Automated Waste Segregation System using Trained Optical and Material Sensors with User Communication Capabilities

Conference Paper · May 2020

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AUTOMATED WASTE SEGREGATION SYSTEM USING TRAINED OPTICAL AND MATERIAL SENSORS WITH USER COMMUNICATION CAPABILITIES

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Abstract - As the world's population grows, so does the amount of generated waste which continues to be an issue being faced around the world. Waste segregation is an effective way to lessen waste that could go to landfills while increasing the amount of recyclable materials. In this paper, a segregation system was developed using trained optical and material sensors to categorize the waste, while a mechanical segregating system was introduced. Aside from this, a web application where users will be able to view data gathered and will be able to validate the system's categorization of wastes. By using this system, waste may be categorized into four: metal cans, plastic bottles, paper and other wastes. A model was trained using a dataset to recognize these four types of waste, while an inductive sensor aids in recognizing the material. The mechanical system consists of servo motors that rotate flaps which allow the trash to fall into the target receptacle. The current model has an accuracy of 83.54% but can be improved using the web application, where users will validate images captured by the system to improve the machine learning model.

Keywords - Solid Waste Trash, Segregation, Machine Learning, Neural Networks.

I. INTRODUCTION

The world's population is expected to reach 8.5 billion people by the year 2030 [1]. The Philippines is expected to reach 145 million by the year 2045. 40 000 metric tonnes of waste is generated per day in the Philippines. The rise in population will increase the amount of solid waste generated and is expected to increase by at least 165% [2].
Republic Act 9003 was proposed in 2000 in the Philippines to combat this increase in waste. This law focuses on proper waste management whose goals are to reduce the volume of solid waste [3]. To achieve these goals, various methods: re-using, reducing, recycling, recovery, treatment, and proper waste disposal are enacted, among other solid waste management practices. Proper segregation at source is the first step with these methods. This is implemented to improve the volume of waste recycled and treated.

Segregation of solid waste may be done indirectly using sensors to detect the material properties of the object, such as its inductance and capacitance [4] [5]. A mixed use of sensors is able to distinguish wastes such as metals, glass, and wet waste as an object passes through its range [5]. Lasers and optical sensors have also been used to distinguish wastes from each other by detecting multiple features at a time which include color, shape and textures [6]. This method is more complicated than the previously mentioned method but can distinguish multiple objects at the same time. Another method of distinguishing types of waste is through computer vision. Images are taken by a camera and are inputted into a pipeline which classifies the image using Convolutional Neural Networks (CNN).
Our paper proposes an automated waste segregating system that will be able to classify the type of waste using a computer vision model and material sensors. The system will be able to mechanically segregate their respective waste receptacle, and will enable users to monitor and interact with data gathered to improve the system. The classifications used in this system include metal cans, plastic bottles, paper, and other wastes not mentioned

II. DETAILS EXPERIMENTAL

2.1. Hardware

The Waste Bin is a vertical rectangular prism whose dimensions are 0.6 m by 0.6 m by 1.3 m. The upper third of the bin consists of an enclosure that ensures waste does not fall out of the sensing area. The enclosure houses the infrared (IR) proximity sensor module, the inductive sensor module and the camera. When waste is thrown into the receptacle, the IR proximity sensor module gets activated and in turn activates the camera and inductive sensor. The object slides down an incline and falls onto a flap where the inductive sensor and camera are used to classify the waste into one of the four classifications: metal, paper, plastic and other trash. Once a classification is made, data on the type of waste, time, and date of when the waste was thrown is sent to the database.
Waste is dropped and segregated into its corresponding receptacles below via three servo motors. The first servo motor is used to drop the waste from the sensing area while the remaining two servo motors are used to move the waste into one of

four receptacles at the bottom third of the receptacle. Once the waste has dropped into its corresponding receptacle, an ultrasonic sensor is used to measure the level of the trash in each receptacle. This data is then used to update the information on waste receptacle fullness in the database. Four RGB LEDs are found on the front face of the segregator. They use the data collected by the ultrasonic sensor on waste level in the receptacle and lights up with green if the receptacle is 0 to 50% full, orange if the receptacle is 51 to 80% full, and red if the receptacle is 81 to 100% full. Fig. 1 is the diagram of the waste bin.

