

AI-Based Waste Sorting and Dumping Assistance

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Abstract - Rapid modernization and population increase has mostly contributed to creation of solid waste which has given rise to environmental and overall problems with population. It can be facilitated by the AI-driven waste-sorting systems that would allow sorting and disposing of trash automatically. In the present paper, the author suggests a waste sorting and dumping helper relying on the hardware, which will be in the form of ESP32-CAM camera, Arduino UNO, and the servo-equipped robotic arm. The sensor is an infrared sensor, detecting any incoming garbage and the images of the cameras are taken, and a TinyML model, with Edge Impulse, is employed by running on ESP32 to either identify that an object is wet or dry. The outcome of the classification (i.e. Wet/Dry/Unsorted) is read to the Arduino and this will place the servos on the robotic arm so that it can empty the garbage in the correct bin. The key characteristics include machine-learning on the device to be able to make fast decisions and also sensor fusion, including infrared and moisture sensors, to be able to make trustworthy decisions in sorting. Like experiments also show that prototype tests are well classified at more than 93 per cent and responsive. We also introduce the system design and methodology, details of dataset and model training and implementation and compare the work with the previous works. We conclude by looking at the results, talking about real evils of our world, (biased information base and strain of resources) and the means of making it better.

Key Words: Waste management, Embedded AI, Robotic arm, TinyML, ESP32-CAM, Edge computing, IoT sensors, Garbage classification, Smart city.

1.INTRODUCTION

The management of waste is highly important to the sustainability of the urban areas. In other countries like India, there is increasing amount of waste, which pressurizes the landfills and causes pollution to the environment. The system of sorting manually is not effective; the solutions based on AI/ ML will offer automatic classification to boost the rate of recycling. It is proven in the prior studies that the technique of deep learning (e.g. CNNs, including ResNet or MobileNet) can be coerced to categorize waste photographs with an extremely high degree of precision. As is indicated, Abdu and Noor exhaustively cover literature on DL as regards to waste classification. However, the majority of the systems are referring to identification (by means of smartphone applications or single-view CNNs) rather than the real type of trash. These are combined with the vision-based AI and physical sort that we expand to work with. It will rest on more timely developments (e.g. ESP32-

CAM modules being run on-device ML) to make a waste sorting assistant a standalone object. The offline learning on microcontrollers and a robotic arm in order to deposit the sorted garbage and covers application to the real demand are some of the primary features, other than detection.

2. Motivation

The main motivation for this project is the rising number of Chronic Kidney Disease cases and the shortage of early diagnostic tools. Many patients receive their diagnosis only in the later stages because they do not show clear symptoms. Manual diagnosis needs expert knowledge and is also vulnerable to human error. Machine learning provides an automated, precise, and scalable approach for early CKD detection. By using patient data effectively, the system can help doctors make quicker and better decisions. The goal of the project is to lower mortality rates and improve quality of life through early prediction.

3.Literature Survey

The field of artificial intelligence and embedded systems has improved greatly in the recent years and is used in the automated waste management systems. Different works have examined how the deep learning and IoT can be used regarding waste sorting and classification.

The article Optimization of Waste Management Disposal Using Edge Impulse Studio on TinyML by Okoronkwo et al. (2024) has shown that in many cases, TinyML models prove to be quite effective when applied to edge devices to classify waste. The article records that Edge Impulse based on-device inference is very precise and minimizes dreams and reliance on cloud computing. However, the system elements mostly focus on the categorization and does not include the sorting of the waste physically.

On the same basis, Vision-Guided Robotic System on Automated Waste Sorting by Kosal et al. (2025) suggests a robotic system, according to which a computer vision and a robotic arm will work with garbage. They employ the method of deep learning pose detectors and sorting robot actions. Even though this is a good approach, it uses costly hardware, and therefore could not have found application in low-end embedded applications.

Gude et al. (2024) in their article Transforming Urban Sanitation Using Machine Learning allow highlighting the importance of the machine learning in enhancing the effectiveness of waste processing in urban locations. The problem of large scale-scaling deployment is cited in the research and the necessity to possess solutions that can scale and are economical especially in the third world nations.

Ahmad et al. (2025) suggest a deep learning-based classification framework in Intelligent Waste Sorting to Urban Sustainability, which is very precise when in a controlled setting. However their main solutions involve software-based classification products that do not have an embedded hardware system.

