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AUTOMATIC WASTE SEGREGATION SYSTEM USING ARDUINO

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ABSTRACT

The increasing global population has led to a significant rise in waste generation, creating a pressing environmental challenge. Effective waste segregation can significantly reduce the volume of waste sent to landfills and enhance the recovery of recyclable materials. This paper presents a waste segregation system that utilizes trained optical and material sensors to classify waste, alongside a mechanical sorting mechanism. The system categorizes waste into four groups: metal cans, plastic bottles, paper, and other materials. A machine learning model was developed using a dataset to identify these waste types, supported by an inductive sensor for material recognition. The mechanical component features servo motors that operate flaps, directing waste into designated containers. Currently, the model achieves an accuracy of 83.54%, which can be enhanced through a web application that allows users to validate images captured by the system, thereby refining the machine learning model.
Keywords: Solid Waste, Segregation, Machine Learning, Neural Networks.

I. INTRODUCTION

By 2030, the global population is projected to reach approximately 8.5 billion people, with the Philippines expected to see its population rise to 145 million by 2045. This population surge correlates with the generation of around 40,000 metric tonnes of waste daily in the Philippines, and projections suggest that solid waste could increase by at least 165%. In response to this growing challenge, Republic Act 9003 was enacted in 2000 to address waste management issues. This legislation aims to minimize solid waste volumes through various strategies, including reusing, reducing, recycling, recovery, treatment, and appropriate disposal practices. Effective waste segregation at the source is essential for enhancing recycling and treatment efforts. Current methods for waste segregation include indirect detection of material properties, such as inductance and capacitance, using sensors. A combination of these sensors can differentiate between waste types like metals, glass, and organic materials as they pass through the detection range. More advanced techniques involve using lasers and optical sensors to assess various features of waste, such as color, shape, and texture, allowing for simultaneous identification of multiple objects. Additionally, computer vision techniques utilize cameras to capture images of waste, which are then analyzed through

Convolutional Neural Networks (CNN) for classification. This paper proposes an automated waste segregation system that employs both computer vision and material sensors to classify waste types. The system will facilitate mechanical sorting into designated receptacles and allow users to monitor and interact with the collected data, thereby enhancing the overall effectiveness of waste management. The waste categories targeted by this system include metal cans, plastic bottles, paper, and other miscellaneous waste types.

II. DETAILS EXPERIMENTAL

2.1 Hardware

The Waste Bin is designed as a vertical rectangular prism with dimensions of 0.6 m × 0.6 m × 1.3 m. The upper third of the bin features an enclosure that prevents waste from falling out of the sensing area. This enclosure contains an infrared (IR) proximity sensor module, an inductive sensor module, and a camera. When waste is deposited into the receptacle, the IR proximity sensor is activated, which subsequently triggers the camera and inductive sensor. The waste slides down an incline and lands on a flap, where both the inductive sensor and camera classify the waste into one of four categories: metal, paper, plastic, or other trash. Upon classification, information regarding the type of waste, along with the time and date of disposal, is transmitted to a database.

The waste is then segregated into corresponding receptacles below via three servo motors. The first servo motor is responsible for dropping the waste from the sensing area, while the other two servo motors direct the waste into one of four receptacles located in the bottom third of the bin. After the waste has been deposited into its respective receptacle, an ultrasonic sensor measures the trash level in each compartment. This data updates the database to reflect the fullness of each receptacle. Four RGB LEDs are positioned on the front face of the waste bin; they indicate receptacle fullness, lighting up green when the receptacle is 0-50% full, orange when 51-80% full, and red when 81-100% full.

Fig. 1 illustrates the waste bin design.

2.2 Dataset and Data Collection

For this project, a dataset comprising 2,286 images was created, divided into four categories: metal, paper, plastic, and other trash. This dataset combines images from a trash image dataset developed by Yang and Thung [7] with additional images collected specifically for this research. Each category contains between 600 to 700 images, except for the "other trash" category, which includes only 333 images.

The images not included in Yang and Thung's dataset were captured using a webcam in the entry area of the receptacle, with a painted white background. To ensure diversity, variations in object position, lighting, and framing were introduced during image capture. Data augmentation techniques, including random scaling, shearing, shifting, and zooming, were applied to enhance dataset variability and simulate different waste positions that may enter the system.

