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A Technique Using Machine Learning to Anticipate and Differentiate Between Biodegradable and Non-Biodegradable Waste

Menaka. S[1], A. Gayathri[2]
[1]Research Scholar, Institute of Computer Science and Engineering,
Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences (SIMATS),
Chennai, India.
phdsm2020@gmail.com
[2]Professor, Institute of Computer Science and Engineering,
Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences (SIMATS),
Chennai, India.
gayathribala.sse@saveetha.com

Abstract—Urban waste has become a significant issue for planners due to the challenges of identifying and disposing of it. The rise in urban populations has resulted in a corresponding increase in waste and garbage. To address this issue, in this study, the researchers introduce a concrete approach that utilizes a Deep Learning (DL) framework to perform waste sorting at its basic level. In contrast to recognizing objects of a specific category, waste can have various characteristics such as color, shape, material or size making it challenging to detect. To overcome this, the authors proposed a material-based deep learning model called Smart-Bin, which employs an Improved Faster Recurrent Convolution Neural Network (IFRCNN) approach to differentiate between biodegradable and non-biodegradable waste. The aim of this study is to evaluate the performance of various IFRCNN models such as AlexNet, ResNet, InceptionNet, and VGG-16 together with the hardware system implemented for waste classification within the bin, the suggested technique demonstrated superior performance compared to other models. The InceptionNet Neural Network achieved remarkable precision rates of 98.15% and a training dataset loss of 0.10, while achieving 96.23% precision and a loss of 0.13 for the validation dataset.

Keywords-Biodegradable, Deep Learning, InceptionNet, Garbage, ResNet

I. INTRODUCTION

Cities are increasingly recognizing the drawbacks of traditional waste collection methods, and there is a growing need for intelligent waste management systems. To effectively manage waste, mitigate environmental pollution, and ensure public safety are paramount objectives. While the intelligent tracking system can oversee overall waste volume, it lacks the ability to distinguish between biodegradable and non-biodegradable waste. Biodegradable waste, encompassing natural waste, edible leftovers, and kitchen refuse, holds potential as agricultural fertilizer. However, inadequate decomposition could harm the ecosystem. On the other hand, non-biodegradable waste, including food packaging, plastics, face masks, polyethylene covers, and metals, poses the risk of chronic illnesses and environmental damage, potentially leading to chronic diseases and environmental degradation. Waste can be categorized into domestic, medical, and commercial waste categories. Mismanagement of waste can pose threats to all life forms, contaminating air, water, and soil. This jeopardizes the well-being of individuals with serious health conditions.

Chennai, home to a large population with a growing influx of residents, generates over 3,200 tonnes of waste annually. The city relies on two landfills, Kodungaiyur and Pallikaranai, for waste management. Unfortunately, many of these sites lack proper waste management systems, leading to manual garbage burning and the release of harmful emissions, including carbon dioxide and greenhouse gases. Consequently, air pollution affects the ecosystem. By segregating waste into biodegradable and non-biodegradable categories, a practice often done manually, recycling processes can be mechanized for materials like plastics, paper waste, biodegradable substances and metal. A recommended approach based on the smart bin initiative involves automated waste separation into compound waste, wet waste, and metal waste. IOT devices equipped with ultrasonic sensors interact with authorities via GSM communication to manage waste collection efficiently. Cutting-edge algorithms, such as single-layer CNNs, rapidly identify materials within images. In parallel, IoT devices discern waste type and quantity, enabling diverse environmental applications, including biological factors, vegetation, monitoring greenhouse gas levels and other pollution.

II. RELATED WORK

As per reference [7], the most rapid algorithms for material identification in images leverage a single-layer CNN. When compared to Faster R-CNN and YOLO, SSD achieves higher overall accuracy on average within the Pascal VOC 2007 format. For instance, it achieves results like 71.07% for chairs, 97.76% for people, and 99.76% for vehicles. Another study [8] exhibited a pre-training system utilizing a SSD that adeptly differentiated between cars and humans in a live webcam stream. This study also experimented with diverse techniques for object identification via OpenCV and assessed the effectiveness of SSD employing the Caffe framework.Source [9] presents an alternative to RetinaNet, utilizing the COCO database and reducing FLOPs by 10-20% in the SpineNet architecture. SpineNet 190 achieved an AP score of 52.1% on the Mask R-CNN sensor and an AP score of 52.5% on the RetinaNet sensor for COCO, employing a unified design with testing time augmentation. YOLO V3 was harnessed in a separate study to detect both RGB and thermal images of chili harvests, delivering high-precision support for robotic inspection. An enhancement to the traditional non-maximum suppression technique, SoftNMS, was introduced to enhance the Pascal VOC 2007 and shared COCO dataset [10]. SoftNMS employs continuous functions to tackle the challenge of declining element detection rates.A waste management system rooted in IoT and ultrasonic sensors was proposed in [11]. This system gauges the trash volume in bins and employs GSM to alert authorities when bins are full. Another study utilized (DBSCAN) Density-Based Spatial Clustering of Applications with Noise and K-Means segmentation to identify submerged humans in underwater sonar visual data.Addressing the central issue, the unsupervised learning segmentation technique revolves around discerning consistent datasets of diverse classes within a database. Enhanced K-Means can effectively categorize identified group types [12]. The most intricate aspect of object detection is singling out a specific object amid others in an image. Researchers in [13] endeavor to uncover reliable, swift, and efficient object detection methods.

