-S3. A Python middleware connects to the Google Gemini vision API. The final decision on how to sort the waste is made by combining the AI prediction with metal detection, moisture readings how reliable the classification is and if there is space, in the bin

The main objectives of the proposed system are:

1) To identify waste items using image-based AI classification.
2) To combine predictions, with independent physical sensor measurements.
3) To automate segregation into Wet, Dry and Metal.
4) To monitor waste weight and bin fill levels.
5) To provide time operational information through an IoT dashboard.
6) To handle classifications, full bins and system faults safely.

The suggested method wants to create a real-world model for trash sorting and linked trash tracking. The idea is to build something that works in life. The goal is to make a system that can separate trash properly. Another part of the plan is to keep track of the trash using technology. This system should help manage waste. The focus is on making something that can be used in situations. The project is about creating a working example. The aim is to show how this can be done. The plan includes both sorting and monitoring. The whole thing is about improving waste management. The approach is meant to be useful and practical.

The purpose is to develop a model that can be used in life. The idea is to make a working version. The goal is to create a system that can be used in conditions. The project wants to prove that this can be done. The plan is to build something that works. The focus is on making an example. The intention is to develop a prototype that can be used. The aim is to make a functioning model. The idea is to build something that can be used in practice. The plan is to create a working version of the system. The goal is to make an example. The approach is, about making something that can be used in life.

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II. SYSTEM ARCHITECTURE

The IoT cloud platform connects to everything for remote checks. Alerts come from the notification service.
The four layers handle the automation of waste identification and segregation along with monitoring. The application layer the backend the hardware and the waste bins are included. They work together but it is not totally clear how each one fits exactly. Some parts might overlap a bit. It seems kind of complicated when you look at the whole thing.

A. User

The user reaches the system through the application layer. They can monitor overall status and manage settings as well as view waste bin status. Notifications regarding bin conditions and activities are received too. It seems straightforward but maybe not all details are included.

B. Application Layer

The application layer serves as the user-friendly interface for engaging with the smart waste management system. It includes several key modules.

- View System Status: This feature lets users monitor the current operational status of the system.
- View Bin Status: This module shows the current fill levels and conditions of different waste bins.
- Receive Notifications: Users get alerts and updates regarding bin capacity and other system activities through this feature.

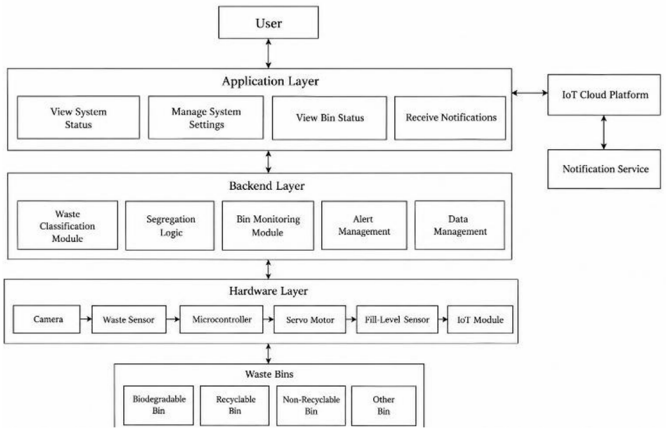


Fig.1.1.System Architectur

C. Backend Layer

The backend layer is where all the heavy lifting happens in the system. It's made up of five key modules:

- Waste Classification Module: This part takes the images of waste we've captured and uses AI to figure out what type of waste it is.
- Segregation Logic: Once we know the waste category, this module decides which bin it should go into.
- Bin Monitoring Module: This module keeps an eye on how full each waste bin is, thanks to some handy sensors.
- Alert Management: When a bin hits its set filling level, this module sends out alerts to let us know.
- Data Management: This is where we store and manage all the results from waste classification, the status of the bins, and other important system info.