2.3 Model

Convolutional Neural Networks (CNNs) are structured with multiple layers that extract features from input images [8]. The convolutional layer applies a series of filters to the input image, with early layers identifying primitive features and later layers capturing more complex details [9].

Three pre-trained models—VGG16, ResNet50, and Xception—were evaluated without data augmentation. These models, trained on the ImageNet dataset, served as feature extractors. Their outputs were subsequently fed into a Softmax layer, which calculates the probabilities of the image belonging to one of the four waste categories: metal, paper, plastic, and other trash. Each model was further trained on the waste dataset for 100 epochs.

Figures 8 to 11 illustrate the accuracy and loss metrics of the models following the 100 epochs of training. Among the three models, Xception achieved the highest training accuracy of 100%, though it also exhibited an increasing test loss of 120%. In contrast, the ResNet50 model performed poorly, achieving only 55% accuracy. VGG16 was selected as the primary model for this research due to its high accuracy of 92% and lower loss of 60% compared to the others.

The top classification layer of the chosen pre-trained model was removed and replaced with a dense layer and a Softmax layer. The Softmax layer assigns decimal probabilities to each of the four classes based on the features extracted by the pre-trained model and the preceding Dense layer. The Softmax function, commonly used in multi-class classification problems, outputs probabilities normalized to sum to one (1) based on the input feature vectors and their exponential values [10].

2.4 Web Application

A prototype web application was developed to enable users to view collected data, interact with the system, and contribute to the improvement of the machine learning model. The application was built using the Flask framework, with the user interface designed in HTML. The website comprises three pages: the main page, the statistics page, and the help page. Users can validate the classification of items thrown into the system, register their emails to receive alerts when any of the four receptacles are full, and view images captured by the system for validation purposes. These validated images, along with their correct classifications, will be utilized to enhance the model's accuracy. All images are stored locally for this project.

III. RESULTS AND DISCUSSION

The model was trained with a training/validation split of 80/20, using an image size of 150 × 150 pixels and a batch size of 12. The RMSprop optimizer, with a specific learning rate, was employed to refine the weights. Training occurred over 30 epochs, with all processes handled through Keras [11]. After 30 epochs, the training accuracy reached 77.60%, while the validation accuracy was 83.54%. Training loss was recorded at 62.69%, and the validation loss varied significantly, concluding at 39.83%. This fluctuation in validation loss may be attributed to the limited number of images in the validation set, particularly for the "other trash" category, which has about half the number of images compared to the other categories.The model was tested in the system by randomly throwing waste into the enclosure. Out of 100 tests, the trained model achieved an overall accuracy of 89%. Notably, the metal classification was the most accurate at 100%. This high accuracy is likely due to the inductive sensor's assistance in identifying metal objects in conjunction with the model. The average time for the entire process—from waste entry to segregation—was 8.12 seconds, with a standard deviation of 0.47 seconds. The classification time remained consistent within one standard deviation, indicating that it does not significantly affect the overall processing time.

Table I summarizes the results of the tests:

Classification	**Accuracy**	**Time (seconds)**
Metal	1.00	8.13 ± 0.47
Paper	0.80	8.10 ± 0.41
Plastic	0.92	8.33 ± 0.51
Other Trash	0.84	7.94 ± 0.39
Overall	**0.89**	**8.12 ± 0.47**

IV. CONCLUSION

The automated waste segregation system demonstrates the ability to effectively sort waste at the source, leveraging machine learning and material sensors. This system can be easily replicated, allowing multiple waste bins to utilize the same trained model. With further enhancements, it could significantly improve waste management practices. The trained model has potential applications beyond this specific system.

However, the system does face limitations. It can only segregate one piece of waste at a time, and its accuracy could be improved. Additionally, larger waste items cannot be processed, and the time taken for segregation may be excessive. Future improvements could include redesigning the receptacle to accommodate larger items, retraining the model with a more extensive dataset to boost classification accuracy, and optimizing the code to reduce processing time. By minimizing the segregation time, the system could handle multiple waste items more efficiently. Finally, expanding the model to include additional waste categories would facilitate the recycling of a broader range of materials.

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