Implementation of Convolutional Neural Network of Non-biodegradable Garbage Classifier and Segregator Based on VGG16 Architecture

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Abstract—**Problems posed by solid waste management have been raising alarming threats today. The increasing number of garbage clogging the drainage systems and the limited space for waste disposal are some of the vivid indications of the waste crisis. One of the solutions for this problem is an intelligent system for classification and segregation of non-biodegradable wastes is implemented with the aid of Convolutional Neural Networks. The system is trained with an initial dataset coming from the images of the waste categories such as plastic bottles, plastic wrappers, plastic cups, and metal canneries. Through VGG16 deep learning architecture, the system can identify the garbage input and classify them accurately. The significance of this study is regarding automation of the garbage segregation process in building an image classifier model that can be deployed into the Materials Recovery Facilities. This is where they sort and market recyclable wastes for the user-end manufacturers. In this manner, it lessens the production of synthetic materials and magnifies the recycling process. The results are shown through graphical representations of the total accuracy of the system against the images subjected in the testing. Although indirect, this research serves as a solution to present the capability of CNN to solve real-world situations.**

Keywords— Convolutional Neural Network (CNN), VGG16 Architecture, Garbage Segregator, Garbage Classifier, Graphical User Interface (GUI)

I. INTRODUCTION

Garbage has become one of the pressing problems in the world today. According to the Los Angeles Times [1], the battle against solid waste is assuming terrible proportions today. In the old times, rubbish is generally comprised of organic materials which quickly disintegrate. Be that as it may, the introduction of plastics and other non-biodegradable materials has worsened the problem since most of these materials never degrade. In the provisions of the Ecological Solid Waste Management Act RA (9003) [2], the management of waste is based on the following processes: a.) Source reduction and minimization of waste generated at the source, b.) Reuse, Recycling and Resource recovery of wastes at the barangay level, c.) Efficient collection, proper transfer and transport of wastes by city or municipality, and d.) Efficient management of residuals. Recycling non-biodegradable wastes is possible, but the segregation and classification of recyclable materials is a tedious process. Thus, automating these actions would bring significant ease to the substantial waste problems that are evident today.

Waste segregation is a means of separating biodegradable from non-biodegradable waste [3]. Every community has emphasized this matter because it may alleviate the dangers caused by improper solid waste management. However, people still tend to forget the importance of it as they often mix the wastes all in one place. Some of the ecological effects of improper waste management are air pollution, climate change, soil and water contamination [4]. As poor waste disposal continues to run the cycle, many ecosystems and species suffer the consequences of man's recklessness. Given these points, it is necessary to create a system that immediately implements the segregation of non-biodegradable materials to prevent it from hitting the landfills and causing pollution to the environment.

The proponents of this study aim to systematize the segregation and classification of non-biodegradable wastes. VGG16 Deep learning architecture is used to structure algorithms in layers to create an artificial neural network that can learn compositions of materials to be classified [5]. In ImageNet, this model attains an accuracy of 92.7%, effectively categorizing a vast dataset of more than 14 million images across 1000 distinct classes. Furthermore, the researchers intend to propose this technology to the community to aid the best practices in mitigating the problems on waste disposal.

II. METHODOLOGY

Fig. 1 illustrates the key stages involved in executing this research. The initial component or phase involves gathering photographs that were utilized as inputs for the subsequent image processing stage. The image processing part is divided in two stages, the pre-processing and processing using VGG16 [6]. The former is the preparation of the images as they go through cropping, color space correction, adjustment and resizing. Meanwhile, the latter is the actual subjecting of the dataset into the deep learning algorithm. Following the thread, once the dataset is uploaded into system, it will be divided into the following percentage: (64%-16%-20%). This means that 64% of the total images are subjected to training, while the 16% is for validation. Once the classifier model is intelligent enough, it will be then used for the testing phase to verify if it is already capable of classifying garbage types in the real-world scenario. In this part, the remaining 20% of the pre-processed photos are used for the testing alone. As a result, the image classifier will be able to identify if the inputted image in the system is a metal can, plastic bottle, plastic wrapper, or plastic cup.

