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Smart Waste Segregation System: Proximity-Triggered Waste Classification Using Convolutional Neural Networks

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Abstract—The rapid increase in the amount of waste produced by human societies has led to the urgent need for proper waste management so as to curtail risks to both health and the environment. The infrastructure facilities and public awareness are a prerequisite for effective automation, still are often neglected. This paper introduces a Smart Waste Segregation System (SWS) aimed at increasing efficiency in managing waste by automating its classification and disposal activities. The Arduino microcontroller is used in this system along with an OV7670 camera and an ultrasonic sensor for accurate contactless classification and disposal of waste into different categories. When waste is placed on a designated flap, the image is captured by an OV7670 camera. The image is subsequently analysed by a deep learning model trained on a diverse dataset containing images of various category waste items. Based on the model's classification, the waste can be disposed in the appropriate bin.

Index Terms—Automated waste segregation, deep learning, Arduino microcontroller, OV7670 camera, ultrasonic sensor, image classification, EfficientNetB0, CNN model.

I. INTRODUCTION

The rapidly growing volume of waste generated globally has stressed the urgent need for efficient and effective waste management practices. Management of waste has become a critical challenge for municipal corporations and environmental agencies. Further, improper waste management practices pose significant risks to public health and the environment, and also serve as an obstacle to achieving sustainable development goals. Segregating waste into different stacks, such as recyclables, organic garbage, and plastics, is a critical component of proper waste segregation. This process not only reduces environmental pollution but also saves resources and minimizes health risks associated with improper waste disposal. Due to these reasons, developing an innovative solution for waste segregation is imperative. Hence, SWS is designed to automate and streamline the waste classification process using advanced technologies, such as deep learning and sensor-based systems.

The initial approach was based on a hardware system relying on Arduino Uno microcontroller to coordinate and manage the system's functions. Ultrasonic sensors were integrated to measure dustbin levels, while a moisture sensor aided in identifying and segregating waste as either dry or wet. A servomotor facilitated the tilting of a flap dedicated for waste disposal.

However, this hardware-based approach had its limitations. For example, the categorization of wet waste was simply based on moisture content, which led to inaccuracies, resulting in classification of non-biodegradable wet plastics as wet waste. On the other hand, certain types of dry household waste, such as fruit and vegetable peels, were incorrectly disposed as dry waste despite their biodegradable nature.

The proposed approach builds upon the initial hardware-based system and tries to overcome prior encountered limitations by integrating advanced technologies for more accurate waste segregation. An Arduino Uno microcontroller continues to manage the system, ensuring smooth operation. The ultrasonic sensor detects the user's hand movement close to the bin, triggering the waste classification process. One of the most noteworthy upgrades in this system is the incorporation of an OV7670 camera for image capture. When a disposal signal is detected, the camera captures an image of the waste, which is then transmitted and stored on a server. This image data is crucial for the waste classification process that follows.

This method is a huge advancement in the domain of waste segregation. Instead of relying only on hardware-based sensors to classify waste, this system leverages the power of deep learning algorithms. The system incorporates EfficientNetB0, a powerful Convolutional Neural Network (CNN) architecture, to analyse captured waste images. This integration of deep learning model enables the system to address the flaws of the hardware-based approach, like inaccuracies in classifying wet waste and misclassification of biodegradable dry waste.

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II. LITERATURE REVIEW

In [1], authors developed a smart waste bin and named it Automated Teller Dustbin. In this, an object recognition and detection model for classifying garbage items was implemented using an AlexNET based on CNN by training it with a dataset of 20 images for each of the 10 categorized objects. But the drawback is that training the CNN model on only 20 images per object category might be too small for high accuracy and generalizability since it may not capture appearance variability of waste items in size, shape, and orientation.

Paper [2] introduces an automated waste segregation and management system for households, utilizing an Arduino microcontroller and Raspberry Pi. The system includes sensors for moisture and metal detection, segregation bins, and a camera for image analysis. However, the accuracy and reliability of sensors can be affected by environmental conditions, and sensor quality. Moreover, moisture sensors and metal detectors may not always correctly identify waste types, leading to incorrect segregation.

[3] involved creating a system that uses an RLC metal detector circuit to identify and separate metallic waste from non-metallic garbage. Two compartments make up the waste bin, and the method of classification depends on how an object affects the coil's inductance when it gets close to it. A plate tilts toward one side of the bin partition when it comes into contact with metallic waste, which is detected by large variations in inductance. An Arduino microcontroller with Wi-Fi connectivity and a 9V battery was used to power this device. However, the system only segregates metallic waste from non-metallic garbage.

