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Rclaws: Recyclable Waste Classification System Using Convolutional Neural Network

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Abstract:
Waste Management is one of the common ways to manage waste generation and waste disposal. The Philippines is one of the highest ranks in terms of trash collection rates in South East Asia and the third (3rd) water resources serve as the biggest dumping areas of plastic [24].

The use of Convolutional Neural Networks to open a new way to address this issue is to manage and lessen garbage generation every day. The application of image processing is capable to identify and monitor the garbage that can be recyclable. The system will collect useful data and categorize with the use of CNN classification. The CNN model is trained each recyclable waste materials by putting a label for test and training. The system was tested on recyclable waste materials dataset which achieved an accuracy of 96.67% on the dataset. This kind of segregation process of waste becomes faster and perceptive which can reduce human involvement in classifying recyclable materials and eventually can have an efficient and correct way of sorting recyclable materials.

***Keywords**: Waste, Classification, Recyclable Waste Segregation, Convolutional Neural Network, Machine Learning*

Introduction:

In today's time, Waste management is known to all but neglected by many that are used to describe activities for waste segregation to solve problems caused by inappropriate waste disposal [28].

Waste segregation process leads to recycling of waste, energy generation out of waste, reduction of waste and lessening of landfills. Many waste management strategy approaches are carried out to deal with the multifaceted challenges due to urbanization. Time, waste materials were greater than the production[10].

Garbage is a global problem that affects everyone and all living beings. A study shows that 74% of the plastics leaking into the ocean from the Philippines come from garbage[24].

The process in which the waste is segregated is parting of waste into dissimilar components. This is normally done by hand-picking manually which sometimes cause bad and hazardous to human health if not properly done[1], to address this concern, waste classification and identification is introduced to help everyone especially the government officials and law-makers to efficiently segregate wastes especially the recyclable ones. Segregation can be made by everyone; however, not doing it properly and with caution, a challenging diversity of segregation tasks happen [14].

Several companies and family does not practice proper waste segregation and disposal. 15 percent of waste can be segregated so that it will easier to recycle. Most segregated and recycled materials are sold with a high value but uncollected waste finds its way to different dumping sites[14][26].

To automatize the recycling process, it is important to propose clever systems that can perceive waste components correctly [4]. With an aid of image processing technique that recognizes wastes according to their color, size, dimension, and shape [4][28]. A machine learning approach to identifying and key features of image recognition. It is also a vital component of a convolutional neural network to learn related data from sample images.

May – June 2020
ISSN: 0193-4120 Page No. 9410 - 9419

[28]. A deep learning approach to image recognition may involve the use of a convolutional neural network to automatically learn relevant features from sample images and automatically identify those features in new images [8] One method to classify waste into various categories is the use of Convolutional Neural Networks. It covers better recycling and reuse processes for effective waste management. By using the concepts of Artificial Neural Networks[27] and image analyzing specifically the image recognition algorithm, the project is aimed at designing and developing a system that can be effectively utilized to segregate waste [15][30].

Convolutional neural are man-made neural networks used to identify images, sort it and perform scene recognition [16][22]. High efficiency in the image classification was proved among different models [6], it is a kind of deep neural system that has a structure and approach varying from different deep neural networks [9]. CNN models can perform classification and forecasts, flexible, and adaptable in a wide variety of complex challenges in? [21].

Thus, this study aims to classify different kinds of waste recyclable materials, through image processing along with a convolutional neural network.

II. LITERATURE REVIEW

2.1 Image Processing

Image processing is a structure of signal processing, which the input is an image; for example, a photo or video outline[5]. The image processing performance can also be a picture or a lot of qualities or parameters identified with the image[23][33]. The goal of image preprocessing is upgrading image data that irrelevant images were removed, and the image includes that are important for further processing are emphasized [2][33]. Preprocessing approaches aim to improve image details to remove unwanted distortions and enhance some characteristics of the input image [11]. Image processing can remove unnecessary features and can convert the RGB image to grayscale and binaries it [18]. The image is acquired by a digital gadget such as camera then convert it into grayscale. The grayscale conversion consists in calculating the average value of the three components of the two colors (0 and 255, respectively) [12]. A fixed threshold, 127 in this case, is used to specify which intensity of color values are converted to 0 and which, to 255. Image processing, either as an improvement for the human observer or independent analysis software offers costs, speed and flexibility advantages [29].

2.2 Convolutional Neural Network

Primarily to classify images, cluster them by similarity, and perform object recognition with scenes are functions of convolutional neural networks in which deep artificial neural networks**.** Convolutional neural networks ingest and process image as a tensor, and tensors are matrices of numbers with additional dimensions and perform a sort of search[34]. The three-dimensional objects are some of the examples which perceive the images as volumes [13][15].

