Real-Time Solid Waste Sorting Machine Based on Deep Learning

Original Scientific Paper

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Abstract *– The collection and separation of solid waste represent crucial stages in recycling. However, waste collection currently relies on static trash bins that lack customization to suit specific locations. By integrating artificial intelligence into trash bins, we can enhance their functionality. This study proposes the implementation of a sorting machine as an intelligent alternative to traditional trash bins. This machine autonomously segregates waste without human intervention, utilizing deep learning techniques and an embedded edge device for real-time sorting. Deploying a convolutional neural network model on a Raspberry Pi, the machine achieves solid waste identification and segregation via image recognition. Performance evaluation conducted on both the Stanford dataset and a dataset we created showcases the machine's high accuracy in detection and classification. Moreover, the proposed machine stands out for its simplicity and cost-effectiveness in implementation.*

Keywords: *Waste, deep leaning, raspberry pi, artificial intelligence, sorting machine*

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1. INTRODUCTION

The surge in population and industrialization has led to a significant increase in daily waste production. According to statistics from the World Bank, global municipal solid waste generation exceeds 2 billion tons annually, a figure expected to soar to 3.4 billion tons by 2050 [1].

Waste in gaseous, liquid, or solid form poses a significant environmental threat if not properly managed and segregated. The Senior Director of the Social, Urban, Rural, and Resilience Global Practice at the World Bank underscores the urgency of implementing effective solid waste management practices to achieve sustainable development goals, which prioritize waste reduction and recycling [2].

Recycling is crucial for ecological preservation and promoting circular economies [3]. However, its benefits are limited because only 13.5% of global waste is recycled, primarily due to insufficient collection and sorting infrastructure. Furthermore, 33% of waste is openly discarded without preliminary sorting, while mixed waste disposal remains prevalent [4].

While manual sorting persists in some waste management systems, it introduces various challenges. These include the risk of contamination from bacteria and viruses, the requirement for a large workforce, and the associated expenses of training and oversight [5].

Developed nations are steadily adopting automated waste management systems to facilitate the advancement of intelligent and sustainable cities. These systems harness cutting-edge technologies like robotics [6], artificial intelligence [7], and the Internet of Things [8], sparking considerable research interest in this field.

In robotics, Aitken et al. [9] have devised an automated system for nuclear waste treatment utilizing a robotic arm. This system aims to execute tasks that are repetitive and hazardous for humans. On the other hand, Gupta et al. [10] have presented a cost-efficient solution for defining routes for the mobile autonomous robot assigned to litter emptying. This proposal aims to alleviate the impact on workers' health, reduce greenhouse gas emissions, and minimize operational expenses.

Given the success of artificial intelligence in various fields like medicine [11], biology [12], and environment [13], recently several researchers have conducted studies on using AI for automatic waste management. For example, Majchrowska et al. [4] used deep learning to detect waste in natural and urban environments. Furthermore, the studies presented by [14-18] have proposed a deep-learning model for waste classification. Mittal et al. [19] created a smartphone application called Spotgarbage, which utilizes a Convolutional Neural Network (CNN) and enables citizens to monitor the cleanliness of their neighborhood by tracking garbage. In contrast, The dangers posed by medical waste, such as viruses and bacteria, motivated Zhou et al. [5] to propose a classification method based on deep learning for medical waste classification. This method identifies eight types of medical waste: gauze, gloves, infusion bags, bottles, infusion apparatus, syringes, needles, and tweezers. Machine learning methods are employed in municipal solid waste classification [20] and are also utilized in container management through sensor measurements [21, 22]. Yang and Thung [23] combined machine learning and deep learning techniques by using the support vector machine and convolutional neural network to classify waste into six classes: glass, paper, metal, plastic, cardboard, and trash. On the other hand, the Internet of Things (IoT) technology has been employed with both machine learning in [24] and deep learning for waste management systems in [25].