In [4], the "Automatic Waste Segregator" system sorts waste into metal, dry, and wet categories using sensors and mechanisms like flaps and blowers. Moisture and IR sensors are used to distinguish between dry and wet waste, the system also detects and separates metallic waste, and alerts when garbage tanks are full. Hardware includes ARM LPC2148, sensors, motors, and a GSM module, with software requirements in Embedded C and Kiel M vision.

The paper in [5] utilizes a PIC16F877A microcontroller for its versatility and flash memory technology. A GSM modem enables wireless communication, while an IR sensor detects objects via infrared transmission. An LCD display shows data output, and gas and rain sensors monitor hazardous gases and rainfall, respectively. A kit breaker sends alerts for maintenance issues, ensuring operational efficiency.

The waste segregation process in [6] involves setting up a conveyor system with an integrated camera for image analysis. Develop image processing software to identify waste types, control conveyor movement based on sensor signals, and parameters of systems are tuned appropriately for high accuracy.

The paper [7] details the design and development of a smart trash bin prototype aimed at improving municipal solid waste management. The proposed system integrates various sensors, including level detection sensors and GPS modules, to monitor bin status and optimize waste collection routes. The smart bin features a communication interface that sends real time data to a central management system, allowing for efficient scheduling and reducing unnecessary collection trips. This approach seeks to make waste management more efficient and cut down on management costs. However, its success depends heavily on how well the sensors and communication network function, which can affect how smoothly the system runs, especially in different urban environments.

The paper [8] introduces to the realization of a smart waste management system through the use of IoT to enhance efficiency in waste collection. This involves the placement of sensors in bins to monitor fill level by height and send this information instantaneously to a central system. As bins get filled up, notifications are transmitted for proper timing in collecting them as well as for route optimization, reducing unworthy traveling. The developed system was perceived to help cut costs and increase the orderliness of cities and offer better-informed decisions in managing waste. However, sensor reliability and network infrastructure may be significant problems that are more acute in different urban settings.

The authors in [9] propose a smart waste management system to realize effective and environmentally friendly waste segregation and collection by automatically categorizing the waste into groups such as biodegradable, recyclable, and nonrecyclable through sensors using machine learning and IoT. If it utilizes image processing and deep learning technology to attain very high levels of accuracy in garbage sorting, then this is what makes proper waste stream management possible. Such real-time data from the system leads to optimal collection routes where unnecessary trips are reduced thus cutting on the costs. The authors pay attention to how this solution can improve urban sanitation on the grounds of sustainability principles but at the same have raised issues related to technological solutions regarding absorption capacity toward them being highly advanced and also questioned scalability for megacities.

The paper [10] discusses an IoT-based smart dustbin management system for reducing manual work and to maintain cleanliness in cities. The system uses an IoT based sensor in the bins to detect the garbage level. The information collected by the systems is passed on to optimization algorithms of waste collection routes so that time and efficiency are observed with a reduction in unnecessary trip collections as well. These sensors provide real-time information regarding fill levels from bins across a centralized platform or system. It also applies various machine learning models for estimating the trend in accumulating waste so that actions could be taken much earlier based on prediction rather than waiting until when it happens. The review portrayed great potential for improving productivity, lowering expenses, and decreasing environmental footprints connected with such technologies but mentioned that issues like network reliability, as well as sensor accuracy, were valid constraints felt under different conditions for which performance systems strongly influence them.

The paper [11] presents an ANN-based integrated feature data of automated waste sorting and recycling classification system for urban management to enhance productivity. Many data features, such as visual and sensor inputs, are integrated by the system to increase the accuracy of waste classification. The combination supports enhanced ways of sorting and recycling waste so as to meet the circular economy goals in urban areas. As digital technologies help optimize these processes, they also decrease operational costs and improve sustainability within smart cities. The authors explore its application from a practical standpoint for achieving efficient waste recycling and resource recovery.

The paper [12] explains deep learning methods for object detection. It examines how Convolutional Neural Networks (CNNs) and Vision Transformers have been used in this context. The authors discuss the evolution of these techniques, comparing the ability of CNN to extract features with Vision Transformers ability to communicate globally through self-attention mechanisms. They also highlight the progress that has been made in designs that combine both CNNs and Transformer architectures to leverage on their respective strengths. It should be noted that the importance of Vision Transformers in improving detection accuracy and efficiency is increasing.