It is uploaded in many applications in the real world, including face recognition. and object detection. It's one of the most successful non-trivial tasks. CNN has different alternative layers [28][3] CNN has three distinct layer types that are considered a component of CNN, in constituent to neural networks. The convolutional layer, subsampling layers and fully connected layer [25]. In patterns, and image recognition problems, CNN is commonly used as these have several advantages compared with other methods.

2.3 Classification

Classification is a process in which there is some systematic arrangement of an individual thing into group category according to set criteria. Thus, a classifier differentiates categories and to make hierarchical, semantic, informative representations [20][31].

TEST Engineering & Management

May – June 2020
ISSN: 0193-4120 Page No. 9410 - 9419

2.4 Segregation of recyclable waste

Waste segregation is very important because it is one of the biggest problems of our planet. Items that are not decomposable can be reused and recycled. A large part of the world's waste can be converted to compost [19].

Recyclable waste is a term that refers to raw or processed materials that can be removed from a waste stream, reused, and repurposed into another item[17]. It is important to segregate waste materials and separate the recyclable one. Recyclable wastes are categorized into plastics, paper, cartoon, and other materials [25][32].

The source of recycling is through salvaging which in turn can be profitable[7]. In that way, recyclable waste materials will be prevented from going to waste processing disposal sites and using landfill space. With it, it can protect national resources as well as cost and efforts[8][32].

To have a sustainable economy, waste management and recycling are the ultimate ways to do it. Using intelligent system instead of hiring humans as workers in the dump-yard is a safer and efficient way of recycling. It can be the innovations which demonstrate the efficiency of the latest intelligent approaches. [30].

III. MATERIALS AND METHOD

A. Image Data Acquisition

An average of 1000 images of each recyclable waste of various forms, dimensions, colors, sizes, and shades acquired under ordinary controlled illumination conditions which constitutes of 10000 images. Experts manually classified the recyclable wastes as a standard procedure. Multiple kinds of standard cameras were used to acquire the images, extracted from four viewpoints (front, back, right, left). The images acquired were used for tests and training sets for Convolutional Neural Network. Each variety of recyclable materials labeled using the image labeler application. The marked areas were taken from the original image, converted into a standard square of 320 x 240 pixels. Each recyclable materials has 1000 average images per category and training sets. The image resolution needed for this network is 320 x 240 matrices. The images went threshold to enhance the images data and to remove irrelevant images. The image characteristics or attributes important for further processing were highlighted.

B. Data Set

Table 1. Recyclable Waste Used for Training

Recyclable Waste	Training 80%	Testing 20%	Total
Carton	800	200	1000
Eco Bag	800	200	1000
Paper	800	200	1000
Paper cup	800	200	1000
Paper Plate	800	200	1000
Plastic	800	200	1000
Plastic Bottles	800	200	1000
Plastic Cup	800	200	1000
Plastic Cutlery	800	200	1000
Tin Can	800	200	1000

A total of 10000 images were used, for the number of training the data sets for recyclable materials which consist of 10 categories, 800 pictures were used for each recyclable materials. **Table 1** shows the dataset used, consisting of 10000 images of different types of recyclable materials to be segregated. 80% images were used as training sets comprising of 800 pictures and 20% of the images were used as a testing image comprising of 200 pictures.

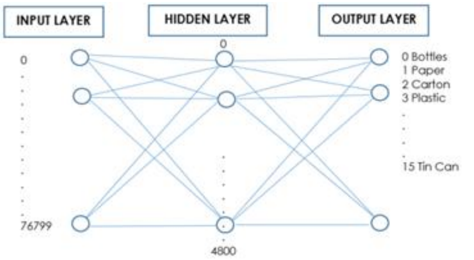


Fig. 1. Convolutional Neural Network Design

Fig. 1 depicts the input layer which represents the pixels of an image from 0 to 76999 based on the resolution of an image. Hidden layer takes part in the activation in which there is an experimental number for a hidden layer from 0 to 4800. The purpose of which is to breakdown the image into smaller parts or piece. That smaller piece will be the basis for classification. The links from input to the hidden layer have its weights that are being adjusted every time there is a new image entered in a neural network. The output layer is the wastes such as plastic bottles, paper, carton, plastic, tin can and a lot more.