D. Hardware Layer

The hardware layer is made up of physical devices that work together to automatically detect, identify, and sort waste. Here's a quick rundown of the key components:

- Camera: This captures images of the waste to help with identification and classification.
- Waste Sensor: It detects when waste is present and plays a crucial role in the detection process.
- Microcontroller: This little powerhouse processes the inputs from the sensors and manages the connected hardware.
- Servo Motor: It's responsible for moving the segregation mechanism, guiding waste into the right bin.
- Fill-Level Sensor: This measures how full each waste bin is.
- IoT Module: It connects the hardware system to the IoT Cloud Platform, enabling remote monitoring.

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Hardware Requirements

- Processing: ESP32-S3-DevKitC-1-N8R8
- Image capture: OV2640 2MP Camera
- Waste detection: LJ12A3 inductive sensor and capacitive moisture sensor
- Weight measurement: 5 kg load cell and HX711
- Distance measurement: VL53L0X ToF
- Movement and segregation: NEMA17 stepper motor, A4988 driver, MG996R servo
- Monitoring: SSD1306 OLED and active buzzer
- Power supply: 12 V SMPS and LM2596 buck converter
- Mechanical structure: PVC funnel, circular platform, three collection cups, base and mounting accessories.

E. Waste Bins

The waste bins serve as the last stop for sorted waste. According to the AI classification results, the system sorts the waste into one of three categories:

- Dry Waste Bin: This bin is for dry items like paper, cardboard, and plastic.
- Wet Waste Bin: Here, we gather biodegradable and organic materials, including food scraps, fruit peels, and vegetable leftovers.
- Metal Waste Bin: This one is designated for metallic waste, such as iron, aluminium, and other metal objects.

F. Notification Service

The notification service is designed to send out alerts to users as soon as a dustbin hits its set filling capacity or when there are significant system updates. This way, we can make sure that waste is collected on time and avoid any messy overflow situations.

III. METHODOLOGY

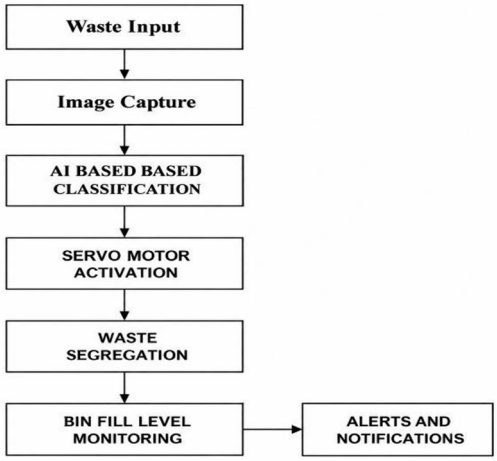


Fig.2.1. Methodology

- Waste Item Inserted Waste item inserted by user. Waste is inserted into inspection chamber.
- Waste Item Image Captured OV2640 camera takes an image of the waste. System records data from sensors (moisture, metal detection & weight).
- Waste Classification Using Gemini Vision API, Image is analysed to determine the type of waste. Sensor data is used to confirm classification (WET, DRY, METAL).
- Servo Motor Activated Depending on final classification, ESP32-S3 controls stepper motor to move correct bin into place. Servo motor actuated to open release flap.
- Waste Separation Waste is automatically separated into correct bins (WET, DRY or METAL). Manual separation is not required.

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- Bin Level Detection VL53L0X Sensors measure distance between sensor and waste in bins. This will give an indication of how full the bins are.
- Notifications Bin status and system data is sent to Blynk IoT Dashboard via Wi-Fi. Notifications are triggered when bins reach set fill limit.

IV. LITERATURE REVIEW

I find research in automated waste management. In this research sensor-based segregation, mechanical sorting, computer vision and IoT-enabled monitoring have all been studied. These methods give the base, for building integrated waste management systems.