The paper [13] presents an advanced deep learning-based object detection system designed to improve accuracy and efficiency in image analysis. The system aims to enhance accuracy and efficiency in image analysis by optimizing feature extraction and neural network architectures. Their approach incorporates advanced techniques to address challenges such as detecting small objects and handling various backgrounds. The system illustrates notable improvements in detecting speed and precision compared to existing methods, making it suitable for real-time surveillance and industrial quality control applications.

The literature review highlights the important developments as well as the continuous challenges faced by automated waste segregation systems. Various approaches, from microcontroller-based systems to machine learning models, have demonstrated the potential for efficient waste management. However, limitations such as the inability to handle certain waste types and the need for frequent maintenance underscore the necessity for further innovation. The project uses ultrasonic sensors for contactless disposal, OV7670 cameras for image capture, Arduino microcontrollers for control, and a deep learning model (EfficientNetB0 CNN) for precise waste classification to overcome these difficulties. This integrated strategy seeks to improve on the shortcomings of previous systems in waste management.

III. PROPOSED METHODOLOGY

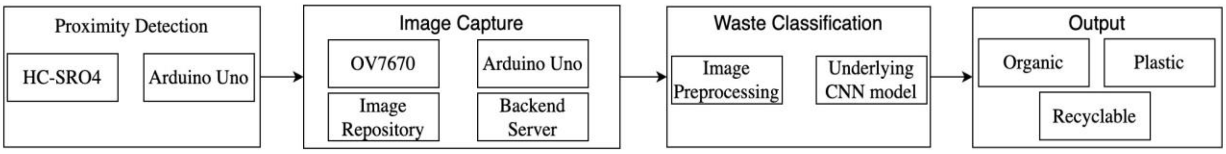

Fig. 1. Proposed Methodology

A. Proximity Detection

1. Ultrasonic sensor HC-SRO4

The HC-SR04 ultrasonic sensor module is a widely used distance-measuring device that operates by utilizing the ultrasonic waves' echo time. It is made up of a receiver and a transmitter. The sensor emits ultrasonic waves that bounce off nearby objects and then return to the receiver. On measuring the time, it takes for the waves to return, the sensor is equipped to calculate the distance to the object. When a user approaches, the HC-SR04 ultrasonic sensor senses their presence and activates the camera module to capture an image for contactless waste disposal. This ensures convenience and hygiene. Additionally, the bin's fill levels may also be tracked using this module.

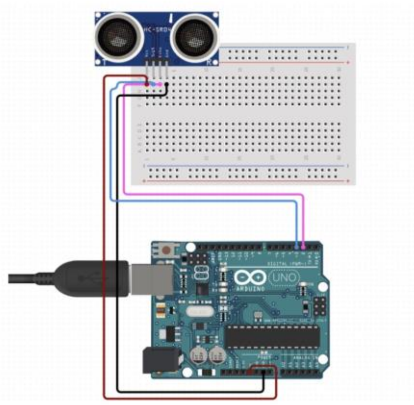

Fig. 2. Ultrasonic sensor HC-SRO4 connection

2. Arduino Uno Microcontroller

Based on the ATmega328P microcontroller, the Arduino Uno is a popular microcontroller board. It has six analog inputs, a 16 MHz quartz crystal, 14 digital input/output pins (six of which can be used as PWM outputs), a USB port, a power jack, an ICSP header, and a reset button. It is renowned for being straightforward and simple to use, which makes it an ideal choice for beginners as well as professionals working on electronics projects.

In SWS, signals from the OV7670 camera and the ultrasonic sensor are received by the Arduino Uno, which is then responsible for controlling the system. It processes these signals to manage the waste segregation tasks efficiently.