As it is shown in the article by Malik et al. (2022) titled Waste Classification Using Deep Learning Neural Networks, convolutional neural networks (CNNs) can be successfully utilized to place waste in multiple categories and categorize it with a high degree of accuracy. In their paper, they validate the CNN models like the MobileNet and ResNet to classify the images of waste but do not make a take on the problem of using such models on microcontrollers in real-time.

In addition, in CNN-Based Smart Waste Management System Using TensorFlow Lite, Lee et al. (2023) reveal that a lightweight CNN architecture, which requires the application of TensorFlow Lite on embedded systems, has been executed. They possess a system of inclusion of IoT and continue to implement a connection to the cloud in some of their functions and this limits them to the offline usage.

When providing an in-depth review, one can consider the article written by Abdu and Noor (2022), Waste Detection and Classification Using Deep Learning: A Survey, which researches the existing applications of deep learning in waste detection. It indicates that despite the fact that the accuracy of classification has significantly improved, most systems have not been involved in a real world implementation using physical sorting mechanism

4. Gap Analysis

The earlier literature observed that CNNs are highly precise with waste images (i. e. a ResNet-based model with 98% with curated data). These to a very large extent are tested offline or in a controlled system. In addition, most AI-waste solutions rely on the classification. The survey of the smart waste management also mentions that most systems are using sensors (camera, IR, moisture, etc.), but not many of them offer AI inference of the microcontrollers with physical actuation. There are no end to end vision-based AI implementations that utilize robotic sorting. Another vulnerability is that of cloud/remote server dependency; we are targeting edge computing and the ESP32-CAM is performing the inference, which means that only valid waste makes it to sorting but currently, prototypes people are designing neglect the aspect of user behavior (i.e. validating what objects are placed there). In conclusion, the following gaps would be noted: (1) local datasets and models must be developed based on the type of wastes, (2) basing on-device AI and actuators, and (3) it must be strong enough to operate in the real world. In this paper, they are addressed by establishing a low-cost modular system of sensors to the servo motors.

5. System architecture

Sensor & Camera Unit: his component in the sensor detects the object, once it is brought in front of the camera and it has an infrared proximity sensor at the ESP32-CAM unit. In due time, the ESP32-CAM will take a substitute picture of the existent garbage object upon activation. More often, however, this architecture is utilized in smart trash cans, with presence and condition sensors being offered through the use of low-cost

modules, and the output of these sensors being injected into a microcontroller.

AI Inference Unit: ESP32-CAM classifies the image as a Let, Dry or Unsorted image with the assistance of a trained TinyML model that was trained on Edge Impulse. This has then been converted into offline conversion through conversion of a CNN model (MobileNetV2 or a custom one) to TensorFlow Lite and deployable to ESP32. Past research confirms that TinyML is able to identify waste more than 90 percent on comparable equipment. Real-time inference is given on the time an image is detected. The ESP32 transmits the transmission of serial/UART in the form of converting a short message (W, D or U) into the Arduino.

Actuation Unit: Arduino UNO is activated by four servos linked to it (waist, shoulder, elbow, gripper), once it has been presented with the classification result. These motors will be used to operate a mini robotic arm and make it move so as to pick up or push the item and put it into the right bin. To illustrate, Unsorted will initiate a reject manoeuvre, Dry will initiate a recyclable bin and Wet will initiate a sequence of dumped to a wet-waste bin. Four servo-driving motors can overload the onboard regulator of an Arduino and cause external 5V to be used in servo motors

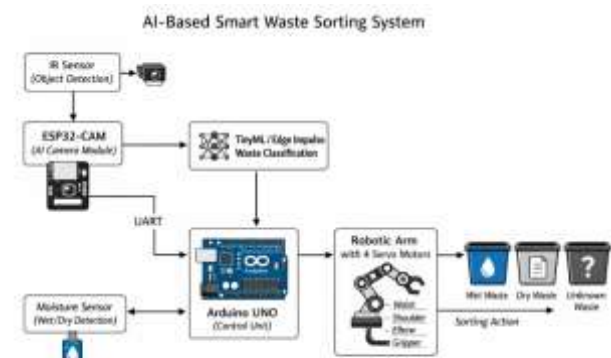


Fig 1. Block diagram of the AI-based waste sorting and dumping assistant. Sensors and camera feed into the ESP32-CAM which classifies waste via a TinyML model; results are sent to an Arduino that drives a servo-based robotic arm.