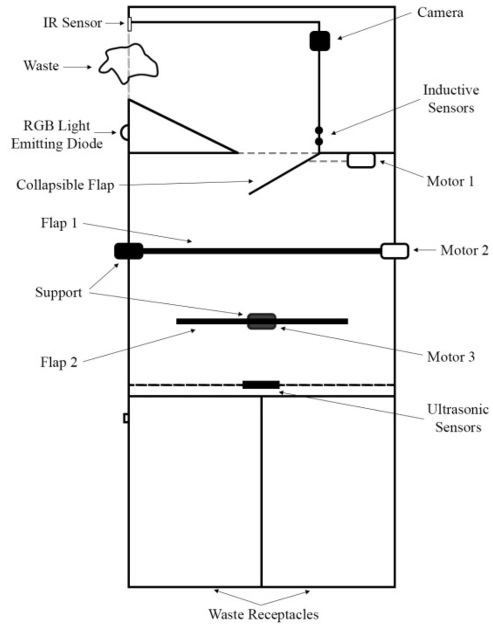

Fig.1. Waste Bin Diagram

2.2. Dataset and Data Collection

For this work, a dataset containing 2 286 images subdivided into four categories: metal, paper, plastic and other trash. The dataset is a combination of a trash image dataset created by Yang and Thung [7] and images that were collected for the purpose of this project. Each category contains 600 to 700 images each, besides the “other trash” class which has only 333 images. The Fig. 2 to 5 below show example images from each of the classes. The data acquisition for the images that were not originally part of Yang and Thung’s dataset was done by hand. The data acquisition process involved using the webcam that was acquired to be used in the system and the images were taken in the entry area of the receptacle using the painted white of the trash can as the background. The position of each object, the lighting, and whether the object is contained fully in the image varies to introduce variation in the dataset. Data augmentation was performed on the images to further improve variation of the images. The techniques used are random scaling, shearing, shifting, and zooming of each image. These techniques were used to simulate the different positions of waste that could enter the system.

Fig. 2. Metal

Fig. 3. Paper

Fig. 4. Plastic

Fig. 5. Other Trash

2.3. Model

Convolutional Neural Networks consists of multiple layers with different functions to extract features out of images that are inputted into the network [8]. The convolutional layer convolves the inputted image using a sequence of filters. Primitive features are extracted in the early layers while later layers extract more detailed features [9].

Three pre-trained models, VGG16, ResNet50, and Xception were tested without data augmentation. These models, pre-trained on the ImageNet dataset, were used as feature extractors, whose output were then fed into a Softmax layer that would output the probabilities of the image into the four waste categories: metal, paper, plastic, and other trash. The three models were then trained again on the waste dataset for 100 epochs.

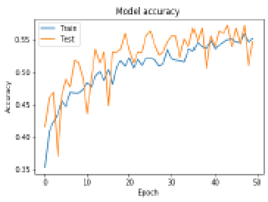

Fig. 6.ResNet50 Accuracy

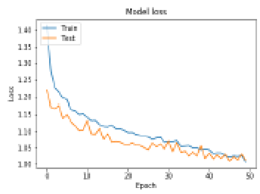

Fig.7. ResNet50 Loss

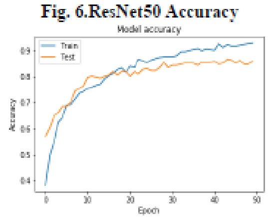

Fig.8. VGG16 Accuracy

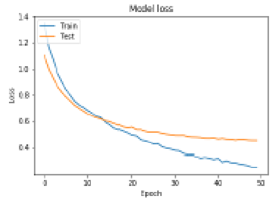

Fig.9. VGG16 Loss

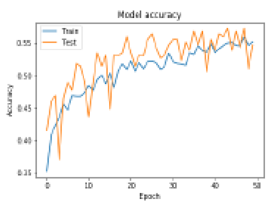

Fig.10. Xception Accuracy

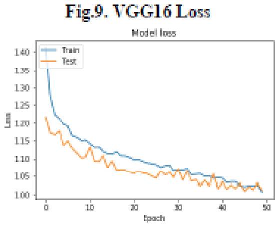

Fig.11. Xception Loss

Fig. 8 to 11 showcases the accuracy and loss of the models after 100 epochs. Out of the three models, Xception had the highest accuracy reaching a training accuracy of 100% but had an increasing test loss of 120%. The ResNet50 model performed poorly in this dataset, reaching only an accuracy of 55%. VGG16 was chosen as the base model for this research due to its high accuracy of 92% and lower loss of 60% compared to the other models.

The top classification layer of the chosen pre-trained model was removed. A dense layer and Softmax layer were used in its replacement. The Softmax layer assigns decimal probabilities to each of the four classes based on the features extracted by the pre-trained model and the Dense model that precedes the Softmax layer.

The Softmax function is used in classification problems. It is a machine learning technique that is usually used in multi-class classification methods [10]. This function is usually the last layer in a neural network. It accepts feature vectors and outputs decimal probabilities. The probabilities are based on the feature vectors and its exponential value which is then normalized to sum up to one (1).

$$P(y(i) = k | x(i); \theta) = \frac{e^{\theta^{(k)\top} x^{(i)}}}{\sum_{j=1}^{K} e^{\theta^{(j)\top} x^{(i)}}} \quad (1)$$

The equation above is the Softmax function. Here, x represents the feature vectors that were extracted using the model, while θ represents the weights for that layer that were set.