B. Image Capture

1. OV7670 Camera

The camera module can be easily connected to other hardware devices due to its low cost. It is suitable for image

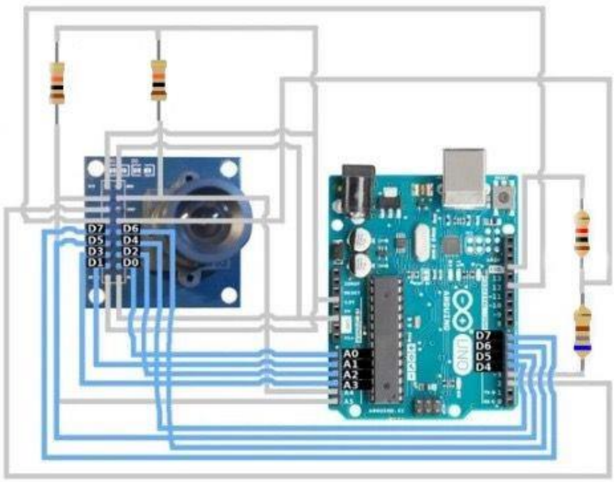

Fig. 3. OV7670 camera connection

processing applications and also interfaces well with microcontrollers. The module supports the connection to other hardware devices through its multiple pins. The camera module can successfully link with other hardware components via its several pins for power, ground, data transfer, and control signals. The primary pins include power (VCC), ground (GND), and several data and control pins (SIOC, SIOD, VSYNC, HREF, PCLK, XCLK, and D0-D7) for communication and synchronization.

The OV7670 camera captures images by connecting to an Arduino-based system. The camera's internal settings are configured using setup routines, which also determine important details for taking pictures, like color format and image resolution. After the setup is complete, the camera begins taking pictures, changing light into electric signals and then into digital image data.

The Arduino setup initializes the OV7670 camera and any linked displays, and it also sets the system's clock rates if necessary. The processFrame() function manages the primary image capture procedure inside the program loop. The way this function behaves depends on the setup parameters, such as pixel-by-pixel processing or buffered processing. When the camera is set to buffer mode, the code reads lines from the camera and displays them on the screen during blank lines. Once the camera is set to pixel mode, data is processed pixel by pixel, with each pixel reading loop delivering data to the screen. Through the collaborative approach, hardware and software components are seamlessly integrated, enabling continuous image capture and presentation on connected output devices.

2. Arduino Uno Microcontroller

Besides managing proximity detection, the Arduino Uno regulates the OV7670 camera, ensuring timely and precise image capture. The Arduino transmits the image data to the image repository after capturing the image.

3. Image Repository

The captured images are stored in a designated image repository, where they are temporarily held before being processed for waste classification. The repository ensures that the latest image is readily available for analysis by the backend server.

4. Backend Server

The backend server gets signals from the Arduino Uno, fetches the most recent image from the repository, and processes it with a pre-trained Convolutional Neural Network model. The server categorizes the waste based on the image data, and the classification results are forwarded for further processing.

C. Waste Classification

1. Image Preprocessing

Images are preprocessed before being fed into the CNN model. During this stage, they are resized to a standard resolution of 180x180 pixels, which enhances efficiency and consistency in classification. Additionally, normalizing pixel values through re-scaling ensures that the image data falls within the suitable range for the model.

2. Underlying CNN Model

The processed images are given to a CNN (Convolutional Neural Network) model, specifically EfficientNetB0, which has been optimized for this classification task. This model utilizes pre-trained weights from ImageNet to categorize the images into one of nine waste types. Leveraging its deep learning architecture, the CNN effectively determines the type of waste by extracting and analyzing details from the images.

D. Output

The waste classification model organizes waste into nine specific categories: Aluminium, Carton, Glass, Organic Waste, Plastics, Paper and Cardboard, Other Plastic, Textiles, and Wood. These categories are further consolidated into three main groups: Plastic, Organic, and Recyclable. The strategy includes utilizing a servomotor to align the correct bin beneath the flap, ensuring proper waste disposal. This approach seeks to enhance the efficiency and precision of waste management, resulting in a more automated disposal process.

IV. EXPERIMENTATION

1. Description of Dataset

The dataset [14] used for this project includes images sorted into nine categories: Aluminium, Carton, Glass, Organic Waste, Plastics, Paper and Cardboard, Other Plastic, Textiles, and Wood. To maintain consistency in input dimensions for the model, each image is resized to 180x180 pixels. Figure 4 offers a visual representation of some images from the dataset, showcasing the variety of waste types included.