A. Waste Separation Smart Dustbin

The base paper, Waste Separation Smart Dustbin (2020) explains a waste segregation system that uses sensors. The system uses an Arduino Mega 2560. The system uses proximity sensors. The system uses a moisture sensor. The system uses a conveyor mechanism. The system uses sensor readings to identify waste. The system uses material properties to identify waste. The design shows how sensor inputs and motor control can work together. The design shows how to automate separation. The paper also shows the need to check how each sensor works. The paper also shows the need to check the sorting system in different conditions.

B. Smart Dustbin Using IoT for Efficient Waste Management

The base paper Smart Dustbin Using IoT for Efficient Waste Management (2026) describes a waste management system that uses IoT. Smart Dustbin includes an ESP32 controller, a camera that classifies waste with AI, various physical sensors, servo-driven parts, ultrasonic sensors that check how full the bin is and a dashboard that is linked to the cloud.
I think this approach shows that Smart Dustbin can combine recognition, automatic actuation and remote monitoring all, inside one Waste Management application.

C. Sensor-Based Waste Classification

Sensor-based waste classification uses sensors to gather useful evidence about waste characteristics. Inductive sensors are good, at detecting metallic objects while moisture sensors estimate relative wetness. Weight measurements give information about items or the amount of accumulated waste. In practice sensor readings can be affected by material composition, object shape, placement, calibration and environmental conditions. Therefore sensor-based waste classification must be evaluated carefully.

D. AI-Based Waste Recognition

Computer vision can look at things. Figure out what they are made of by using pictures. Using images it can tell what kind of material something is. Image-based classification can help in finding objects like bottles, paper, food waste and cans.. Sometimes things look alike or they are not clean or they have more than one material or the light is different. All of these things can make it hard to tell what something is. So the results, from the vision models should be checked using waste samples instead of thinking that every guess is right.

E. IoT-Based Waste Monitoring

IoT-based monitoring allows the transmission of sensor data to a remote dashboard. Fill-level measurements can allow operators to assess the timing of bin collection. Such information can be stored and used to generate waste statistics and future collection planning. However, the connectivity of bins does not guarantee the segregation process's correctness and must be combined with effective processing and control logic.

F. Research Gap

The proposed system tackles these challenges head-on by creating a smart waste segregation solution that's powered by AI and connected through IoT. It employs a camera along with AI-driven image classification to sort waste into three categories: Dry Waste, Wet Waste, and Metal Waste. A microcontroller paired with a servo motor automatically directs the sorted waste into the correct bin. Plus, fill-level sensors keep a constant eye on how full each bin is, while IoT technology allows for remote monitoring and sends alerts when a bin is about to hit its filling limit.

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Expected Contribution of the Project

- Cuts down on the need for manual waste sorting.
- Automates the identification and separation of dry, wet, and metal waste.
- Combines AI-based image classification with IoT capabilities.
- Offers real-time updates on the filling levels of each bin.
- Sends alerts to help avoid overflowing bins.
- Enhances waste management efficiency and bolsters recycling efforts.

V. WORKING

A. Waste Detection and Image Acquisition

The process starts by inserting a waste item through the PVC funnel into the inspection chamber. It is placed for measurement and image capture.

An OV2640 camera linked to the ESP32-S3 captures a JPEG image of the item. This is used as the visual input for AI-based identification. The consistency of the item placement and adequate lighting are significant to avoid occlusion, reflection, and poor image quality issues that may affect the outcome of the classification.

The proposed prototype will process one item at a time. Processing multiple items on top of each other can be considered in future improvements.



Fig. 5.1. Waste

B. AI-Based Waste Classification

The process starts when a junk item is thrown into the system through the PVC funnel, the item is placed for inspection and measurement. The picture is captured by the OV2640 camera connected to the ESP32-S3 as JPEG image, used for visual identification of the item. Items should be placed in the same spot for inspection, and lighting conditions should be consistent for reliable identification. Obstruction, reflections, or low image quality might affect the results.

The proposed prototype can only identify one item at a time, multiple items can be considered for future improvements

C. Physical Sensor Measurement

The paper describes the physical sensors that can complement the visual classification. The first is the inductive metal sensor. LJ12A3 inductive sensor provides an independent indication of the compatible metallic material. When metal is detected reliably, this evidence can override a conflicting visual classification according to the configured decision rules.