DESCRIPTIONS	NON-BIODEGRADABLE WASTE				BIODEGRADABLE WASTE			
CATEGORIES	METAL	PLASTIC	GLASS	SIMILAR	PAPERS	SYNTHETIC	BOARDS	PIC COUNT
PIC.COUNT	1552	1300	1354	540	1232	1940	1802	9720
%	17.2	16.14	11.5	4.2	14.3	19.34	17.33	

TABLE I. DETAILS ABOUT THE DATASETS

Within Indonesia, a network integrating physical and digital components has been employed to enact a clever waste management program that provides information to waste collectors about bin statuses and guides them on necessary actions [14]. Personal layer-generated features in CNNs are believed to significantly aid small object detection. Proposals such as VGG16 aimed to expedite R-CNN for recognition and multi-object identification.Modeling building information and SSD were employed to evaluate architectural quality, encompassing tasks like detecting wall edges or corners and identifying structural flaws [15]. To boost computational speed, SSD proposed real-time object identification devoid of a CNN.In the realm of real-time video recording systems, webcam coding standards were pivotal in enhancing image quality [16]. Performance evaluation of video object planes based on MPEG-4 encoding standards depended on the chosen approach [17]. Swift object movements between frames posed challenges in reliable identification, which could be mitigated through a combination of spatial image division and entropy-based frame variation detection.An unmanned aerial surveillance vehicle was deployed for spotting patches on train tracks. Employing the SSD technique, damaged railroads and track demarcation issues were successfully identified. A robot was employed to extract unordered objects from containers using sensor inputs, addressing object classification complexities. Previous research findings have shown that passive infrared sensors have not been fully substituted by self-governing computer vision systems. Despite the utilization of the YOLO V3 algorithm for identifying chili crops, its capability was limited to recognizing only one object in each frame. The novel approach presented in this study introduces a real-time video technique for identifying diverse objects and differentiate between biodegradable and non-biodegradable waste within bins.

III. COLLECTION OF DATA

The data employed is sourced from three distinct origins. The initial source is a collection named "trashnet," within it, images are categorized into five distinct groups: paper, glass, metal, cardboard, and plastic. The second source entails data on waste classification, including images of both recyclable and organic items. Additionally, this source features images depicting different forms of beverage waste, such as glass,High Density Polyethylene (HDPE),aluminum-cans and Polyethylene Terephthalate (PET). These images boast high resolutions and were captured against neutral white backgrounds to minimize interference from extraneous objects. The database is divided into 7 category, with cardboard, organic waste, and paper waste constituting 52% of the content,plastic,metals and white glass make up the remaining 48% of the non-biodegradable elements. For visual depiction, refer to Figure 1: A map of the database

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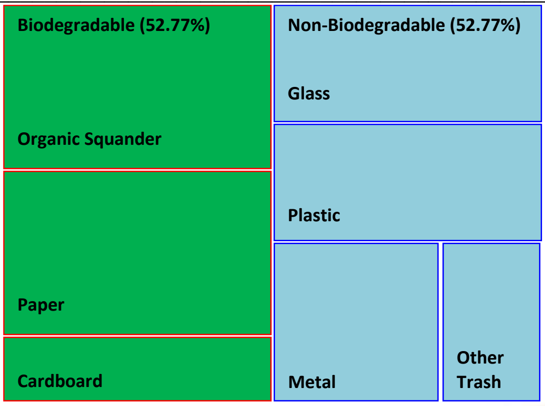

Figure 1. A map of the database

IV. SYSTEM DESIGN

The proposed solution to sort waste into non-biodegradable and biodegradable portions using image classification is called the Smart-Bin.It employs a revolving a detachable disk that disengages from the motor and is supported by a motor-mounted axle [22]. Presently, this technology is configured to segregate distinguishing one item from another. However, implementing this paradigm would aid in identifying and addressing the issue of segregating waste with multiple entities. Table 2 presents an estimated cost for installing the proposed solution at testing environment and in the ground level.

S.No	SUGGESTED ELEMENT			
	CATEGORY	*QUANTITY*	*TYPE*	*COST*
1	CHIP	1	RASPBERRY Pi	3020
2	MOTOR	1	WATER HEATER	70
3	CAMERA	2	IR SENSOR	850
4	BIN	1	COOKER	740
	TOTAL			4680

TABLE II. EXPENSES FOR THE MODEL (A)

S.No	EVALUATION ELEMENTS			
	CATEGORY	*QUANTITY*	*TYPE*	*COST*
1	CHIP	1	PC CHIP	510
2	MOTOR	1	STEPMOTOR	240
3	CAMERA	2	LOW COST SAMPLE	720
4	BIN	1	PLASTIC COVER	630
	TOTAL			2100

TABLE III. EXPENSES FOR THE MODEL (B)

There are two configurations that can be implemented depending on the available equipment. The first configuration may not perform well in low-light conditions, whereas the infrared camera components would deliver precise outcomes even in low-light conditions. Once the different components are implemented and tested, the system should be able to distinguish between different types of waste accurately. The proposed system solution utilizes IFRCNN image classification, which is currently the highest-performing image classification method, resulting in Precise and effective waste segregation [23]. The training data set would depend on the type of camera used, by having trainees gather a dataset of IR image graphs for IR cameras and generic images for regular cameras.

V. METHODOLOGY

The Smart Bin comprises two key operational elements: real-time image classification and onboard devices. These components collaborate seamlessly to execute the essential operational functions. The unit is physically segmented into two sections: the sensor unit and the waste separation unit. The sensor module triggers the camera to capture an image, which is subsequently processed by the image classification system. This system then guides the waste into the appropriate compartment based on its detected type. The horizontal axis divides the identified waste into two categories: non-biodegradable and biodegradable materials.