A growing trend in automatic waste management involves the implementation of Smart Waste Bins [26]. Initially, researchers suggested improving waste bin control through level detection sensors [27, 28] and utilizing remote control via mobile applications or Global System for Mobile Communications (GSM) technology. For example, Monika et al. [29] employed an intelligent bin equipped with an ultrasonic sensor to monitor the saturation of the dustbin. The authors employed the GSM technology to alert the authorities to manage the dustbin. Additionally, convolutional neural networks have been integrated into waste bins for efficient trash segregation [30, 31].

Despite ongoing research, the current waste collection and sorting involves using trash bins equipped with labels or colors to help individuals correctly dispose of waste into designated containers. However, variations in these labels across countries can confuse some individuals.

Moreover, citizens frequently make errors in their waste disposal practices. Another limitation of existing trash bins is their lack of customization based on specific deployment locations. For instance, waste generated in hospitals differs significantly from that produced in stadiums, public gardens, educational institutions, and other settings.

In this research, our focus is on educational institutions, where we propose the implementation of a sorting machine as an alternative to conventional trash bins. We designed this machine to autonomously segregate waste without requiring human intervention. Since plastic bottles and paper are the primary waste generated in educational institutions and universities, efficiently collecting and sorting these items has become crucial for streamlining the recycling process.

Plastic waste constitutes a significant threat to the environment. The United Nations Environment Programme (UNEP) estimated that there could be more plastic than fish in the ocean by 2050 [32]. Plastic waste not only affects our oceans but also infiltrates our food supply as microplastics and nanoplastics, posing a significant threat to human health. Paper is also a part of our daily waste and impacts the environment. Discarding paper due to printing errors, packaging, and advertising posters is a daily practice that we engage in without fully recognizing its ecological and economic impact.

The primary contributions of this article include:

- Introducing the structure of the sorting machine along with its operational diagram.
- Evaluating two mobile architectures — MobileNet and NASNet-Mobile — as the backbone for our final model.
- Sharing the paper and plastic waste images dataset, and the Python source code of the machine.

The manuscript is structured as follows: The Materials section presents an overview of the machine's components and functionality. In the Method section, we will elaborate on the convolutional neural network model utilized in our proposal. We will present the evaluation results in the Results and Discussion section. Section 5 presents the conclusion of the article.

2. MATERIALS

2.1. GENERAL OVERVIEW OF THE PROTOTYPE MACHINE

The machine aims to identify and categorize paper and plastic bottles waste. By doing so, the machine can aid in simplifying the waste segregation process for municipal corporations. We chose these two types of waste due to their high frequency of being discarded in educational institutions and their recyclable nature.

The prototype machine works as follows:

As a student approaches the waste disposal machine, a motion sensor detects their presence, and the machine's window opens to allow them to dispose of their waste. After the disposition of the waste, a Raspberry Pi camera captures an image, and a convolutional neural network (CNN) model identifies and classifies the waste type. The servomotor then swings the support that holds the waste towards the appropriate container. The machine contains two compartments: one for paper waste and the other for plastic bottles.

To further encourage students to recycle waste, we designed the prototype machine to provide a reward after throwing a fixed number of plastic bottles, for example, nb=4. A box containing pens opens, allowing them to claim a pen as a reward.

This approach creates an educational and interactive way to promote waste segregation and recycling, encouraging students to engage in sustainable practices. Fig. 1 presents the UML state machine diagram that illustrates the various states and the responses to different events. We create this diagram using Astah software.