C. Recyclable Waste Category and Characteristics

Table 2. Characteristics of Recyclable waste materials

Waste	Characteristics
Carton	Made from waste paper waste textile
Eco Bag	made up of reclaimed post-industrial organic and natural cotton scrap
Paper	natural attributes of the wood pulp or even recycled paper
Paper Cup	made out of paper and often lined or coated with plastic or wax
Paper Plate	made up recycled paper
Plastic	made of high-density polyethylene
Plastic Bottles	made of polymers
Plastic Cup	made of polymers
Cutlery	Made of polymers
Tin Can	is a silvery-white, soft, malleable metal that can be highly polished

Table 2 represents that different characteristic of recyclable waste materials and what it made for.

Table 3. Data Attribute

	Description	Value
Color	Black White	0 255
Size	The different size of the recyclable waste	16kb, 12MB
Dimension	The measurement of the recyclable waste entered in the neural network	1560x1170
Shape	Of any shape (crumpled, flat, bent, etc)	

Table 3 shows the attribute of the data being used in the training of recyclable materials to be classified and segregated. Considerations such as color, size, dimension, and shape were determined.

D. Training Data Preparation

D.1 Threshold process

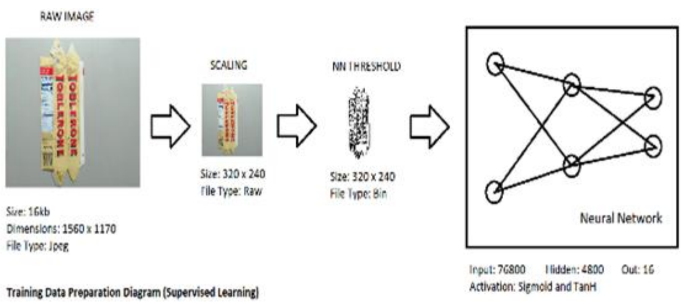


Fig. 2. Training Data Preparation Diagram.

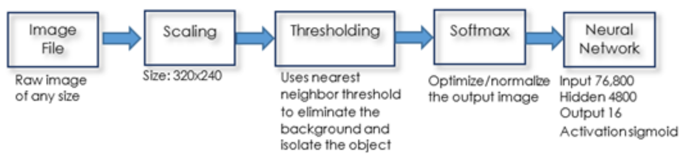


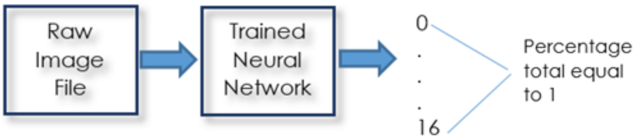
Fig. 3. Representation Diagram

Fig. 2 is the histogram threshold reference of the sample data. It was used before the data was put into training. From the raw or original image entered in the neural network, it was scaled down to a smaller size 320 x 320, it was done to ensure that the database will not consume bigger memory. After the image was scaled it was passing thru the threshold to guarantee that the images were able to quantify the output of a neuron in the output layer (Simplilearn, n.d.). Threshold enhance the image, make the image black and white and remove unwanted background, digitized the image and binarize.

Fig. 3 indicates the representation diagram from the image file up to the neural network for the classification. It was started from the raw image of any size then scaled down into smaller size which is 320 x 240. With the help of neighbor threshold, it eliminated the background and isolated the object. Softmax were utilized to optimized and normalized the output image after passing thru the threshold. And the neural network was able to classify the image with the help of activation sigmoid and computed as $\sigma(z) = \frac{1}{1+e^{-z}}$ or there are other options such as $tanh$

$$\theta(z) = \frac{e^z - e^{-z}}{e^z + e^{-z}}$$

The purpose of this is to collaborate the weights on each node and generate the highest percentage to the given input. This formula was used to normalize and adjust the data or value to provide an output number closer to the origin or raw image ranging from 0 to 1.



E. Testing

Fig. 4. Testing the Data

Fig. 4 shows a diagram of how the data were tested. It was noted that from the raw image file feed into a neural network, it was able to test all the recyclable waste materials. Percentage results to 1.

F. Evaluation Measures

F. 1 Confusion matrix

To identify the effectiveness of the classification process made by the research, it used the confusion matrix in which there is a set of sample data used that is meant by the true values. With the use of this method, it summarizes the number of correct and incorrect predictions with count values and then run-down into pieces by each class.

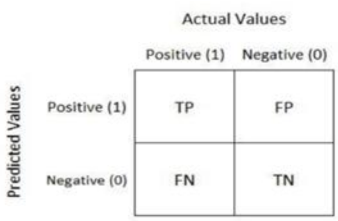


Fig. 5. Confusion Matrix

Fig. 5 shows the confusion matrix which the researcher used. The diagonal elements show the number of images where the label predicted is equal to the true label, while the classifier mislabels non-diagonal elements.