2.4. Web Application

A prototype web application was designed for the purpose of enabling the user to view data collected, interact with the system and help improve the system by improving the machine learning model. Flask was used as the framework for this web application while the user interface used HTML. There are three pages to the site — the main page, the statistics page and the help page wherein users may be able to validate the classification of the items thrown into the system. Users will be able to register their emails to be alerted if any of the four receptacles are full. Images taken by the system can be viewed in the help page where users will be able to validate whether the classification done by the model is correct. These images will then be used, with their correct classification, to further improve the accuracy of the model. All the images are stored locally for this project.

III. RESULTS AND DISCUSSION

The model was trained with a train/validation split of 80/20, an image size of 150 × 150, and a batch size of 12. The optimizer used to refine the weights used is the RMSprop optimizer with a learning rate of 1×10^{-5}. The model was trained for 30 epochs. The training and data augmentation was all done using Keras [11]. After 30 epochs, the training accuracy reached 77.60% and validation accuracy 83.54 %. Training loss reached 62.69% and the validation loss varied notably, but ended on 39.83%. We believe that the fluctuation in validation loss relates to the lack of images being used in the validation set and that the "other trash" category has only about half of the amount of images as the rest of the images which could have biased the results and cause some imbalance across training and validation sets. Fig. 12 and Fig. 13 below show the accuracy and loss of the model after training.

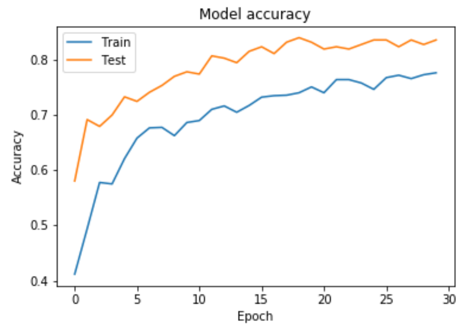

Fig.12. Model Accuracy

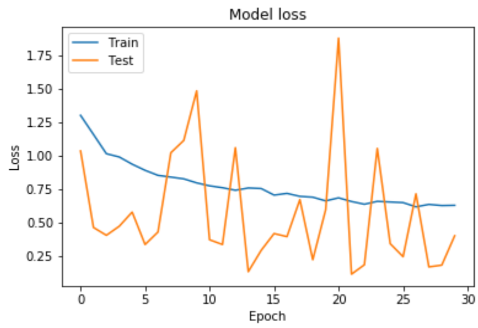

Fig.13. Model Loss

The model was tested with the system, throwing waste in the enclosure in random positions. Out of 100 tests, the system with the trained model achieved 89% accuracy overall. Individually, the class that is most accurate is metal with 100% accuracy. This high accuracy compared to the others is most likely due to the presence of the inductive sensor that aids in the classification of metal objects in junction with the model. It took the system an overall average of 8.12 seconds with a standard deviation of 0.47 seconds from the input of waste into the system to segregation into its receptacle. The average time for each classification falls within one standard deviation of the overall average time; therefore waste classification is not a variable when considering the time it takes for the system to segregate waste. Table I below shows the summary of 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

Table 1: System Accuracy and Speed

IV. CONCLUSION

The automated waste segregation system can successfully segregate waste at source. This is possible with the help of machine learning and material sensors. This system can be easily produced again because multiple waste bins will be able to use the same model that was trained. This system, if further improved, may be used to improve the waste management situation. The model that was trained can also be applied to different uses not only for this system. One of the biggest pains is the possible wide variation of waste that may be inputted into the system. Therefore, for the system to be accurate, the dataset needs to be quite large and continuously updated. The ability for the users to validate the images taken for the waste classification model is invaluable because it will allow for the dataset to grow and for the model to be retrained to be more accurate.

The system has its own limitations. It can only segregate waste one at a time and its accuracy can be improved. Also, wastes that are large cannot be segregated with the system, and the time it takes for waste to be segregated is too long. Thus, improvements can be made to improve the whole system. The design for the receptacle should be changed to allow for larger wastes to be segregated using the system. The model could be retrained further with a larger dataset to allow for the accuracy of classification to improve. The code could be optimized to lessen the time it takes from sensing the waste has entered the system to it being segregated. Since, the time for segregation can be minimized; multiple wastes can be thrown in a shorter span of time. Finally, additional waste classes could be added to the model. This would help in recycling more materials.

ACKNOWLEDGMENTS

Engr. Marie Fe Novia, Professor in Electronics Engineering, has been very helpful with regards to the devopment of this paper.

Victor S. Recto, for helping in the design and construction of the model, which provided the base of our system.

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