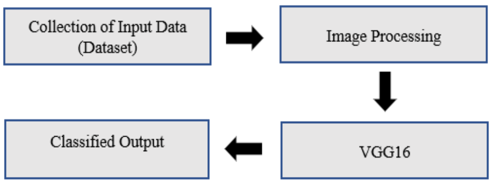

Fig. 1. Block Diagram of Methodology

III. IMAGE PROCESSING

Extensive efforts have been dedicated to the advancement of image processing, particularly in the domain of image recognition. Its widespread applications encompass various fields, such as medicine [7], automation [8], communications [9], and safety [10]. Hence, the utilization of this approach aligns well with the current study.

To underscore the methodology employed in this research, image processing is bifurcated into two essential components: pre-processing and VGG16-based processing. These stages hold immense significance, as they constitute the bedrock of image recognition within the convolutional neural network framework. Omitting these steps would render the accomplishment of image recognition unattainable.

First, image preprocessing is explained. Fig. 2 shows the camera that was used in this study. The preparation of the images is done in this step. In this stage, the image goes through cropping, color space correction, adjustment, and resizing. The initial step in acquiring the dataset is capturing images of the garbage samples. Fig. 2 shows that A4tech web camera is used to capture images of the garbage to be part of the dataset. As shown in Fig. 3, Fig. 4, Fig. 5, and Fig. 6, minimum of 30 images per garbage sample, including the different angles and phases is implemented during the image capturing phase. After collecting the images, it undergoes image cropping, color space correction, adjustment and resizing. All these operations are executed using the Adobe Photoshop software, since all these features are readily available in this application. Images are cropped to remove the unwanted noise in the image and improve its overall composition. Following is the image adjustment where the brightness and contrast of the captured photos are corrected and improved to remove unwanted color cast for a conducive image recognition pattern. Then, the images are resized and set the resolution to 800x600 pixels which is the native resolution for the 7-inch display on the GUI. Lastly, these pre-processed images are stored in designated folders to be used in image processing using VGG16 model.