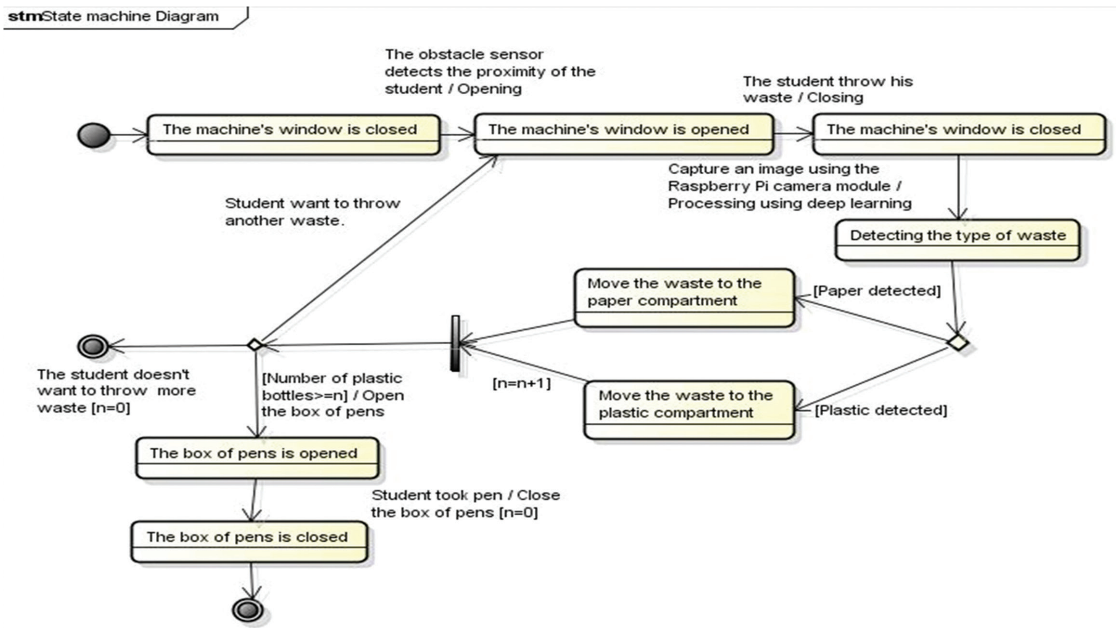

Fig. 1. The state machine diagram

2.2. MACHINE COMPOSITION

The machine has two main components: the electronic component box and two physical parts.

The top part of the machine handles the processing tasks, including the detection, recognition, and classification of waste.

The bottom part houses the containers designated for paper and plastic waste. The design of the prototype machine shown in Fig. 2 was modeled using SolidWorks software.

- Electronic component box

The electronic components used in the prototype machine, including the Raspberry Pi, Pi Camera, and servomotors, are housed in the electronic component box for protection. Fig. 3 shows the electronic circuit of the prototype machine.

The source code for the prototype machine is accessible at the following link: https://github.com/Nedjar-Imane/Sorting-Machine/tree/main

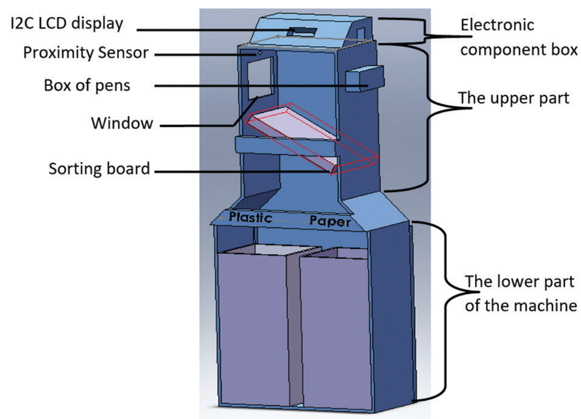

Fig. 2. Machine's design

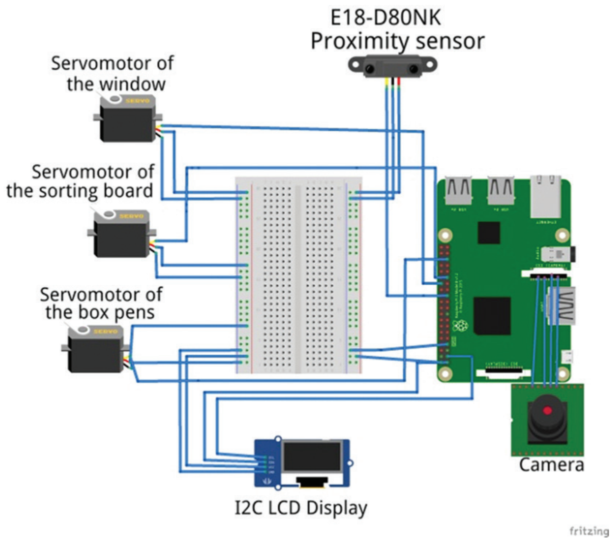

Fig. 3. Electronic circuit of the prototype machine created using FreeCAD software