The second is the moisture sensor. The capacitive moisture sensor provides a relative moisture measurement, which is compared to experimentally determined thresholds to differentiate suitable wet-waste samples from dry-waste samples. The threshold value must be determined by testing representative materials since wetness alone does not indicate whether the item is organic or recyclable.

The third is the load cell. The load cell and HX711 module measure force, which is converted into an estimated weight after calibration. The resulting measurement can be used for item-level or bin-level statistics depending on the final physical configuration.

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The last is the bin fill-level sensors. Three VL53L0X time-of-flight sensors measure the distance from each sensor to the waste surface. A small measured distance generally indicates a full bin. The distance estimate is converted into fill-level estimates using the dimensions and calibration of individual compartments.

D. Sensor-Fusion Decision-Making

Sensor fusion is the process of combining the AI classification with actual measurements taken by sensors prior to the initiation of the sorting mechanism.

Inductive sensors thus provide evidence for METAL, moisture sensors provide evidence for WET, the vision model furnishes evidence for whatever object is being classified, and weight is informative but not used as a direct classifier.

The following rules are applied:

- If reliable metal detection is performed, the controller assigns the METAL class to the detected object.
- If metal was not detected, but the AI response and (calibrated) moisture sensor reading support the possibility of wet waste, then the controller can select the WET class.
- If the detected object matches one of the supported dry-waste categories, and there is no contradictory evidence, then the controller can select the DRY class.
- If the AI response is invalid, the evidence is conflicting, or if no explicit rules apply, then the controller defaults to the UNKNOWN class.
- If one of the target collection bins is full, the corresponding sort action is blocked, and the operator is alerted.

Sensor calibration and thresholds must be established through trial and error. In cases where the evidence is inconclusive, the controller should not attempt to “force” the detected item into one of the three classes.

E. Automatic mechanical segregation

The sorting mechanism comprises a circular platform, which houses three collection compartments labelled WET, DRY and METAL.

The NEMA17 stepper motor, via the A4988 driver, rotates the platform to the intended classification location. A home microswitch provides a reference point for the controller to calibrate the machine's position.

The MG996R servo opens the release flap for the waste item to be placed in the selected bin and closes again to return the platform to the required standby state.

The system holds back waste release until movement finishes, preventing wrong segregation. If the motor, homing, or positioning fails, the machine halts. Manual intervention is required to restart it.

F. IoT Dashboard monitoring

Wi-Fi carries the ESP32-S3’s data to the Blynk IoT dashboard. You need to program that interface to track several specific metrics.

Watch the counts for WET, DRY, and METAL items. Keep an eye on the last detected object alongside its predicted classification.

The AI response and its confidence value matter too. Measured item or bin weight displays based on your sensor setup. Also monitor estimated bin fills across all three categories.

Connectivity status is key—check Wi-Fi strength, AI service availability, and overall system health.

This setup lets operators spot full bins instantly. They can review recent decisions and observe prototype performance in real-time. Set thresholds for bin fullness to trigger alerts automatically.

G. Handling of failures and UNKNOWN classification

Failure handling rules are necessary to cut down on unintended sorting and boost operational safety. If the Gemini API times out, the middleware tries one reclassification before marking the item as UNKNOWN. Camera malfunction stops auto-sorting cold. Sensors must also be flagged properly so they aren’t misread as legitimate material data.

Hit the fill level threshold for a bin? That category gets locked out. Stepper motor fails to home? Auto-sorting shuts down. Lose Wi-Fi or AI connection? Processing halts unless a tested local fallback is already in place. UNKNOWN isn't a bug. It’s a controlled stop for unclassified items, leaving room for human intervention when needed.

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H. Testing and performance evaluation

Run the system through a full battery of trials. You need a representative sample covering every intended category. Don't just use identical items. Test things with different shapes, materials, conditions, and moisture levels.