Fig. 2. A4tech Webcam

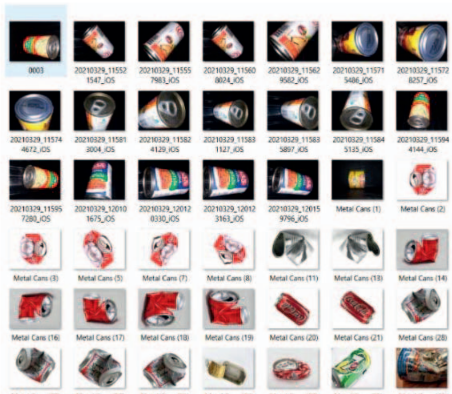

Fig. 3. Sample Dataset for Metal Cans

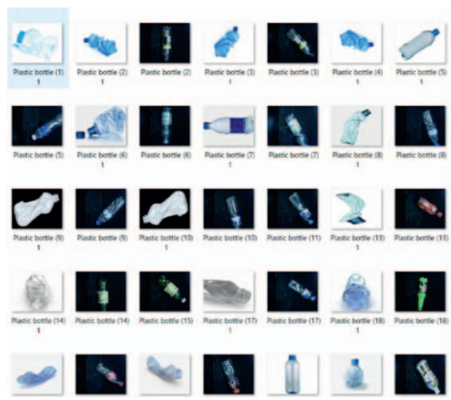

Fig. 4. Sample Dataset for Plastic Bottles

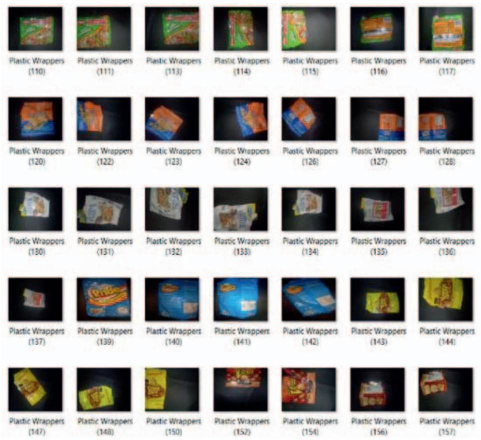

Fig. 5. Sample Dataset for Plastic Wrappers

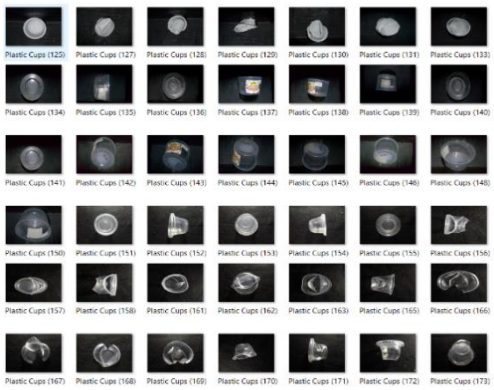

Fig. 6. Sample Dataset for Plastic Cups

In image processing using the VGG model, transfer learning takes place. In which, the weights solved by the VGG architecture on the ImageNet database [11] are used so that it can perform the same features for classification on the researchers' dataset. This model has its classification layers that are fully connected, which are removed and replaced by the new classification layers, intended to classify the type of waste inputted.

In training the system, the researchers need to disable the trainability of the feature extraction layers to preserve the features extraction capability. Then, start the training cycle for the actual classification. The system will be trained for a minimum of three months to make it intelligent enough to perform image recognition. In this stage, 80% of the collected data will be used in the actual training and validation (64% for the training and 16% for the validation). On the other hand, the remaining 20% of the data will be used for testing.

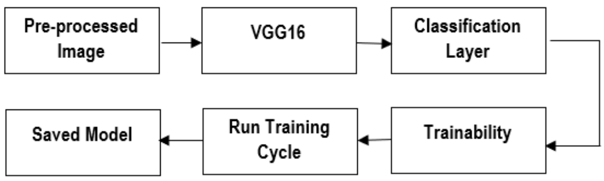

Fig. 7. Classification Model Training Algorithm

Fig 8 shows the run training cycle algorithm. The loss against the epoch is being observed. In this phase, the summation of weight losses or the difference between the actual value and the desired value will be observed. If the loss is low enough, the training process will be stopped and saved the model for later use. Meanwhile, if the loss is high, another epoch will run until the loss is low enough.

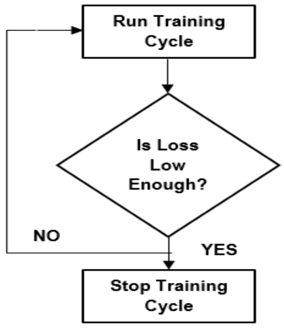

Fig. 8. Run Training Cycle Algorithm

Fig. 9 shows the stimulation of the garbage classifier model using the Graphical User Interface (GUI). After the training phase, the researchers should come up with an intelligent image classification model for the types of garbage specified in this study. Translating all the features of the model in a unified neural network framework without requiring manual editing of the scripts from time to time is a user-friendly attribute for the system.

The GUI generates the trained model on the desktop PC so that writing scripts on the program, adding images to be classified will be done in one clean and structured environment. Additionally, certain parameters like the classification of the image captured as well as its accuracy are displayed for the user's reference.

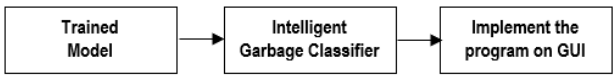

Fig. 9. Intelligent Garbage Classifier

Of all the possible algorithms about image processing, the researchers had adapted the code in the framework to assist in quick development of GUI applications [12]. The code encompasses filters and essential commands essential for constructing the image classifier model. This particular algorithm is executed within the Google Collab environment. Modifications were made due to the variation in the object of detection required for this particular study in the paper.

IV. CONVOLUTIONAL NEURAL NETWORK IMPLEMENTATION

A convolutional neural network serves as a model mirroring the operations of the human mind [13]. This concept is visually represented through a diagram employing nodes (depicted as circles) and connecting lines (represented as arrows). It encompasses input nodes, output nodes, as well as numerous other nodes situated within concealed layers. These nodes symbolize the neurons present in the brain, while the arrows depict the synaptic connections that link one neuron to another. Much like the human brain, the network learns through a sequence of processes and typically adapts its functioning based on specific cognitive requirements at any given moment.

The object classification and detection are the underlying problems in vision research [14]. Also, the differences and similarities between object classification and detection, and object classification and detection of direction based on the expression of deep learning are analyzed. Neural networks are deep learning technologies itself; it is generally designed on solving complex processes [13]. Due to these reasons, the motivation is strengthened to relate image processing and artificial neural network.