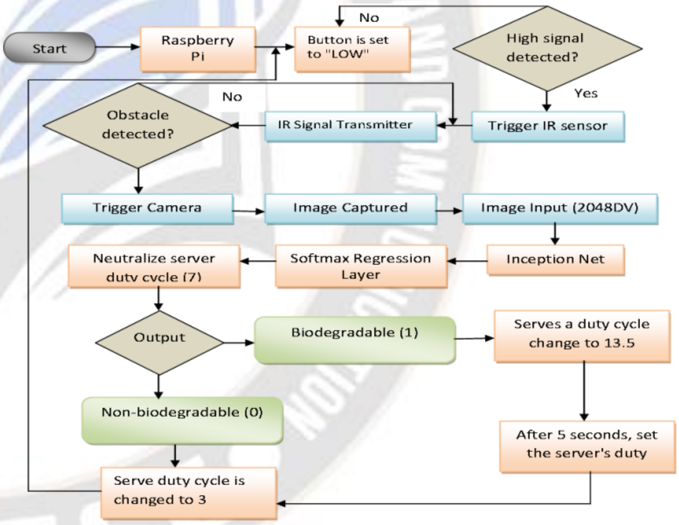

Figure 2. A visual representation of the structure for the resolution

The Figure 2 presents a visual depiction of the operational speed of the proposed system, encompassing integral components like the sensor, motor, and push button. To capture an image of the bin positioned on the bin divider disk, a Pi camera module with a 5-megapixel capacity is utilized. When the push button is pressed, the IR sensor emits infrared waves. In the event that the signal transmission is disrupted amidst the waste along the road, the transmitter is triggered. Following this, the camera captures a video of the IR detector emitting a robust signal.Afterwards a 5-second interval, an image is taken, serving as confirmation of waste stabilization and successful calibration of the video detectors.

Upon capturing a valid image, the image categorization software component initiates. The classification task is efficiently executed through various Improved Faster Recurrent Convolution Neural Network architectures, including InceptionNet, ResNet, AlexNet and VGG16. A notable distinction of IFRCNN is its ability to autonomously recognize significant elements without human intervention. Images are attributed to six categories—paper, glass, metal, cardboard, organic waste and plastic—based on the neural network's output. The software generates a lowermost (0) signal for biodegradable materials and uppermost (1) signal for non-biodegradable.

The motor responsible for rotating the separation disc to segregate the trash operates at a 12.5% duty cycle for biodegradable waste. This action shifts the motor from a balanced orientation at a 90-degree angle to a 7.5% duty cycle (180 degrees) for the biodegradable section. Conversely, if the waste is non-biodegradable, the operational cycle is set at 2.5% or 0 degrees. This maneuver rotates the motor from 90 to 0 degrees, directing the non-biodegradable waste. Within 5 seconds and 90-degree intervals, the motor completes 7.5 cycles, ensuring accurate waste disposal into their respective sections.To introduce interruption capabilities, hardware-triggered interruptions, like those caused by switches depicted in Figure 3, can be integrated. These interrupts can effectively halt the program and break the continuous loop. The time frame for image capture can be adjusted based on camera quality, with optimal outcomes observed within 5 seconds using the economical 5 Megapixel Camera.

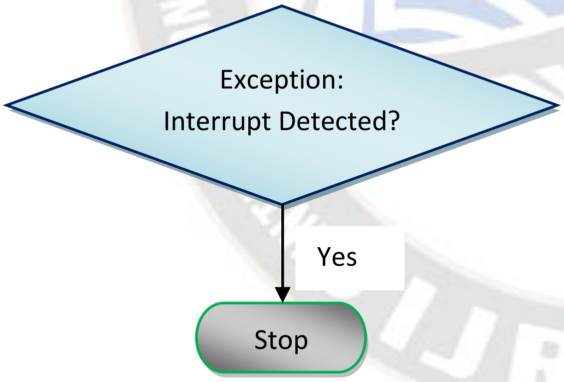

Figure 3. Interrupt flow

A. Model Study

The evolution of machine learning software was significantly shaped by Alex Net, which emerged as the victor in the Image Net LSVRC 2012 competition. Comprising eight layers, it consisted of three fully connected tiers and five convolution layers. This model introduced fundamental techniques that remain standard practices in the field. ResNet50, boasting 50 layers and incorporating skip connections every second level, skillfully tackled the challenge of vanishing gradients. It did so by employing activation's from one layer while awaiting the next layer to refine its weights.

VGG-16, introduced in 2014 as an IFRCNN template, embodies simplicity with its 16 tiers, fewer hyper parameters, and approximately 135 million variables. On a different note, Inception Net V3, spanning 42 layers and holding about seven million parameters, deploys an 11F Convolution block to create an N X N matrix F block, effectively curbing computational demands. This architecture also integrates a dropout layer and label smoothing to optimize network performance and prevent overflow.

The Inception architecture comprises three module types. Inception Module A replaces a 5x5 convolution with two 3x3 convolutions, reducing variable count by 28%. Inception Net-B substitutes a [3x3] convolution with 2 [1x3] convolutions and 1[3x1] convolution, diminishing parameters by 33%. Inception Net-C utilizes an asymmetrical structure to handle high-dimensional representations. Every convolution sub-unit within it is fashioned with additional sub-blocks, and the resulting frames are amalgamated into the component's output. An auxiliary classifier acts as a regulator, operating on the final 17 tiers.

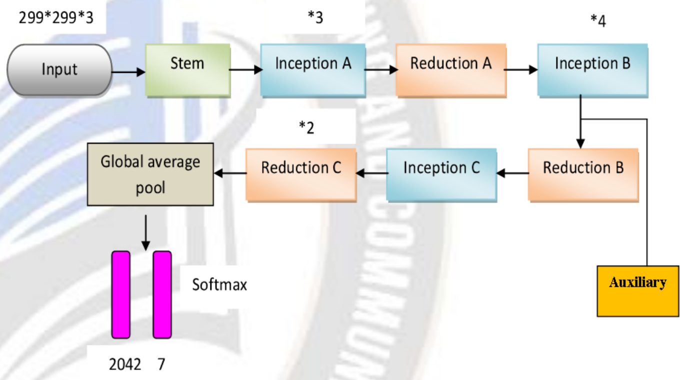

Figure 4. Diagram illustrating the block structure of the Inception network framework.