F.2 Accuracy

$$\text{Accuracy} = \frac{\text{Number of correct predictions}}{\text{Total number of predictions}}$$

Fig. 6. Accuracy formula

The equation shows (Fig. 6.) how the model is evaluated based on accuracy. It is defined as the percentage of correct predictions for the test data. It can be readily calculated by dividing the amount of right classification by the amount of total classification.

IV. EXPERIMENTAL RESULTS

A. Training Dataset Accuracy Results

Table 4. Training Dataset Accuracy Results

Type	Train_loss	Valid_loss	Accuracy	Error_rate
0	0.053525	0.000037	100%	0%
1	0.078843	0.000043	100%	0%
2	0.036775	0.000005	100%	0%
3	0.055004	0.000020	100%	0%
4	0.096853	0.000043	100%	0%
5	0.046887	0.000005	100%	0%
6	0.045004	0.000035	100%	0%
7	0.078843	0.000043	100%	0%
8	0.036775	0.000005	100%	0%
9	0.053525	0.000037	100%	0%

Table 4. depicts the outcomes of the accuracy of the training dataset. It was noted that each recyclable waste category was consistent with each type. It only means that the training image of recyclable wastes is correctly classified and identified, 100% of the time after the training of each type was done. There was a zero percent error rate for every type of image. This only implies that there are proper classification and identification of recyclable waste

materials. In this study, it was used the nearest neighbor for the threshold model, edge detection technology, blur was added on the part of convolutional neural network to give distinction in the image before passing it to neural network, and quadtree to identify every data points.

B. *Result of Confusion Matrix*

The diagonal components reflect the number of images that the predicted label equals the true label (Fig. 7.), while those that are mislabeled by the classifier are off-diagonal elements.

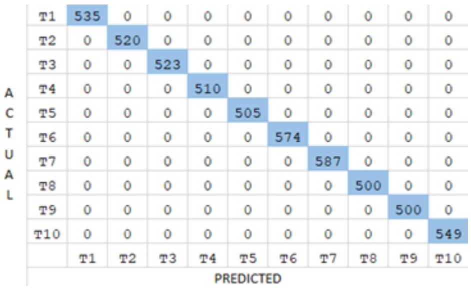


Fig. 7. Result of Confusion Matrix

Fig. 7 describes the validation of the confusion matrix. The different model for recyclable waste materials was classified correctly, a total of 5303 random images were used in the validation stage. Five hundred thirty-five was correctly classified and identified for T1 which is Carton, and no misidentified images were classified. In addition, other recyclable waste category was 100% correctly identified to name T2(Eco Bag, 520), T3 (Paper, 523), T4(Paper Cup, 510), T5(Paper Plate, 505), T6(Plastic, 574), T7(Plastic Bottles, 587), T8(Plastic Cup, 500), T9(Cutlery, 500), T10(Tin Can, 549). This means that the model used for the classification of recyclable materials works well.

Table 5. Validation Dataset Accuracy Result

Category of Recyclable Waste	Number of Images	Identified	Misidentified	Accuracy
T1	535	535	0	100%
T2	520	520	0	100%
T3	523	523	0	100%
T4	510	510	0	100%
T5	505	505	0	100%
T6	574	574	0	100%
T7	587	587	0	100%
T8	500	500	0	100%
T9	500	500	0	100%
T10	549	549	0	100%

Table 5 indicates the number of images classified and identified the model for recyclable waste materials. It was clearly stated that there are no misidentified images and it shows that it is 100% accurate in terms of identifying. T1 to T10 is the code for the different type of recyclable waste materials.

Table 6. Prediction, Actual, Loss, Probability

Type of Waste	Prediction	Actual	Loss	Probability
T1	T1	T1	0%	100%
T2	T2	T2	0%	100%
T3	T3	T3	0%	100%
T4	T4	T4	0%	100%
T5	T5	T5	0%	100%
T6	T6	T6	0%	100%
T7	T7	T7	0%	100%
T8	T8	T8	0%	100%
T9	T9	T9	0%	100%
T10	T10	T10	0%	100%

Table 6 shows the images of types of recyclable waste that every type of class is correctly classified with a likelihood of 100% and a loss of 0%

C. Percentage Output

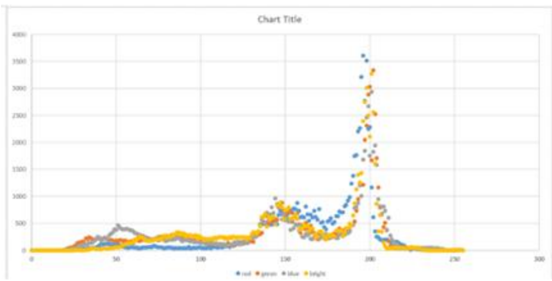


Fig. 6. Color Density

Fig. 6 depicts the color density of an image. It is a sampling of data output per category. It gives how the color affects the training of an image. It shows that as the image was first fed in the neural

May – June 2020
ISSN: 0193-4120 Page No. 9410 - 9419

network, it has a solid color showed. As it was passing through the threshold, it gives the cluttered color which makes an image more enhanced because it was binarized and emphasized.