Fig. 10 shows that the study implemented using convolutional network with the aid of VGG16 deep learning architecture. VGG16 constitutes a convolutional neural network model introduced by researchers affiliated with the University of Oxford. [15]. Within their research, the scholars explored how the depth of a convolutional network influences its accuracy when applied to large-scale image recognition tasks. They accomplished this by meticulously assessing networks of escalating depth, employing an architecture characterized by diminutive (3×3) convolution filters. The results indicated a noteworthy enhancement in image recognition performance by augmenting the depth to encompass 16 to 19 weight layers. In the realm of this study, VGG16 is harnessed to facilitate enhancements in foam image sensor capabilities. [16].

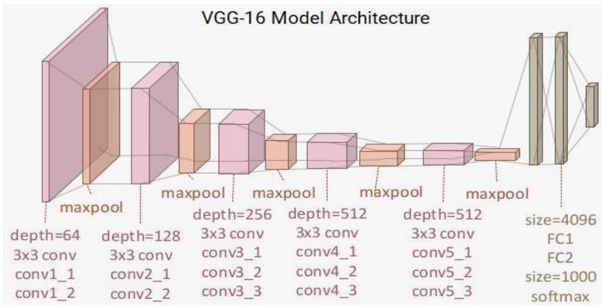

Fig. 10. The VGG16 Model Architecture

V. RESULTS AND DISCUSSION

Fig. 11 shows the output GUI that the proponents achieved, it has a start button that is located on the bottom left corner of the GUI screen. After hitting the start button, a desktop prompt will show, here is where all the test subject is downloaded. The user can choose an item that will be classified as shown in Fig. 12. After choosing an item, it will go back to the GUI as illustrated in Fig. 13 and place the item chosen to the image holder. Image holder is a box that can carry an item that is to be classified. It is the white box at the right side of the start button.

After processing the input image as shown in Fig. 14, it will start classifying the image. Fig. 15 also shows that it was classified accordingly. It is because the system classified the image as 90% metal can. The bar graph at the upper right of the GUI is also updated. It is for the tracking of the numbers of items that was classified.