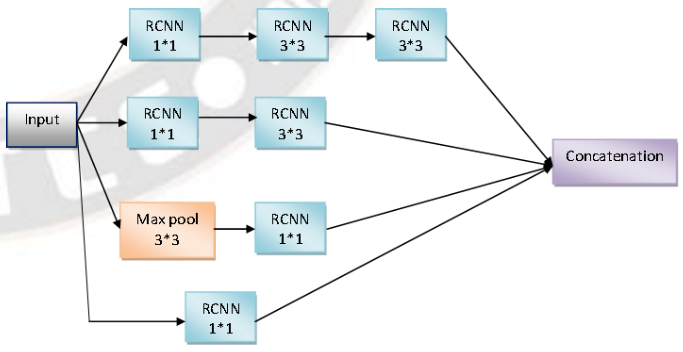

Figure 5. Initial block diagram

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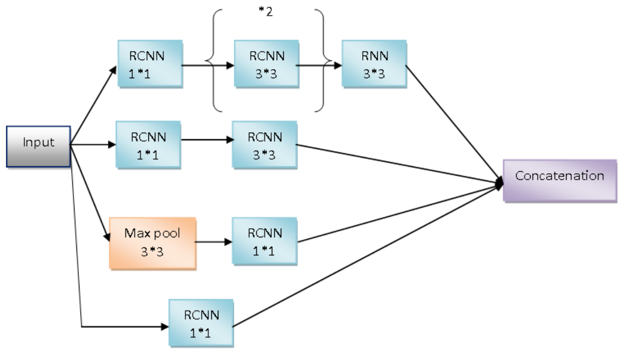

Figure 6. Block diagram representation of Inception

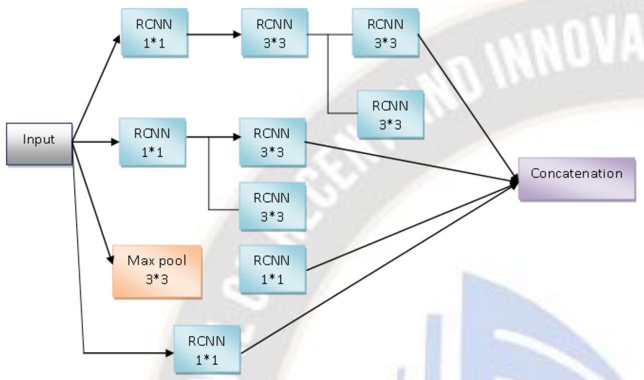

Figure 7. Block diagram depiction of Inception C

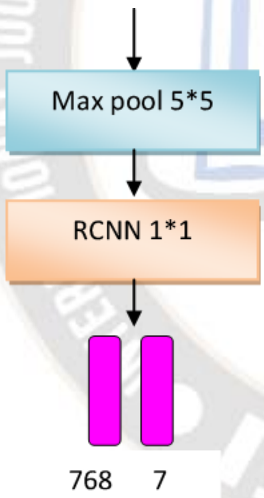

Figure 8. Block schematic illustrating an alternative classification approach.

B. Optimizer

This refers to a method of improving variable updates. It is a type of adaptable learning technique that uses gradient descent to reduce vertical oscillations and accelerate learning by moving towards the achieve the lowest point at a faster pace[27].

$$u_t = \rho u_{t-1} + (1-\rho) * g_t^2 \quad (1)$$

$$\Delta w_t = -\frac{\varphi}{\sqrt{u_t+\varepsilon}} * g_t \quad (2)$$

$$w_{t+1} = w_t + \Delta w_t \quad (3)$$

Where, φ - "learning rate initial value" signifies the initial value of the learning rate; u_t – "exponential of average gradients" refers to the exponential calculation of the average gradients; g_t - "gradient time" relates to the duration over which the gradients are computed.

Another strategy employed to regulate the classification layer involves evaluating the impact of label abandonment during the learning process. Label smoothing encompasses lowering the positive label's score to a value slightly less than 1 (e.g., 0.9), and slightly elevating the negative label's score just above 0 (e.g., 0.1). This smoothing aids in adapting the features of the penultimate layer to produce output values more aligned with the intended class value. Simultaneously, it considerably diminishes the confidence scores assigned to incorrect categories.

$$j_k^{LS} = j_k(1-\alpha) + \frac{\alpha}{k} \quad (4)$$

Where, 'k' indicates the number of classes, indicates the smoothing variable, is a hot-coded tag vector, and indicates the class value.

Transfer learning is a strategy that entails fine-tuning a model's weights by training it on a particular dataset with a predetermined set of classes, as opposed to commencing training from the beginning. This methodology leverages well-established architectures like ResNet, Inception Net, and VGG-16, which reduces the need for expensive hardware and speeds up the model building process [28].

C. Implementation

To enhance the object classification training phase, a set of sample images underwent transformations such as crops, scalings, and reversals to simulate object positions in various scenarios. However, cached bottleneck values are not suitable for distorted images, as they require recalculations for each image. Hence, heterogeneous images were chosen for each class and warped to prevent delays during training [29]. The controller program for the intelligent bin manages hardware operations, runs the categorization application, and downloads necessary modules during boot time. The program runs in an infinite loop, which can be interrupted by hardware or power failures. The IR sensor functions by emitting radiation within the 700 nm to 1400 nm spectrum, which falls outside human visibility. This device serves the purpose of identifying object presence, while the camera captures the respective image frame, which is divided into two categories using Algorithm 2 and managed by Algorithm 1 on the Raspberry Pi, as described in the text.