- The upper part of the prototype machine

Window: the upper part of the prototype machine features an opening where students can deposit the waste. An obstacle avoidance sensor (E18-D80NK) is placed at the top of the window to detect incoming objects. The servomotor (Metal gears RG996R) operates the window to ensure smooth and efficient operation.

Sorting board: once the sensor detects an object, the window opens automatically, and the user can throw their waste into the machine. There is a sorting board inside the prototype machine. It turns to the right for plastic waste and the left for paper waste.

Box of pens: we developed this prototype machine for educational institutions to encourage students to recycle waste. When a student throws a specified number of plastic bottles, the box of pens opens, allowing the student to take a pen. The servomotor operates the opening mechanism of the box.

- The lower part of the prototype machine

This part is designed to sort the waste into two containers.

3. PROPOSED METHOD

3.1. DATASET

We have collected and organized our dataset titled 'Plastic and Paper Waste' by taking photos with mobile phones in our homes and at the university (see Fig. 4).

The 'Plastic and Paper Waste' dataset contains 400 images for each class, encompassing diverse papers and plastic bottles captured in various positions, states, lighting conditions, and backgrounds.

In our experiment, we also used the Stanford dataset [23], which includes images of trash against a white background organized into six classes.

The Stanford dataset contains 594 images of paper and 319 images of plastic bottles. To balance the dataset, we augmented the number of plastic bottle images to 594 using techniques such as rotation and zoom.

(a) (b)

Fig. 4. Images from our dataset with different backgrounds (**a**) Paper, (**b**) Plastic bottle

3.2. CONVOLUTIONAL NEURAL NETWORK MODEL

The remarkable achievements of CNN-based architectures are notably outstanding, particularly in computer vision, where accuracy levels often approach perfection.

Our system is specifically tailored for real-time detection and classification of paper and plastic, utilizing CNN for these tasks. In this study, we opted for the MobileNet and NASNet-Mobile neural network architectures for classification, chosen for their suitability in the context of mobile and embedded devices. Several recent studies have used these neural network architectures, such as [33, 34], in addition to real-time video applications where processing speed is crucial [35, 36].

- MobileNet

Google's MobileNets architecture [37] is tailored for mobile and embedded vision applications due to its lightweight design. Its efficiency stems from the depthwise separable convolutions instead of full convolutions. MobileNet introduces two parameters: Width Multiplier (α) and Resolution Multiplier (ρ), which enhance the architecture's flexibility.

- NASNet-Mobile

Neural Architecture Search Network aims to discover an optimal CNN architecture using reinforcement learning. NASNet is a technique developed at Google Brain for searching through a space of neural network configurations [38]. The optimized version, based on Normal and Reduction-Cells, is known as NASNet-Mobile. Normal Cells are convolutional cells that return a feature map of the same dimension as the input, while Reduction Cells are convolutional cells that reduce the feature map's height and width by a factor of two. These cells are combined to create the complete neural network optimized for a specific task while minimizing the computational resources needed for training and inference.

3.3. RASPBERRY PI AND TENSORFLOW LITE

- Raspberry Pi

Is is a single-board computer developed by the Raspberry Pi Foundation. The Raspberry Pi boards are about the size of a credit card and feature a range of input/output pins that connect to sensors, motors, and other electronic components.

- TensorFlow Lite

It is a lightweight framework for deploying deep learning models on mobile and embedded devices. It is an optimized version of the popular TensorFlow library. With TensorFlow Lite, models can run locally on the device without relying on cloud-based services, allowing for real-time processing and lower latency.

In this work, we installed the proposed system on a Raspberry Pi to ensure real-time detection and classification. Additionally, we have used the library TensorFlow Lite as background for the CNN model.