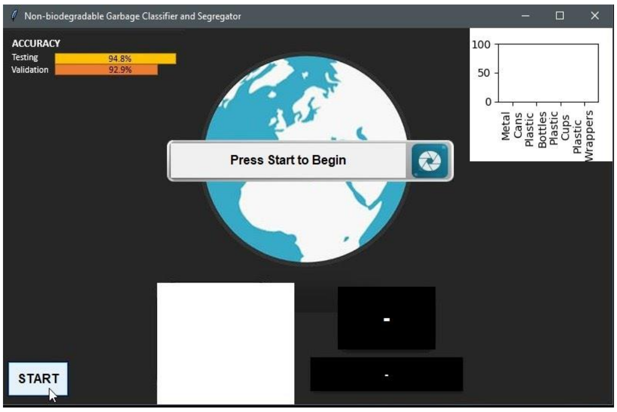

Fig. 11. The Intelligent Garbage Classifier Graphical User Interface

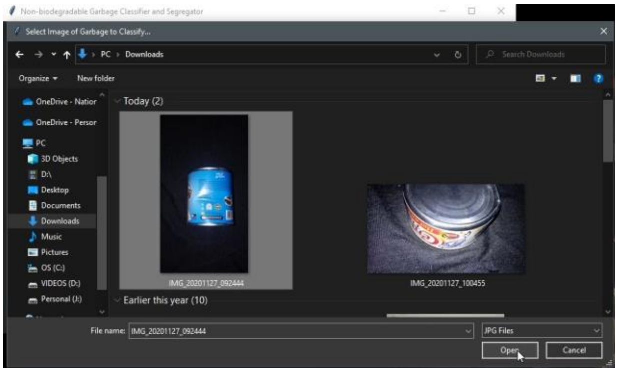

Fig. 12. Selecting an image from the dataset

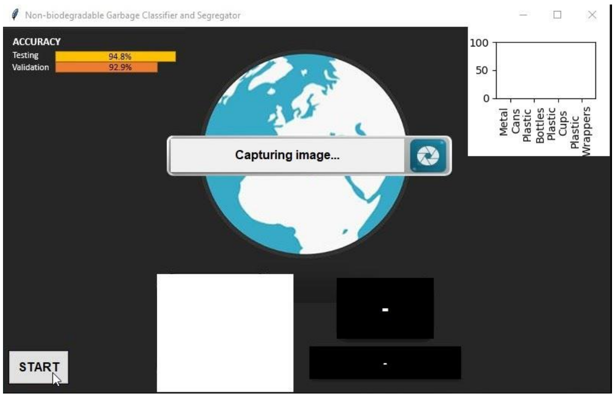

Fig. 13. Capturing the selected image thru the Graphical User Interface

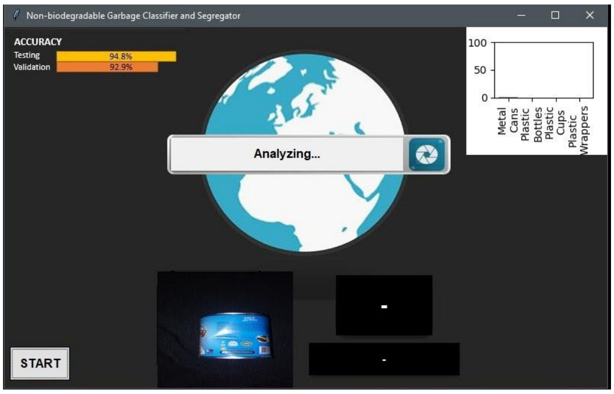

Fig. 14. Analyzing the selected image thru Graphical User Interface

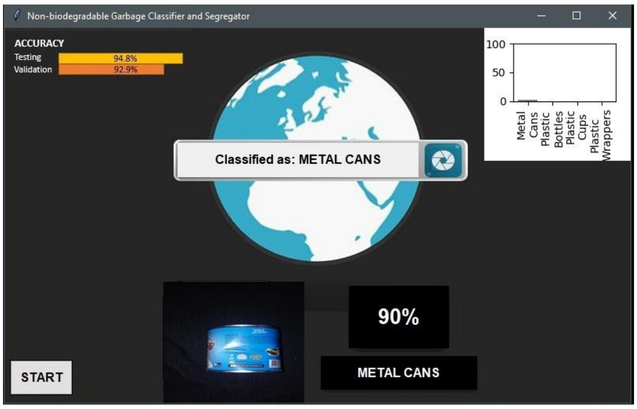

Fig. 15. The classified image displayed in the Graphical User Interface

All the images that were collected was inputted to free GPU (Graphic Processing Unit) provided by google, the Google Collab. The proponents use Google Collaboratory to input the codes and texts and to execute the programs as it is like built on notepad. The utilization of Collab primarily revolves around its ability to import an image dataset, conduct training of an image classifier, and subsequently assess the model's performance. Moreover, it offers the advantage of not utilizing your laptop's GPU, thereby ensuring swifter configuration processes.

Using VGG16's Feature Extraction Layer and by adding the proponents own Classification set with 94.81% accuracy rate.

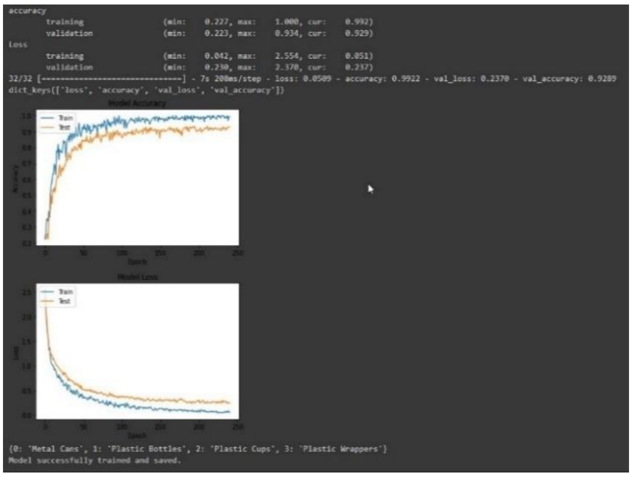

Fig. 16. The Training Set and Validation

The whole database is divided into three subsets: the training and validation phase and the testing phase. The proponents used a dataset of 1200 images. 300 images are for the plastic bottles, 300 images for the plastic cups, 300 images for plastic wrappers and 300 images for metal cans. Out of the 1200 images, 80% of this dataset was used for the training and validation phase, while the remaining 20% was used for testing phase.

Fig. 16 shows the comparison of the validation and the training data sets that was fed onto the training model. The training set is used to train the model, while the validation set is only used to evaluate the model's performance. In the first graph of Fig. 16, you can see that in every epoch done the training and its validation rise proving to have higher accuracy in every epoch.