Algorithm 1: Pseudo-code representing the interface of a Raspberry Pi.

```
 # Pseudo-code
import RPi.GPIO as GPIO # Import the GPIO library
# Set up GPIO
GPIO.setmode(GPIO.BCM)
button_pin = 17 # Replace with the actual GPIO pin number
GPIO.setup(button_pin, GPIO.IN, pull_up_down=GPIO.PUD_UP)
# Main loop
try:
    while True:
        button_state = GPIO.input(button_pin)  # Read the button state
            if button_state == GPIO.LOW:  # Button is pressed
            print("Button pressed!")
            # Perform your desired action here
            # For example, turn on an LED, take a picture, etc.
            except KeyboardInterrupt:
    pass  # Exit the loop when Ctrl+C is pressed
finally:
    GPIO.cleanup()  # Clean up GPIO settings when exiting
```

Algorithm 2: Inception Net Implementation

```
# Pseudo-code for Inception Net Implementation
import tensorflow as tf  # Import the TensorFlow library
# Load your dataset
train_dataset, validation_dataset, test_dataset = load_datasets()
# Build the Inception Net model
model = build_inception_net_model()
# Define optimizer and loss function
optimizer = tf.keras.optimizers.Adam(learning_rate=0.001)
loss_fn = tf.keras.losses.CategoricalCrossentropy()
# Training loop
num_epochs = 10
for epoch in range(num_epochs):
    for batch_images, batch_labels in train_dataset:
        with tf.GradientTape() as tape:
            # Forward pass
            predictions = model(batch_images, training=True)
            loss = loss_fn(batch_labels, predictions)
             # Backpropagation
        gradients = tape.gradient(loss, model.trainable_variables)
        optimizer.apply_gradients(zip(gradients, model.trainable_variables))
        # Validation
    validation_accuracy = evaluate_model_on_validation(validation_dataset, model)
    print(f"Epoch {epoch+1}: Validation Accuracy = {validation_accuracy:.4f}")
# Testing
test_accuracy = evaluate_model_on_test(test_dataset, model)
print(f"Test Accuracy = {test_accuracy:.4f}")
```

$$w_{k+1} = \beta_{w_k} + \frac{e}{\sqrt{g_{k+1}^{-2}}} \nabla f(w_k) \quad (5)$$

end

$$\vartheta = \alpha \hat{\vartheta}_{t-1} + (1-\alpha)\vartheta_t \quad (6)$$

$$\mu_t^2 = \alpha \hat{\mu}_{t-1} + (1-\alpha)\mu_t^2 \quad (7)$$

end

In Figure 9, the proposed system is depicted, where the class response from the softmax layers of models was used to determine the biodegradability of the object. A neutral value of 7.5 was set for the motor duty cycle, and the activation of a device initiated the initialization of the servo motor. In the first production phase, the utilization cycle was extended to 10.5%. Subsequently, this duration was modified to 7.5% following a brief 5-second pause aimed at transferring waste to the biodegradable zone. In cases where the exit value is 0, the service cycle was further adjusted to 4.5% to enable waste to proceed towards the non-biodegradable process. Table 3 provides more detailed information.

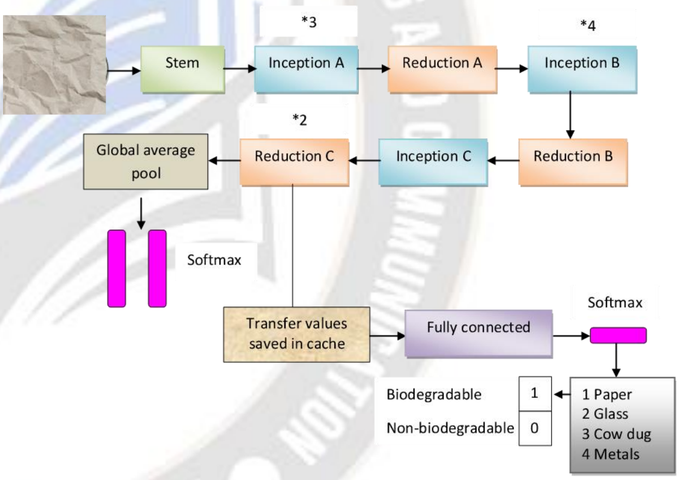

Figure 9. Model based on the Inception Net V3 architecture

Features	**Description**
Processor	1.2GHz Broadcom BCM2837 64bit
RAM	1GB
Connectivity	BCM4348 wireless LAN, Bluetooth
Input/output	40pins GPIO, 4USB ports, HDMI port, CSI camera port

TABLE IV. FEATURES OF RASPBERRY PI

D. Hardware component

Figure 10 illustrates a circuit diagram of the proposed system, employing the Raspberry Pi 3B, which signifies a substantial enhancement in performance compared to its predecessors. The utilization of infrared technology facilitates remote functionalities through sensors and remote controls, categorized into three types based on the electromagnetic spectrum: near-IR, intermediate infrared, and end IR. The near-infrared spectrum spans from 700 nm to 1400 nm, ssituated lower than the range of visible light wavelengths yet higher than the range of microwaves.Direct connectivity of the Raspberry Pi camera to the CSI connector is achieved using a 15-pin MIPI serial interface, enabling efficient high-speed data transmission. The camera module in use, the 5 MegaPixel Omnivision 5647, is cost-effective and widely accessible, compatible with all Raspberry Pi models. Within this system, an electric motor known as a servomotor is employed, regulated by a servomechanism. The nomenclature "DC servomotor" denotes the connection of DC servomotor to a DC servomechanism.

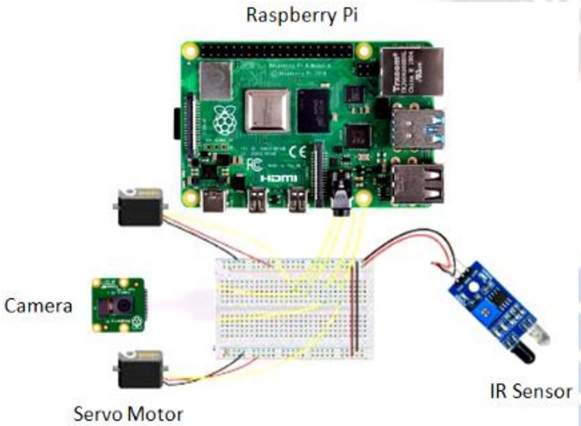

Figure 10. Circuit illustration

VI. RESULTS AND DISCUSSION

In Figure 11, Accuracy vs. Epochs and the loss vs. epoch graphs are shown for each pre-trained CNN. These graphs illustrate how the model's performance changes over time. As the model is trained, its loss decreases and accuracy improves, which are key metrics used to evaluate a system. The observed trend is that the validation accuracy often surpasses the accuracy achieved on the test dataset. Moreover, the loss consistently decreases and converges towards that of the training dataset. These trends are exemplified in the graphs for both InceptionV3and AlexNet models below. These patterns suggest that these models were able to learn their parameters accurately, with minimal fluctuation and distortion.