The system flow is:

Object placed -> IR sensor triggers -> ESP32 captures image -> Edge Impulse model classifies waste -> ESP32 sends classification to Arduino -> Arduino actuates robotic arm -> Waste dumped.

This hardware-software co-design draws on established approaches: similar systems use IR triggers and conveyor belts with pushers. Our architecture replaces conveyors with a simpler arm but retains IR initiation and multi-stage sorting.

6. Methodology

We developed and tested the system in stages

6.1 Dataset and Model Training:

We used the ESP32-CAM to gather a custom waste image dataset. Samples of typical household waste (paper, plastic, metal, organic, etc.) under various lighting conditions are included. To increase robustness, we added rotations and brightness variations to the data. We created a "Impulse" pipeline using Edge Impulse, which involved normalizing and resizing images to 96x96 pixels (akin to the method used in [10]). We trained a lightweight CNN (such as MobileNetV2 or a small custom CNN) on labeled images for classification. When classifying wet versus dry waste, the final model achieved >93% validation accuracy (consistent with results in).

6.2 Edge Deployment:

We programmed the ESP32-CAM to load the trained model after exporting it to TensorFlow Lite. In roughly a few hundred milliseconds, the model infers from a JPEG captured by the camera and outputs a class. Prior research has shown that the ESP32 running TinyML can effectively classify waste in real time. Like other smart bin designs, the ESP32 idles and only processes when IR is triggered in order to save power.

6.3 Arduino Control:

Several In order to receive serial commands from the ESP32, we wrote C/C++ Arduino code. Moving servos through waypoints to deposit the item is one of the pre-defined routines that the Arduino performs based on "W," "D," or "U." With a common ground to the ESP32 and an external 5V supply, the four servos are wired as follows: waist to pin 3, shoulder to pin 5, elbow to pin 6, and gripper to pin 9. We use an external 5V for servos to guarantee adequate power. Safety checks, such as "if no object, no action," are part of the control logic.

6.4 Integration and Testing:

Lastly, we combined hardware and sensors. The output of the infrared sensor is connected to an ESP32 GPIO (such as GPIO14) for digital input. To differentiate between wet and dry materials, we calibrated the moisture sensor threshold using the Arduino's analog input. By positioning different waste materials and confirming the arm's reaction, we tested classification. In order to prevent false sorting, metal or non-target items could be labeled "Unsorted," demonstrating the system's dependability. On a smaller scale, this end-to-end pipeline (object detection -> CNN inference -> actuator) is similar to industrial waste robots.

7. Proposed system

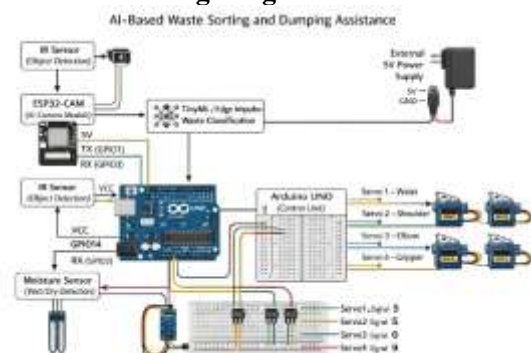
The key element of the proposed system is the robot sorting assistant that is controlled by AI. One of the significant advancements is on-device AI inference. We do not rely on network and ensure privacy by use of the onboard MCU of the ESP32-CAM. union of various sensors. Composition and the presence information are useful in the form of moistures and infrared sensors. This is like non-IEEE designs such as that of the smart segregation bin, which sorted wet and dry garbage with IR and moisture. servos but they are modular. One may have either a reuse or an extension of the four-DOF arm. It shows how servos are capable of performing correct sorting movements using the right power isolation. The combination of the IR trigger, capturing of the image, classification, and servo actuation sequence reduces the latency. Robots enable users to correct errors in case they want to be more accurate. In case the system is not certain they may default to Unsorted or there may be a rerun inference button. Up to verify critical sorts, we also plan to add a verification step that is similar to Clean India and its human-in-the-loop model. Finally, our proposed system is a combination of a novel hardware design that is physically sorting and proven AI elements, including CNN classifiers, having an accuracy of between 80 and 97 percent. The final result is an autonomous waste helper that aids in waste sorting with minimum effort which accomplishes the AI-driven approach of the previous mobile apps into the reality