The image also shows the accuracy of 94.81%. As for the training phase, 64% out of the total images which is 768 photos taken was used for the training phase and the remaining 16% which is 192 was used for the validation phase. There are 240 photos that have been used as the test data for classification of metal cans, plastic bottles, plastic cups, and plastic wrappers.

There are instances that during the training phase when the image did not undergo and was not included into the data set that was fed in the model the accuracy of the classifier decreases to less than 90%, which means that the data sets is insufficient. To solve and fix the issue, the proponents gather more images of the non-biodegradable waste that is being classified provide additional images and once again, fed it to the training model and let the model be retrained to acquire the desired output.

To prove that the classification set the proponents did was reliable; another run of program that compares the output features of their classification set to VGG16 own classification set was done. Fig. 17 below shows that the validation accuracy of the system is 94.81% accurate.

```
testModel()  ## Test with All of Test Dataset and Print Metrics

RANK 1 Accuracy Against Test Data: 94.81 %

CONFUSION MATRIX:
[[57  1  1  1]
 [ 1 55  2  0]
 [ 2  2 42  0]
 [ 1  1  0 65]]
['Metal Cans', 'Plastic Bottles', 'Plastic Cups', 'Plastic Wrappers']

CLASSIFICATION REPORT:
              precision    recall  f1-score   support

           0       0.93      0.95      0.94        60
           1       0.93      0.95      0.94        58
           2       0.93      0.91      0.92        46
           3       0.98      0.97      0.98        67

    accuracy                           0.95       231
   macro avg       0.95      0.95      0.95       231
weighted avg       0.95      0.95      0.95       231


OUTPUT DISTRIBUTION:
Metal Cans: 26.41%
Plastic Bottles: 25.54%
Plastic Cups: 19.48%
Plastic Wrappers: 28.57%
```

Fig. 17. Testing of Accuracy Rate

Fig. 17 also exhibits the confusion matrix, a depiction of correct and erroneous predictions rendered by the classifier. This matrix serves as a gauge for the classification model's performance, facilitating the computation of key performance metrics such as accuracy, precision, recall, and F1-score.

Precision gauges the ratio of accurate positive class predictions within the positive class. In the case of this classification model, the precision for metal cans is registered at 94%. Recall assesses the proportion of positive class predictions made in relation to all positive instances present in the entire dataset. The F1-score furnishes a unified measure that harmonizes the considerations of both precision and recall into a single value, constituting the mean of precision and recall.

The testing model used 240 images (20% of total datasets) 60 images for each class for the testing phase. Overall, the accuracy rate for the testing phase of the whole classifier is 94.81%.

Thus, VGG16 architecture-based garbage classifier and segregator is an application that helps proper garbage deposition. VGG16 Architecture has helped the project to classify image accurately with the rate of 94.81%. Using this technology and providing a system that can capture images and separating solid waste products, segregating non-biodegradable waste will be uncomplicated. Furthermore, if this system is used by materials recovery facilities, solid waste management will be simple and therefore recycling will be maximized.

VI. CONCLUSION

Based on the preceding data accumulated through series of testing, Garbage classification using VGG16 architecture as a basis is efficient. Using VGG16 feature extraction layer capability to train our own classification set by feeding it thousands of images of four types of non-biodegradable waste materials named metal can, plastic bottle, plastic wrapper, or plastic cups and the project worked accurately. The target validation rate was 90% and by strenuous training we have achieved a validation rating of 94.81% accuracy rate.

VII. RECOMMENDATIONS FOR FUTURE WORK

Researchers suggest to the future researchers of this study to work on the limitations of the system. As much as possible either expand the type of non-biodegradable waste or add biodegradable waste as well to be classified and segregated. Other researchers can also alter the training phase by only feeding the classifier with objects that is colored only by red, green, and blue. Also add an algorithm that can detect multiple items in one captured image. The researchers also suggest building a system or a prototype that is intelligent enough to capture images and segregate large amount of non-biodegradable waste materials.

VIII. ACKNOWLEDGMENT

The satisfaction derived from the successful culmination of this research project would lack fulfillment if not for the unwavering backing provided by the Department of Electronics Engineering at the National University – Philippines. So as to the people whom without their cooperation, the achievement would remain a distant success.

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