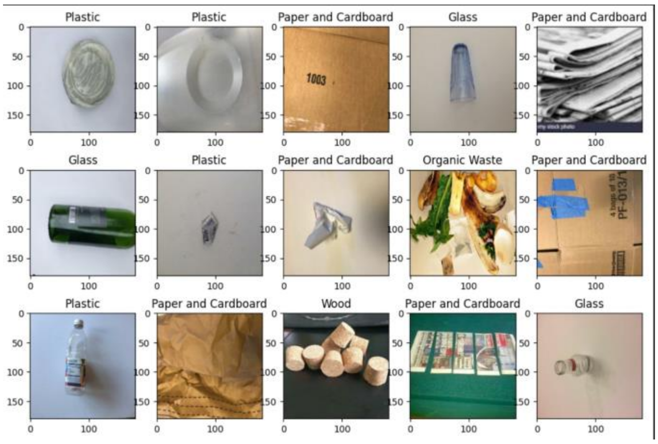

Fig. 4. Training dataset

2. Data Pre-processing

In the data preprocessing step, the images are rescaled to normalize their pixel values from the original range of 0-255 to a range of 0-1. Normalizing the input data ensures that the neural network's learning process is not adversely affected by any single input during training, thus allowing the network to gain more convergence during training. Additionally, TensorFlow's data augmentation techniques, such as random flip, random rotation, random shear, and random zoom, are applied to enhance the dataset's quality. The image augmentation techniques create different versions of the training data.

This expansion of the dataset diversity helps improve the model's robustness and its capacity to perform well on previously unseen data. By exposing the model to various scenarios that it may encounter in the real world, this technique leads to more accurate and reliable results.

3. CNN Model Development

EfficientNetB0 is a type of convolutional neural network (CNN) that has gained popularity due to its efficiency in terms of model size and computation. Its efficiency is achieved through a method called compound scaling, which balances depth, width, and resolution scaling to improve performance without significantly increasing computational costs. To manage the size of the model, it introduces a compound coefficient called phi (Φ), with larger and more powerful models being associated with higher values of Φ. The architecture incorporates MobileNetV2 blocks, depth-wise separable convolutions, and squeeze-and-excitation blocks to efficiently extract and represent features.

This is loaded with pre-trained weights from ImageNet, a large-scale dataset commonly used for image classification tasks. The input shape is set to (180, 180, 3) to match the size of the images in the dataset. The top layer of the model is dropped to exclude the top classification layers of the pretrained model, enabling the addition of custom layers tailored to the classification task.

Further the layers of the pre-trained EfficientNetB0 model are frozen so that they are not updated during training. This is often done to leverage the knowledge learned from ImageNet while fine-tuning the model for a specific task.

The Sequential model is then defined, consisting of the pre-trained EfficientNetB0 model, a GlobalAveragePooling2D layer to reduce spatial dimensions, Dense layers with a swish activation function, Dropout layers to reduce overfitting, and finally, an output layer with 9 units (corresponding to each category in the dataset) and a softmax activation function for multi-class classification.

After training, the model achieved a training accuracy of 98.65% and a validation accuracy of 91.65%. This indicates strong performance in classifying the images into their respective categories. Figure 5 depicts the classification report for model performance insights.

Classification Report:

	precision	recall	f1-score	support
0	0.98	1.00	0.99	631
1	1.00	1.00	1.00	263
2	1.00	0.98	0.99	703
3	1.00	1.00	1.00	154
4	0.98	1.00	0.99	282
5	1.00	0.99	1.00	1090
6	0.99	0.99	0.99	404
7	1.00	1.00	1.00	253
8	1.00	1.00	1.00	283
accuracy			0.99	4063
macro avg	0.99	1.00	1.00	4063
weighted avg	0.99	0.99	0.99	4063

Fig. 5. Classification Report - Training dataset

Finally, a backend server is developed for real-time waste classification functions by leveraging a Flask framework in Python and the trained model for image classification. Upon receiving a signal indicating the user's proximity through the COM port, the server retrieves the latest image from the image repository where the camera stores captured images. This image is then analysed using the trained model for waste classification. The model predicts the category of waste in the image, which is mapped to one of the predefined classes such as organic, plastic, or recyclable.

V. RESULTS

TABLE I

CLASSIFICATION RESULTS FOR TEST CASES

Image	True Category	Classified As / (%)	Misclassified As / (%)
	Recyclable	Recyclable (90.00%)	Plastic (4.00%)
	Organic	Organic (89.29%)	Recyclable (5.36%)
	Plastic	Plastic (95.74%)	Organic (2.13%)
	Plastic	Plastic (95.74%)	Recyclable (4.26%)
	Recyclable	Recyclable (90.00%)	Plastic (4.00%)
	Organic	Organic (89.29%)	Recyclable (5.36%)

To guarantee the SWS' correctness and resilience, a series of comprehensive test cases were created and run. These test cases were created to evaluate key features of the system, such as its overall reliability, input responsiveness, and accuracy in classifying different kinds of waste products. A wide range of parameters were included in the test scenarios, such as the composition of different waste materials, lighting conditions, and distances between the waste and the sensors. The project team carried out very many tests for finding possible trouble spots to weed out inefficiency in SWS.