Here is what to measure.

Classification accuracy. This is the percentage of test items correctly classified against their ground-truth classification. Calculate it as: (Correct Classifications / Total Test Samples) × 100.

Segregation success rate. This tracks the percentage of test items placed in the correct collection compartment. Formula: (Items Sorted Correctly / Total Sorting Trials) × 100.

Response time. Record the duration from image capture or item detection until the item is sorted. You can also measure cycle time, which spans from insertion to successful release.

Sensor performance. Compare results against known test conditions. Check metal detection accuracy, moisture threshold response, weight measurement capability, and bin fill estimation.

IoT dashboard monitoring performance. Did the values publish correctly? Did bin fullness alerts trigger at the designated level? How did the system handle connectivity interruptions?

Present results using measured values. Include tabulated results for each category. Use a confusion matrix where applicable. These experiments will reveal the prototype's strengths and limitations.

VI. FUTURE SCOPE

The proposed system isn't locked into a single use case. It can be expanded and adapted to a variety of contexts. Right now, it sorts common waste items using computer vision and mechanical automation. That's just the baseline. Future work could explore integrating environmental sensors—like temperature and gas detectors—to handle hazardous materials with greater sophistication. We might also swap out current mechanisms for optical or laser-based techniques to boost capabilities.

Beyond the lab, this thing has legs in commercial settings. Think waste management, food sorting, quality assurance. The list goes on. Its compact design changes the game for personal use, too. Imagine sorting through piles of personal mail and bills automatically. Overall, the potential here stretches across both commercial and personal applications.

VII. ALGORITHM

This system relies on AI to sort waste using sensor fusion. It takes the waste item itself plus a captured image and pulls in sensor measurements along with the current bin status.

From there it works out the final category and picks the sorting action while also refreshing the monitoring details. I think the image part helps a lot but maybe the sensors do most of the heavy lifting in some cases. The whole thing feels a bit interconnected so it is not always clear where one step ends and the next begins.

1) Initializing the ESP32 S3 is where it begins and you include the camera sensors and OLED display right away. The communication interface and actuators come into it as well. It seems like that covers the main parts to get everything ready.
2) Moving the stepper motor to its home position is next. This gets done using the reference microswitch. I think that is how it finds the right spot but I am not totally sure if there are extra steps after that.
3) Initialize the Wi-Fi connection and AI middleware communication
4) Display SYSTEM READY when the required initialization checks are successful
5) Detect the presence of a waste item in the inspection chamber
6) Measure the available weight, moisture, and inductive sensor readings
7) Capture the waste image using the OV2640 camera
8) Transmit the image to the Python middleware
9) Send the image and classification prompt to the Gemini vision API
10) Receive and validate the structured AI response
11) If the response is invalid or unavailable after the configured retry, classify the item as UNKNOWN
12) Combine the AI output with the inductive sensor reading and calibrated moisture measurement
13) Apply the predefined sensor-fusion rules to determine WET, DRY, METAL, or UNKNOWN
14) If the result is UNKNOWN, do not perform automatic sorting; notify the operator
15) Check the fill status of the intended collection bin
16) If the bin is full, inhibit the corresponding sorting operation and generate an alert