3.4. EVALUATION METRICS

The measures considered for evaluating the CNN models rely on various metrics, including accuracy, precision, recall, F1 score, and kappa statistic.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{1}$$

$$\Pr ecision = \frac{TP}{TP+FP} \tag{2}$$

$$\mathrm{Re}\,call = \frac{TP}{TP+FN} \tag{3}$$

$$F1score = 2 \times \frac{\Pr ecision \times \mathrm{Re}\,call}{\Pr ecision + \mathrm{Re}\,call} \tag{4}$$

where: *TP* refers to True Positive, and *TN* refers to True Negative, which indicates the correct classification of plastic bottles and paper images.

On the other hand, *FP* refers to False Positive, and *FN* refers to False Negative, which indicates the misclassification of plastic bottles and paper images.

$$\mathrm{Kappa} = \frac{(P_0 - P_e)}{(1-P_e)} \tag{5}$$

The Kappa Statistic [39] is calculated from the variance between the observed agreement (*Po*) and the expected agreement (*Pe*), highlighting the difference between the actual agreement and what would be expected by chance alone.

4. RESULTS AND DISCUSSION

We conducted the evaluation using both our dataset and the Stanford dataset. During the training process, we applied transfer learning, whereby we initialized the CNNs with pre-trained ImageNet weights.

We also employed a fine-tuning strategy to improve the prediction by adding extension layers to the CNNs. These extensions consist of a Global Average Pooling layer, a Dense layer, and a Dropout layer.

The stochastic gradient descent optimizer [40] was used, with a momentum equal to 0.9, a learning rate of 1e-4, and 20 epochs for training. We used the cross-entropy loss function L, as shown in equation (6), which increases when the predicted probability diverges from the correct label.

$$L = -(y\log(p) + (1-y)\log(1-p)) \tag{6}$$

where y is a binary indicator, with values of 0 or 1, denoting whether the class label 'c' accurately identifies observation 'o'. Similarly, p represents the predicted probability of observation 'o' belonging to the 'c' class.

The experiment consisted of testing each dataset individually, followed by combining them.We split the datasets into a training set (80%) and a validation set (20%). Fig. 5 shows that both models achieved accuracy levels above 96% and 98%.

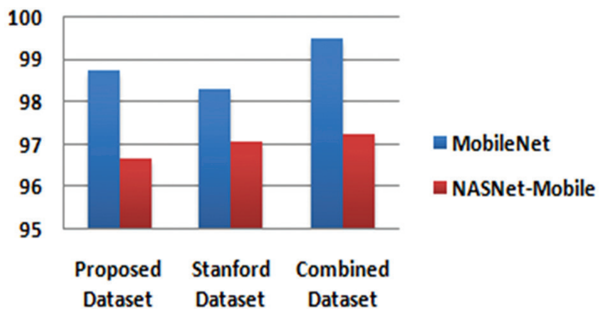

Fig. 5. The accuracy obtained for each dataset

MobileNet outperformed NASNet-Mobile in all datasets. We combined the Stanford and the proposed dataset to address the overfitting issue in classification.

MobileNet achieved the highest score of 99.50% with an error rate of 0.0136 on the combined dataset (see Fig. 6 and Fig. 7). In Table 1, we have compared the metric values of kappa, precision, recall, and F1 score for MobileNet and NASNet-Mobile. The results obtained showed that MobileNet outperforms NASNet-Mobile for all the metrics used. Based on the results of the experiments, MobileNet has been chosen as the base model for our machine (see Fig. 8).