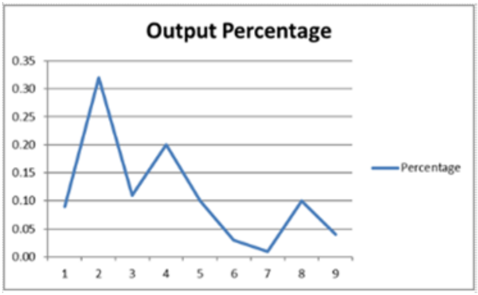


Fig. 7. The output of trained data

Fig. 7 indicates the trained data from 200 up to 1000 images it was trained. The vertical axis shows the vertical percentage accuracy based on the number of training images per recyclable waste category. It indicates that if there are more data to be trained the more accurate the result.

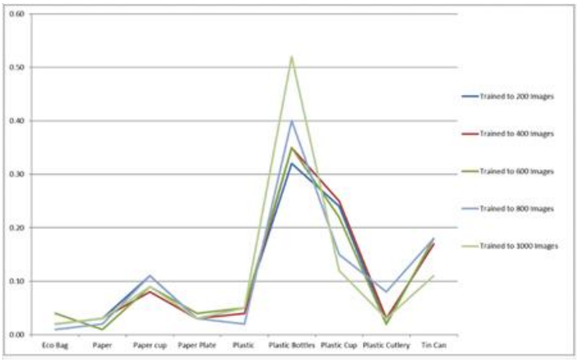


Fig. 8. Output Percentage

Fig. 8 describes a sample of data from a single image. It shows that as more images feed into the neural network, the higher the possibility it has to be more accurate. The vertical axis indicates the percentage accuracy on the feed image.

Table 7. Testing Dataset Accuracy Result

Type of Recyclable Waste	Testing Dataset	Accuracy
T1 Carton	200	96.67%
T2Eco Bag	200	95%
T3 Paper	200	95%
T4 Paper Cup	200	96.20%
T5 Paper Plate	200	98.33%
T6 Plastic	200	97.24%
T7 Plastic Bottles	200	96.25%
T8 Plastic Cup	200	98.44%
T9 Cutlery	200	97.23%
T10Tin Can	200	96.20%

After splitting the dataset into training (80%), and testing and validation (20%), the training accuracy got 100%, and the validation accuracy was also 100%. The studyused different types of a testing dataset consisting of 2000 images, or 20% of the total dataset, 200 images per recyclable waste type to test the model.

Table 7 shows T8 type of recyclable waste has the highest accuracy, with 98.44% of accuracy, followed by the T5 which is the paper plate which consists of 98.33%. It was followed by T6 which is plastic ranging 97.24%. Almost all of the recyclable waste materials types range from 96% up to 98.44%. Meanwhile, the lowest recyclable types were from T2 eco bag and T3 which is paper. It only means that adding more images, removing the noise in the dataset and do some more tuning could attain higher accuracy.

CONCLUSION

The model of identification of recyclable waste materials of different types was based on the Convolutional Neural Network used through the help of Nearest Neighbor and Quadtree model, which enable to classify the ten types of different recyclable wastes. From the result of the experiments, it was noted that it is capable of classifying different types of recyclable materials that depend on their size, color, as well as dimension and shapes.

The results of the experiment on CNN are very reliable with high accuracy, low error rate, and outstanding training efficiency. As predicted, the results show that using more data for the training phase increases the classification and decreases the error rate. With the best-pretrained model and training images (80% of the image dataset, 20% validation, and testing dataset labeled) with an accuracy of 96.67%. Also, with the use of image processing classifying are easier to get higher accuracy result. With an aide of camera to process the input image, processing and classifying of recyclable waste materials are getting better.

Due to some limitations of the current study, the optimization of the CNN model and the use of learning to assess the effectiveness of the method of classification for other applications can be achieved in the future. This study also aims to create a classification model not only to classify different types of recyclable materials but as well to know how many times did these different types were used. Also, classification accuracy can be further improved by providing a large data set of images of the recyclable waste materials. Likewise, enhancing the image segmentation process is essential, and tuning the CNN model parameters to achieve higher accuracy.

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