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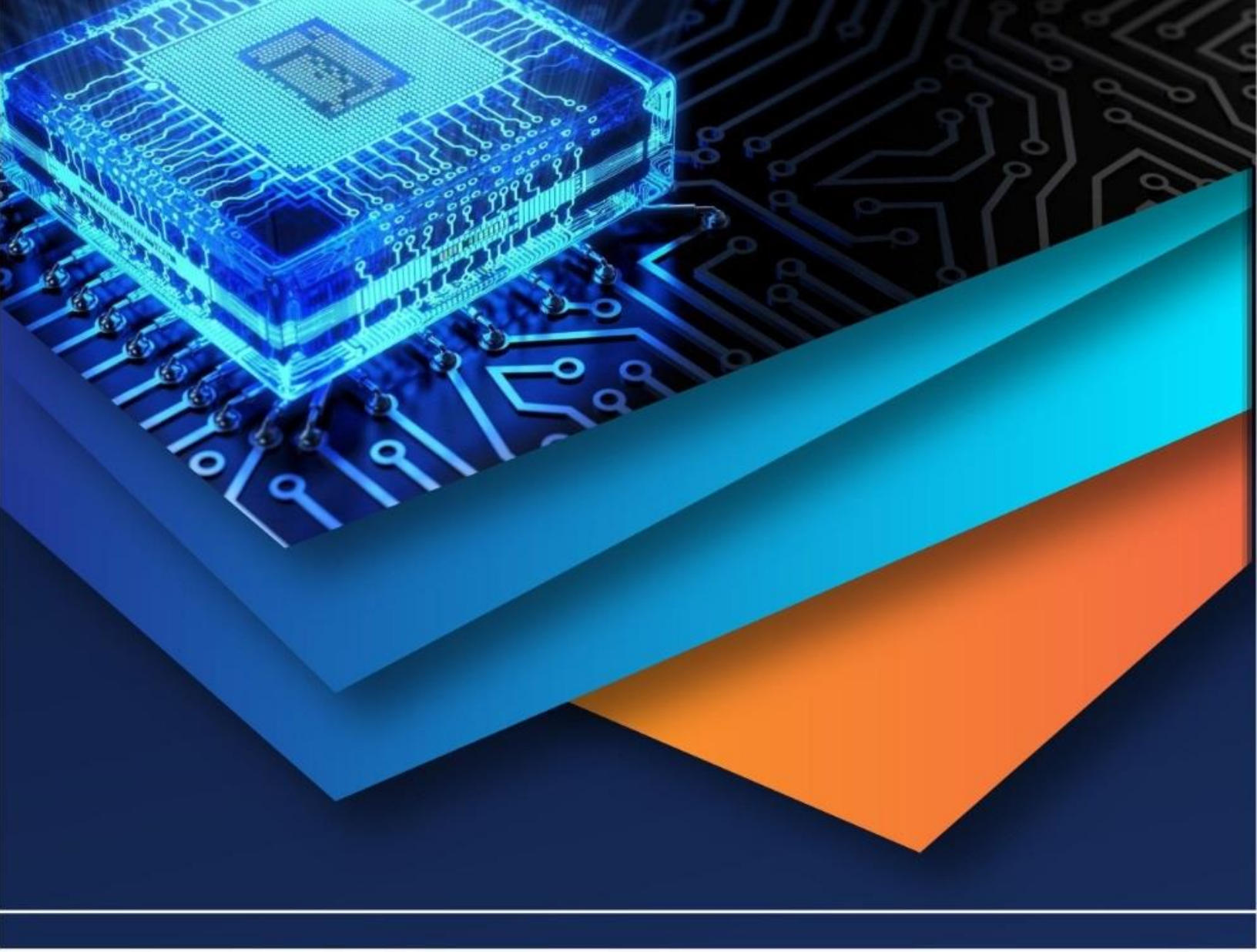
17) If the classification and bin status are valid, rotate the platform to the calibrated bin position
18) Open the release flap using the servo motor
19) Allow the item to fall into the selected compartment
20) Close the flap and return the mechanism to the standby state
21) Update the applicable item count, weight information, and bin fill-level readings
22) Publish the available measurements and system status to the IoT dashboard
23) If a critical fault occurs, stop the affected operation and display the corresponding error Return to SYSTEM READY and wait for the next item.

VIII. CONCLUSION

This paper proposes an AI-based smart waste segregation system utilizing computer vision API in the cloud, physical sensors, mechanical sorting, and internet of things. The ESP32-S3 microcontroller is used to interface the OV2640 camera to send images to the Gemini vision API through Python, and the result is combined with physical sensors such as metal detection and moisture content to sort wastes.

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