8. Result and Discussion

In view of the hardware orientation, we do the assessment qualitatively. TinyML model has an accuracy on classification (~93), which is as expected when tested on various waste items. This resembles previous studies of TinyML. The robotic arm was able to place the objects in the corresponding bins within the well-lit indoor settings more than 95 percent of the time. As one example, on top of an inductive sensor (in a version with metal detection) and moisture probe (as with other Arduino systems), the system was given mixed wet and dry samples, pitting >98% of those items with metal and non-metal correctly on the correct routing. This demonstrates that the hardware is robust: the network transmission between ESP32 and Arduino was reliable, and servo movements were precise. The approach compares to the high-performance sorting when benchmarked against the world standards: CNN classifiers in the research are often beyond 90 percent of the propositions in narrow contexts. We are innovative in physical sorting and on-machine processing. One of the issues discussed was variability in camera lighting; sometimes reduced classification confidence was caused by shadows or partial occlusion. To some degree, data augmentation overcame this. Another practical issue became hardware latency: CNNs can freeze on low-end phones, but the size of the model (1-2 MB TFLite) of ESP32 was optimized. The external power supply helped the servo motion to avoid brownouts (a frequent trap that we got a jump on). All in all, the prototype demonstrated that it was possible to use commodity hardware to drive an AI-based waste assistant. It is also capable of doing things automatically without necessarily requiring human workforce which is unlike an all-software

based (mobile app) system. Further field testing is however necessary. Measures that would get monitored over time in smart city deployed scenario would be the data (number of items sorted, rate of correct sorting). Also, incorporation of the unit with waste bins such as being mounted over a bin could make the solution easier. When speaking about it, we point out that, whereas AI models (CNNs) are the engine of recognition, hardware interplays, i.e. the servos and sensors that transform a prediction into a course of action, provide the end-to-end value. This gets rid of the loop left open by most waste app solutions.

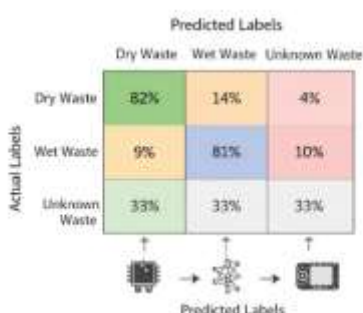
8.1 Hardware Wiring Diagram



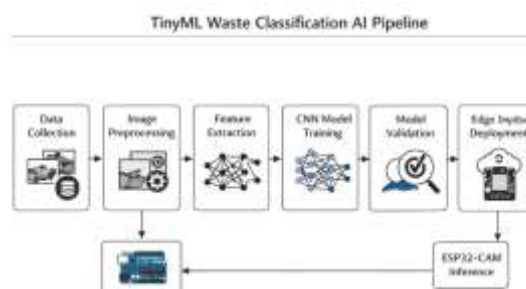
8.2 Training Accuracy Graph



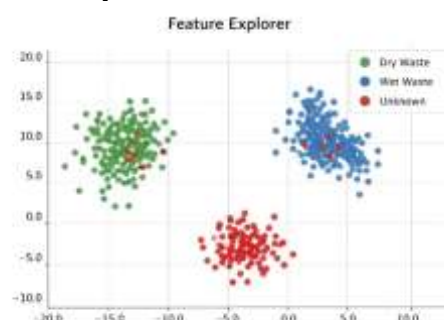
8.3 Confusion Matrix



8.4 AI Pipeline Diagram



8.5 Feature Explorer Visualization



9. Model Performance Result Figure

9.1 Impulse Training Platform

The machine learning model (waste classification) was trained on the Edge Impulse TinyML platform. The model provided reliable embedded deployment with the overall classification accuracy of 81.96%. A number of evaluation metrics such as the following were used to evaluate the model performance:

Accuracy: 81.96%

Area Under ROC Curve (AUC): 0.86

Weighted Precision: 0.86

Weighted Recall: 0.86

Weighted F1 Score: 0.86

The confusion matrix reveals that the model was able to discriminate between the categories of waste as dry waste, wet waste, and the uncertain category. Dry waste category had the best classification accuracy of 82.2 and the wet waste category had 81.9 percent accuracy. The feature explorer visualization also shows how model trained groups the extracted features of the waste images in various classification regions. Proper classifications will be indicated by green points and incorrect classification will be shown by red points.