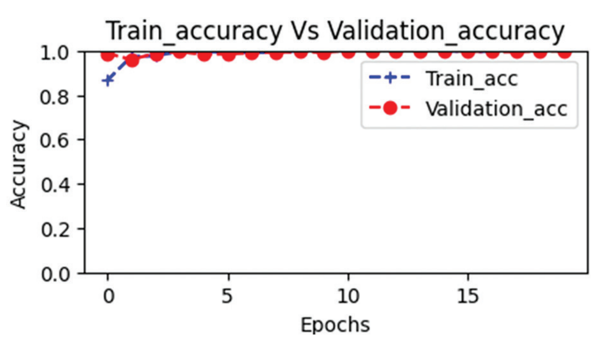

Fig. 6. The accuracy of MobileNet on the combined dataset

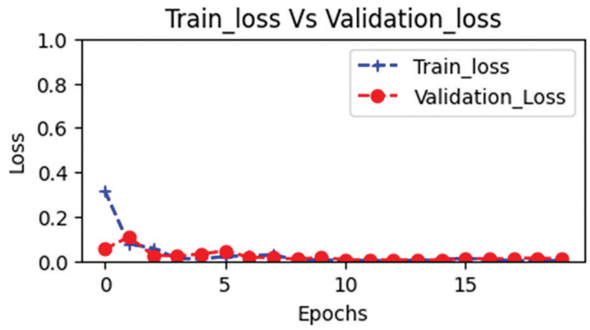

Fig. 7. The loss of MobileNet on the combined dataset

Table 1. Kappa, Precision, Recall and F1 score obtained for combined dataset

	Kappa	Precision		Recall		F1 score	
		Paper	Plastic	Paper	Plastic	Paper	Plastic
MobileNet	0.98	0.99	1.00	1.00	0.99	0.99	0.99
NASNet-Mobile	0.94	0.96	0.98	0.98	0.96	0.97	0.97

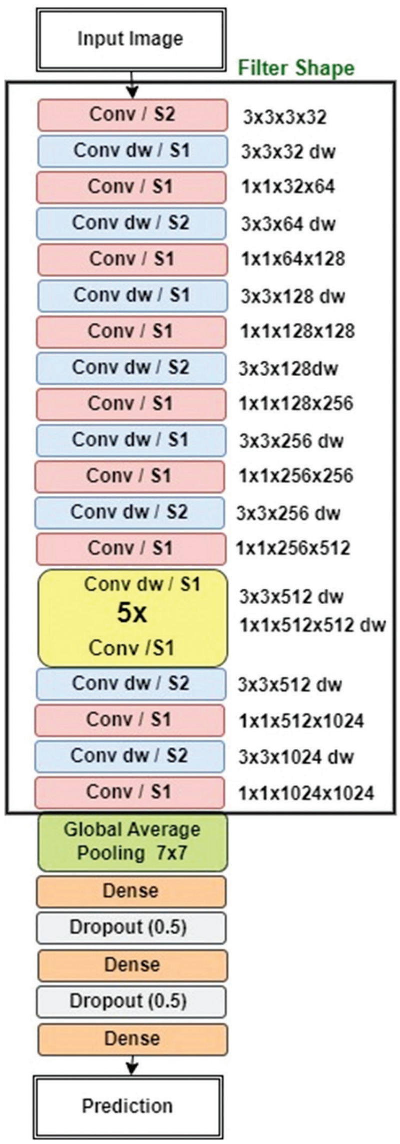

Fig. 8. The architecture of our model based on MobileNet

To enhance the convergence and generalization performance of the model, we applied Cyclical Learning Rates (CLR) to our model.

The concept behind CLR is to discover an optimal learning rate schedule by systematically varying the learning rate throughout the training process. Instead of using a fixed learning rate in training neural networks, CLR dynamically adjusts the learning rate cyclically, oscillating between a minimum and maximum value over a predefined number of iterations [41].

We have chosen a minimum learning rate of 1e-4 and a maximum learning rate of 1e-1.

We present the CLR schedule obtained in Fig. 9.

Applying CLR to our model has improved the accuracy obtained while accelerating the training process. Fig. 10 shows that all the metrics have improved, reaching 100%.