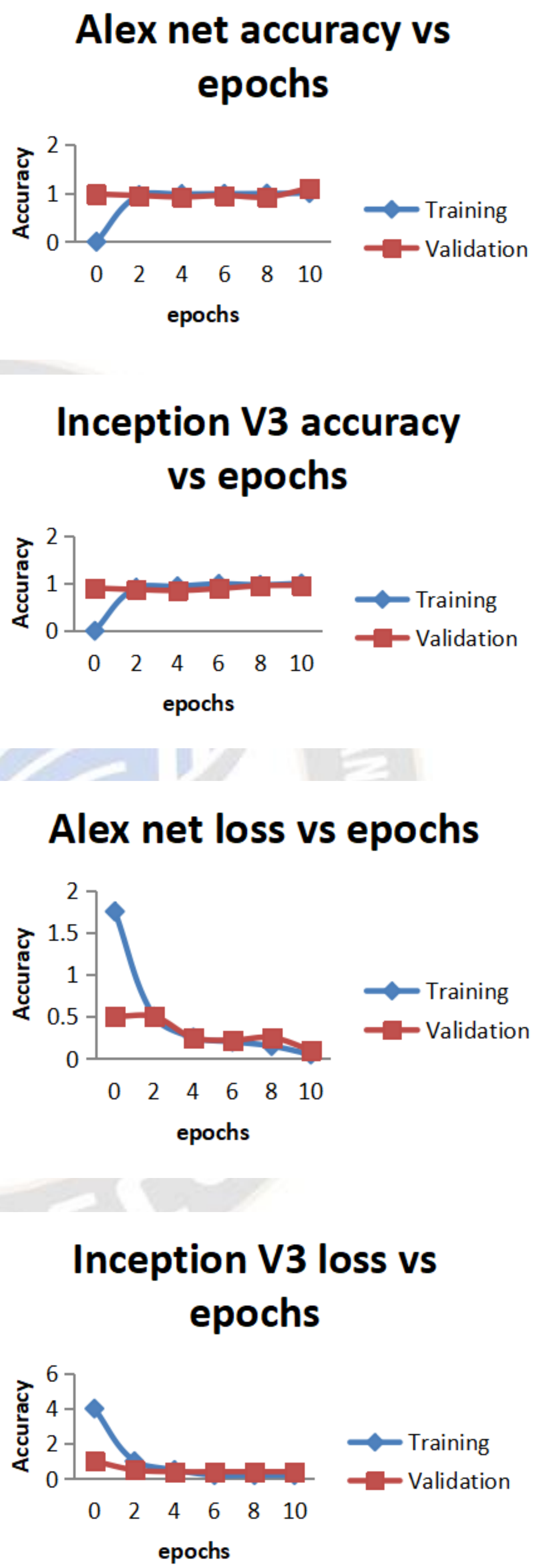

Figure 11. The precision plotted against epochs and the damage plotted against epochs graphs for AlexNet,the Inception Net V3, ResNet50 and the novel system.

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ACCURACY=(True Positives + False Negatives) / (Total Number of Samples)

Where:

- (TP) stands for True Positives, which are the instances correctly predicted as positive.
- (FN) stands for False Negatives, which are the instances incorrectly predicted as negative.
- "Total number of samples" refers to the overall number of instances in the dataset.

Accuracy measures the proportion of correct predictions (both positive and negative) out of all predictions.

$$\boldsymbol{Loss}:\ -\left(j_x \log \hat{j}_x + (1 - j_x)\log\left(1 - \hat{j}_x\right)\right)$$

(9)

Table 4 shows that the accuracy of all algorithms is around 98%. However, VGG-16 - IFRCNN has a much lower accuracy on the validation set than the other models. Resnet and AlexNet performed better than InceptionNet V3 in terms of testing package loss, with mean loss scores significantly lower than their learning counterparts. However, InceptionNet V3 outperformed AlexNet and Resnet in terms of validation package loss. The results suggest that InceptionNet V3 would be the most suitable model the selection of a Raspberry Pi with 1GB RAM for implementation was driven by its rapid classification speed, as demonstrated in Figure 12, as well as its minimal prediction time, rendering it highly efficient.

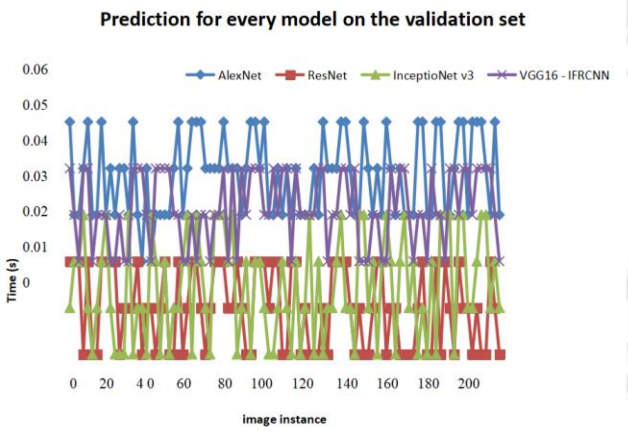

Figure 12. Time taken for prediction by each model in relation to the image instance graph.