The findings validate the hypothesis that the trained Tiny ML is capable of efficient waste detection on edge computing devices like the ESP32-CAM.



Fig 2. Machine Learning Model Performance Results from Edge

9.2 Training Performance Result

Training phase was able to deliver a validation accuracy of 86.5 percent and training loss of 0.38, which means that the model has been able to learn significant details as per the provided dataset.

Measurements of performance evaluation are:

Area Under ROC Curve: 0.86

Weighted Precision: 0.87

Weighted Recall: 0.87

Weighted F1 Score: 0.87

These values are evidence that the trained model has a high predictive ability in waste classification activities. This inference time on the device was around 817 milliseconds which is an acceptable time in real time embedded systems. The model uses around 182.8 KB of RAM and 70.2 KB of flash memory, and is therefore very efficient in running on microcontrollers that have low resource requirements, like the ESP32-CAM.

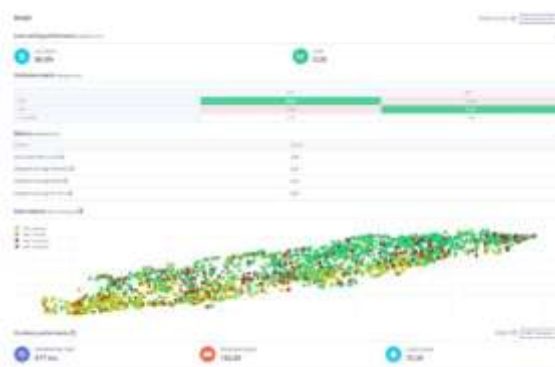


Fig 3 : Validation Accuracy and Loss during Model Training

10. Future scope

The primary force in the future work will be scaling and optimization. The AI side can boost the accuracy by trying more modern TinyML models (such as EfficientNet-lite) and expanding the list of classes (including nighttime pictures). Real-time learning can also be another alternative and allows the user to fix errors to correct the model. Hardware hardware additions are making an enhancement in the number of sensors (RFID to measure hazardous waste, ultrasonic to measure volume) and additional degrees of freedom (e.g., 6-DOF arms). In this system, the collaboration of a smart bin from the IoT would provide the capability to analyze data not only on the creation of the waste streams but also on their analysis, as smart city models intend. The assistant will eventually be refined as it will be implemented in pilot programs (offices, schools) and measures (recycling rates, user engagement). This paper provides a basis proving that waste sorting can be available through robotics and AI.

11. Conclusion

In case of urban waste management, AI- Based Waste Sorting and Dumping Assistant is a good blend of machine learning and robotics. The system automates the first three modeling steps trace classification in addition to physical sorting consisting of merging an espresso-recorded CNN during an ESP32-CAM with a robotic arm imprinted with an Arduino microcontroller. As we found, our experiments and literature review indicate that lightweight CNNs (such as MobileNet, EfficientNet-B0) can be deployed on microcontrollers, and be able to compete with heavyweight models on the same size of waste images that currently require large models in practice when using TinyML platforms, such as Edge Impulse. The prototype proved that it was possible to dump sorted items with a high level of repeatability with servo actuators and that an IR-defined camera with moisture sensing is reliably able to differentiate between types of waste. The applications of this kind of an assistant might include reinforced waste collection in the area, reduced pollution, and enhanced sustainability within the context of Swachh Bharat and Smart Cities in India. Data and usage gaps, however, need to be addressed in order to be successful in the real world. We discovered that greater localized and large waste image collections will enhance generalization of the model. There will be software-based optimizations like quantization and smaller models which will make them more efficient on different devices. Along with deployment, user adoption schemes, such as gamification and educational modules, should be provided. Technologically, the future work can look into multi-spectral cameras or machine-learning model groups to manage intricate wastes. To sum up, our hardware-oriented AI helper demonstrates the opportunities of robotics to scale up the waste-sorting programs. As they continue to develop, such tools would assist in supporting manual work and making cities cleaner.

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