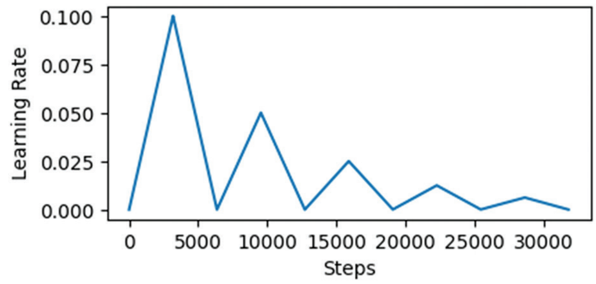

Fig. 9. Cyclical Learning Rates schedule

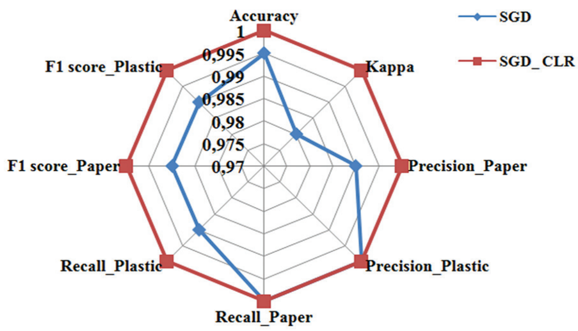

Fig. 10. The metrics obtained using the SGD optimizer with and without CLR on our model for the combined dataset

From 398 test images, which included 199 images of plastic bottles and 199 paper images, there were only two misclassified images by our model without CLR.

We obtained a paper precision of 99%, plastic bottle precision of 100%, paper recall of 100%, plastic bottle recall of 99%, Kappa of 98%, and F1 score of 99%. In addition, When we used the proposed model with CLR, the two misclassified images were correctly classified, resulting in an improvement in the values of all metrics, reaching 100%.

Since our model runs on a Raspberry Pi, balancing performance and computation time was crucial. To achieve this, we opted for TensorFlow Lite instead of TensorFlow.

In real-time, the Raspberry Pi camera captures an image of the waste when the student deposits it into the prototype machine. The proposed model then classifies the waste based on the image, and finally, the prototype machine directs the waste to the appropriate container.

Several researchers have focused on developing models for waste recognition, including medical waste [5], construction and demolition waste [42], and municipal solid waste [14-18].

In this work, we propose both the model for recognition and classification and a prototype machine to make the idea more practical and feasible.

4.1. FUTURE PERSPECTIVE

Our idea is to enhance the existing trash bins with intelligent machines capable of detecting, recognizing, and sorting waste.

The proposed machine has been designed initially for educational institutions, but its application is not limited to them; it can also adapted for use in public spaces and even in houses. For this purpose, certain modifications need to be made to the machine's system and mechanism.

The machine system must identify and classify other types of waste, such as glass, metal, organic waste, food scraps, and non-recyclable waste. The machine can be customized for the place where it will be used. For example, if we want to use the machine in healthcare facilities, biomedical waste generated, such as needles, syringes, and other medical equipment, must be included.

In our proposed prototype machine the sorting board moves the waste to the appropriate container. In cases where there are more than two types of waste, the machine needs to have a rotation mechanism that allows the containers to rotate, allowing the sorting board to direct the waste into the correct container.

5. CONCLUSION

Intelligent waste management is considered a viable solution for achieving sustainable development goals. In this study, we introduce the design of a real-time sorting prototype machine that leverages artificial intelligence for effective solid waste collection and separation.

The machine comprises physical components for waste sorting and a software component for identification and classification. The physical components incorporate an object detection sensor (E18-D80NK), servomotors (Metal Gears RG996R) for movement, and a Raspberry Pi for real-time detection and classification. To identify and classify waste, we tested two baseline models, namely MobileNet and NASNet-Mobile, on both the Stanford dataset and our proposed dataset. The final model chosen was based on MobileNet, achieving an accuracy of 99.50% without employing a cyclical learning rate and 100% when we used it.

To pave the way for potential improvements and industrial realization, we have made the machine's source code readily accessible.

Data Availability Statement

The dataset titled 'Plastic and Paper Waste' is available on GitHub at: https://github.com/Nedjar-Imane/Sorting-Machine/tree/main/Datasets

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