MODEL	ACCURACY		BREAKDOWN	
	Learning	*Testing*	*Learning*	*Testing*
ResNet	97.93	92.24	0.1	0.51
VGG16 - IFRCNN	98.68	96.43	0.1	0.12
AlexNet	92.35	92.23	0.12	0.23
InceptionNetV3	98.14	95.53	0.11	0.14

TABLE V. COMPARATIVE ANALYSIS OF DIFFERENT MODELS

In the study, it was observed that the recommended method worked well when clear pictures of objects were available on a white background. However, the accuracy decreased when the object images were blurry or low-resolution. The objects were categorized into biodegradable and non-biodegradable under two separate headings, and experiments were conducted using various household items. Modifications were made to the hardware template to increase accuracy, and the ISO speed was increased from 240 to 640 to improve image quality. The suggested model underwent a comparison with the latest advancements in technology, as presented in Table 5., which only classified waste into recyclable and non-recyclable but did not separate them physically. The proposed model, on the other hand, physically separated waste and classified it into two categories with a precision ranging from 96.23% to 98.15%, making it more accurate than the previous model.

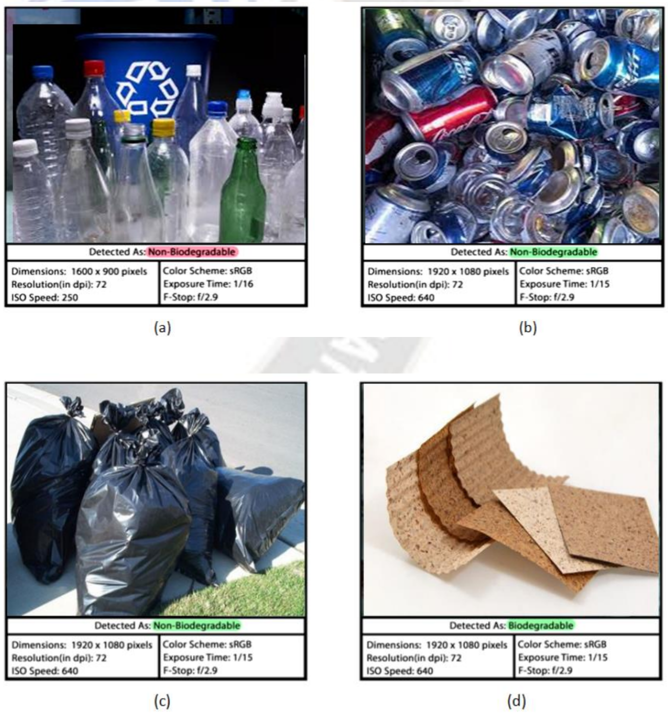

Figure 13. System algorithm output

CATEGORY	DESCRIPTION	ALGORITHM	ACCURACY
[2]	**Utilizing machine learning and YOLO algorithm for**	**VGG16 – Improved Faster Recurrent Convolution**	**98.23**

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CATEGORY	DESCRIPTION	ALGORITHM	ACCURACY
	waste management, identifying and segregating non-biodegradable waste through advanced detection and sorting techniques.	**Neural Network (model)**	
[18]	**Efficient smart city waste management using time-series forecasting for garbage monitoring. Enhances collection and disposal strategies through data-driven insights.**	**Convolutional Neural Network**	**88.43**
[23]	**Real-time solid waste management using IoT-integrated deep learning and SmartBin technology, enhancing efficiency and optimizing waste collection through data-driven insights.**	**Convolutional Neural Network**	**93.01**

TABLE VI. CONTRASTS THE CURRENT CUTTING-EDGE ADVANCEMENTS

VII.CONCLUSION

Numerous endeavors have been undertaken to enhance trash identification and classification techniques, including image recognition applications aimed at identifying litter alongside roadways and software for segregating waste. Additionally, physical approaches have been employed to estimate the volume or level of waste in a bin, triggering alerts when bins become full. A variety of methods, such as Convolutional Neural Networks (CNN), Support Vector Machines (SVM), and You Only Look Once version 2 (YOLOv2), have been utilized to automate tasks related to garbage detection and separation. However, these systems still possess certain limitations. Globally, a range of intelligent bin components have been developed, including infrared sensors for automated bin lids, volumetric filling level estimation, and stage detection of filling levels. By integrating these resources, a unified module could handle all these functions, thereby enhancing the speed of waste identification and separation. The VGG16-Improved Faster Recurrent Convolution Neural Network system was designed with a sufficient number of time frames to ensure accuracy for performance considerations, yet these time frames could potentially be decreased to enhance system efficiency.

REFERENCES

[1] Dessai, H., & Miranda, D. (2021, May). Garbage Segregation Using Images. In 2021 2nd International Conference for Emerging Technology (INCET) (pp. 1-4). IEEE.

[2] Aishwarya, A., Wadhwa, P., Owais, O., & Vashisht, V. (2021, January). A waste management technique to detect and separate non-biodegradable waste using machine learning and YOLO algorithm. In 2021 11th International Conference on Cloud Computing, Data Science & Engineering (Confluence) (pp. 443-447). IEEE.

[3] Koganti, S. K., Purnima, G., Bhavana, P., Raghava, Y. V., & Resmi, R. (2021, August). Deep Learning-based Automated Waste Segregation System based on degradability. In 2021 Second International Conference on Electronics and Sustainable Communication Systems (ICESC) (pp. 1953-1956). IEEE.

[4] Anitha, R., Maruthi, R., & Sudha, S. (2022). Automated Segregation and Microbial Degradation of Plastic Wastes: A Greener Solution to Waste Management Problems. Global Transitions Proceedings.

[5] Soundarya, B., Parkavi, K., Sharmila, A., Kokiladevi, R., Dharani, M., & Krishnaraj, R. (2022, January). CNN based smart bin for waste management. In 2022 4th International Conference on Smart Systems and Inventive Technology (ICSSIT) (pp. 1405-1409). IEEE.

[6] Azhaguramyaa, V. R., Janet, J., Narayanan, V. V. L., Sabari, R. S., & Santhosh, K. K. (2021, May). An Intelligent System for Waste Materials Segregation Using IoT and Deep Learning. In Journal of Physics: Conference Series (Vol. 1916, No. 1, p. 012028). IOP Publishing.