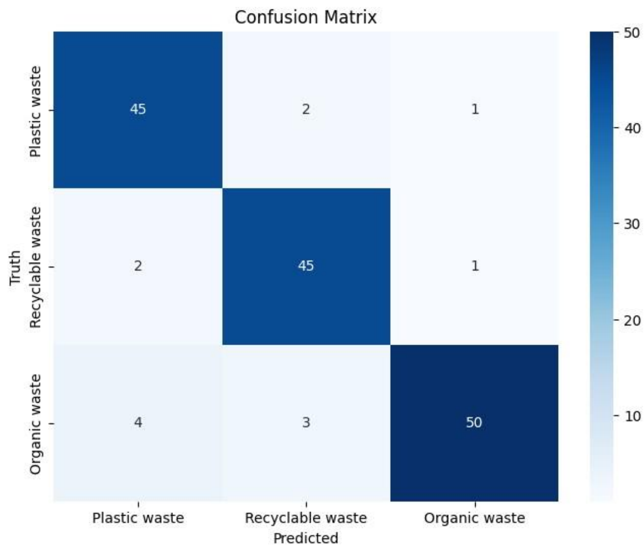

Fig. 6. Confusion Matrix - Test cases

The confusion matrix in Figure 6 helps to understand where this classification model does well or poorly by providing insights into specific areas that it does well or struggles with. It included various test cases classifying waste into three categories: Plastic waste, Recyclable waste, and Organic waste. Some examples of these test cases include Paper, Banana, Organic waste in plastic, Plastic wrappers, Medicinal waste, and Organic waste. The matrix shows that 'Plastic waste' was correctly predicted 45 times but had minor misclassifications into 'Recyclable waste' (2 times) and 'Organic waste' (1 times). 'Recyclable waste' was correctly predicted 45 times, with 2 instances misclassified as 'Plastic waste' and 1 as 'Organic waste'. 'Organic waste' was correctly predicted 50 times but was misclassified as 'Plastic waste' (4 times) and 'Recyclable waste' (3 times).

This confusion matrix explains the capability of the model to differentiate various types of waste and would provide where it mostly errs giving insights into specific instances where misclassifications occur and guiding further improvements.

The confusion matrix above also illustrates that the waste products are misclassified as organic waste with a very low frequency. This is crucial as maintaining the purity of organic waste is a primary goal of our system, ensuring that it remains uncontaminated and suitable for composting or other organic recycling processes.

VI.CONCLUSION

SWS has managed to present a system where solid waste management can be done using advanced hardware and software technologies. The implementation is with the OV7670 camera, HC-SR04 ultrasonic sensor, and robust backend server in real-time classification of the waste, with particular attention to identifying organic waste— which is very important for effective segregation of waste and environmental sustainability. SWS applies pre-trained EfficientNetB0 and data augmentation techniques for high accuracy in classifying the waste into organic, plastic, and recyclable materials; this ensures their proper disposal and helps to enhance general waste management.

The proper sorting of organic waste enhances not only the management of solid waste but also paves the way for prospective use, such as composting or generating biogas. This feature shows how SWS can be instrumental in helping to keep our environment healthy. It is an excellent demonstration of the possibility of using smart and effective solutions to solve common problems. The technology creates a precedent that calls for subsequent scientific work, which may give rise to more sophisticated means of waste management, applicable on a broad basis in homes as well as industries.

VII. FUTURE SCOPE

The future development of the SWS system aims to improve its efficiency and scalability by incorporating a camera, a servo motor-driven partitioner board, and a conveyor belt with a periodic nozzle for automated sorting. This setup enables the camera to identify and sort waste as it moves along the conveyor belt, with the partitioner board directing it into the appropriate compartment. This automated process increases both the speed and accuracy of waste segregation, making the system scalable for larger facilities like industrial sites and recycling centres. Additionally, the system will integrate advanced sensors for improved classification and smart bins with IoT capabilities for real-time waste management data. By expanding the range of waste categories the system can handle, including more complex materials, SWS is intended to contribute to a more sustainable waste management ecosystem by reducing manual labour, lowering operational costs, and enhancing overall efficiency.

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