[7] Zhang, H., Peeters, J., Demeester, E., Duflou, J. R., & Kellens, K. (2022). A CNN-Based Fast Picking Method for WEEE Recycling. Procedia CIRP, 106, 264-269.

[8] Ravishankar, A., Murthy, A., Sharma, M., Chitra, R. K., & Anitha, R. (2021, October). Automated Waste Segregation using Convolution Neural Network. In 2021 International Conference on Smart Generation Computing, Communication and Networking (SMART GENCON) (pp. 1-4). IEEE.

[9] Anas, M. M., Athiram, M., Suresh, A., Archana, K., & Shaji, M. (2022). Water Cleaning Bot with Waste Segregation Using Image Processing. In International Conference on Electrical and Electronics Engineering (pp. 161-171). Springer, Singapore.

[10] Mookkaiah, S. S., Thangavelu, G., Hebbar, R., Haldar, N., & Singh, H. (2022). Design and development of smart Internet of Things–based solid waste management system using computer vision. Environmental Science and Pollution Research, 1-15.

[11] Bharathiraja, N., Shobana, M., Manokar, S., Kathiravan, M., Irumporai, A., & Kavitha, S. (2023). The Smart Automotive

Webshop Using High End Programming Technologies. In Intelligent Communication Technologies and Virtual Mobile Networks (pp. 811-822). Springer, Singapore. https://doi.org/10.1007/978-981-19-1844-5_64

[12] Sruthy, V., Anjana, S., Ponnaganti, S. S., Pillai, V. G., & Preetha, P. K. (2021, February). Waste Collection & Segregation using Computer Vision and Convolutional Neural Network for Vessels. In 2021 International Conference on Computing, Communication, and Intelligent Systems (ICCCIS) (pp. 1043-1048). IEEE.

[13] Bharathiraja, N., Padmaja, P., Rajeshwari, S. B., Kallimani, J. S., Buttar, A. M., & Lingaiah, T. B. (2022). Elite Oppositional Farmland Fertility Optimization Based Node Localization Technique for Wireless Networks. Wireless Communications and Mobile Computing, 2022. https://doi.org/10.1155/2022/5290028.

[14] Saad, S., Alaloul, W. S., & Ammad, S. (2022). Role of Cyber-Physical Systems in Smart Cities. In Cyber-Physical Systems in the Construction Sector (pp. 111-129). CRC Press.

[15] Singh, D. (2021, January). Polyth-Net: classification of polythene bags for garbage segregation using deep learning. In 2021 International Conference on Sustainable Energy and Future Electric Transportation (SEFET) (pp. 1-4). IEEE.

[16] Singh, D. (2021, January). Polyth-Net: classification of polythene bags for garbage segregation using deep learning. In 2021 International Conference on Sustainable Energy and Future Electric Transportation (SEFET) (pp. 1-4). IEEE.

[17] Sahoo, P. K., Kanungo, P., Mishra, S., & Mohanty, B. P. (2022). Entropy feature and peak-means clustering based slowly moving object detection in head and shoulder video sequences. Journal of King Saud University-Computer and Information Sciences, 34(8), 5296-5304.

[18] Mishra, D., Vajire, S. L., Saxena, S., Gupta, P., Saini, D. K., Srivastava, A. K., & Rao, G. M. (2022). GRUBin: Time-Series Forecasting-Based Efficient Garbage Monitoring and Management System for Smart Cities. Computational Intelligence and Neuroscience, 2022.

[19] Yarlagaddaa, J., & Ramakrishna, M. (2019). Fabrication and characterization of S glass hybrid composites for Tie rods of aircraft. Materials Today: Proceedings, 19, 2622-2626.

[20] Pant, M. M., Gupta, M., & Tripathi, M. M. (2022). Garbage Classification Using YOLOv3. In Advances in Mechanical Engineering and Technology (pp. 163-169). Springer, Singapore.

[21] Anjanappa, C., Parameshwara, S., Vishwanath, M. K., Shrimali, M., & Ashwini, C. AI and IoT Based Garbage Classification for the Smart City Using ESP32 Cam. International Journal of Health Sciences, (III), 4575-4585.

[22] Gupta, T., Joshi, R., Mukhopadhyay, D., Sachdeva, K., Jain, N., Virmani, D., & Garcia-Hernandez, L. (2022). A deep learning approach based hardware solution to categorise garbage in environment. Complex & Intelligent Systems, 8(2), 1129-1152.

[23] Sivakumar, M., Renuka, P., Chitra, P., & Karthikeyan, S. (2022). IoT incorporated deep learning model combined with SmartBin technology for real-time solid waste management. Computational Intelligence, 38(2), 323-344.

[24] Umamageswari, N. Bharathiraja, D. Shiny Irene,A Novel Fuzzy C-Means based Chameleon Swarm Algorithm for Segmentation and Progressive Neural Architecture Search for Plant Disease Classification,ICT Express,2021,ISSN 2405-9595, https://doi.org/10.1016/j.icte.2021.08.019

[25] Raamesh, A., Kalarani, S., Narmadha, T. V., & Hemapriya, N. (2021). A methodical and intuitive image classifier for trash categorization based on deep learning. International Journal of Modern Agriculture, 10(2), 4638-4652.

[26] Zubair, M., Mathur, Y., Rathore, H., Gupta, P., & Banerjee, S. (2022, February). Smart Waste Bin: Mechanical and AI Based Waste Segregation. In 2022 Second International Conference on Artificial Intelligence and Smart Energy (ICAIS) (pp. 63-66). IEEE.

[27] Sun, Y., Cao, N., Duan, C., Wang, Q., Ding, C., & Wang, J. (2021). Selection of antibiotic resistance genes on biodegradable and non-biodegradable microplastics. Journal of hazardous materials, 409, 124979.

[28] Faria, R., Ahmed, F., Das, A., & Dey, A. Classification of Organic and Solid Waste Using Deep Convolutional Neural Networks. In 2021 IEEE 9th Region 10 Humanitarian Technology Conference (R10-HTC) (pp. 01-06). IEEE.