# Classifying Plastic Waste Using Deep Convolutional Neural Networks for Efficient Plastic Waste Management

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***Abstract***— Plastic waste recycling has not been adopted by a large percentage of plastic manufacturing companies due to the enormous amount of effort required to sort the plastic waste and remove dirt. Consequently, the lack of efficient practice of automated sorting and separation of different types of plastic during the management of plastic waste has caused most of it to end up in landfills instead of being reused and recycled back into society's consumption. Accumulation of plastic waste eventually causes pollution which will then result in negative effects on ecosystems, underwater and on the ground as well as carbon emission. To leverage machine learning technology in optimizing the process of recycling plastic waste, this study proposes an intelligent plastic classification model developed using a Convolutional Neural Network (CNN) with 50-layer residual net pre-train (ResNet-50) architecture. The proposed model was trained with a dataset consisting of over 2000 images that were compiled and organized into seven plastic categories. The model compared favourably with related previous studies producing a considerably high accuracy classification model of 94.1%.

***Keywords***— Convolutional Neural Networks (CNNs), Image Classification, Plastic Waste, Waste recycling, Sustainable Development.

## I. Introduction

Plastic waste is the accumulation of used products made from plastic; a derivation of a chemical substance called polymer. The amount of unrecycled plastic objects that were dumped into landfills or unregulated sites all over the world and especially in some developing countries has been a cause for concern. The widespread usage of plastic objects increased exponentially upon discovery due to their significant properties, viz; able to be molded and shaped through the application of heat and pressure. In addition, the invention of Bakelite in 1907 marked the beginning of the mass production of synthetic plastic that is capable of insulation with high durability aside from being heat resistant [1]. A study conducted in 1962 shifted people's opinion towards this simple and convenient invention as the study revealed its material persistence towards degradation in nature. This issue has raised many concerns even further for the past few decades as researchers discover the threat plastic waste poses to human health as well as the ecosystems.

In 2019, as opposed to the Basel Convention designed by the United Nation, it is revealed that developed countries such as the UK, US, Canada, and Japan have been redirecting waste containers full of contaminated plastic waste to other developing countries after China issued plastic import ban [2, 3]. The plastic import ban, officially tagged "Prohibition of Foreign Garbage Imports: The Reform Plan on Solid Waste Import Management", is China's first step in treating their mounting health and environmental problems [4, 5]. The aforementioned treaty aims to protect human health and the environment against adverse effects of the generation, management, transboundary movement, and disposal of hazardous and other wastes. This treaty also exists to prevent illegal and excessive transportation of plastic waste from one country to another [6]. As a consequence of this incident, not only has it alerted the organization to make global trade in plastic waste more transparent and better regulated but also a wake-up call for other nations to rebuild their plastic waste management for efficiency and replace it with a more sustainable solution.

Efficient plastic waste management is the key to making sure recycled plastic waste will be handled efficiently and effectively to not endanger wildlife and humans. However, the process of sorting may take a long time and requires a lot of manpower. Hence, it would cost a lot to properly clean and upcycle this form of waste. Many would rather opt for methods of managing waste that causes air pollution and exuding hazardous particles into the air that might cause severe health problems to humans due to negligence or not they deemed this matter to be none of their concerns out of ignorance. For instance, some developing countries have become US plastic recycling management centres thereby constantly exposing low-paid labor workers to toxic fumes and providing little to no protection for them [7].

Several countries of the whole have proposed measures to reduce plastic consumption among their citizens such as payment on some specific days for plastic packs. This has not been effective as people continue to pay to use plastic since the amount charged is not that expensive. Unfortunately, recycling used plastics has been considered more expensive compared to producing new ones.

From the foregoing, the motivation for this study is to propose a model where people can be billed for the plastics they use at the point of disposal. The idea is to make people pay for the recycling of the plastics they use so that the balance cost of recycling paid by the users can motivate and be more rewarding for the recycling companies to put more effort into recycling to protect the planet.

In this work, a plastic waste classification model is developed using Convolutional Neural Networks (CNNs). The data needed for modeling were acquired through self-collected pictures and some were taken from open source image repository online and existing research publications. Subsequently, the collected data will be converted into a workable format to suit the classification approach made for the proposed CNNs. The data was then passed through splicing, separating it into validation, testing, and training categories before proceeding with training the model. Subsequently, the fine-tuning process is carried out to improve the classification model even further. Afterwards, the model performance is evaluated based on the performance metrics such as accuracy, viz; the number of all correctly classified images divided by the total number of images from the training dataset.

This work is an initial stage of the proposed sustainable business model for plastic waste recycling focusing on automatic recognition of plastic types, determining the respective cost of recycling, and billing system. Hence, to lessen the effort and cost of separating plastic waste, a plastic waste classifier model based on deep learning is necessary. By using this model, the sorting process would take a shorter time, thus increasing the efficiency of the process in the long run. Furthermore, this model is not intended to be implemented only at the industrial level but with proper platform and tools, it can also be applicable in residential areas. In accordance with the United Nations' Sustainable Development Goals (SDGs), this research paper aligns with Goal 12, 13, 14, and 15, namely, Sustainable Consumption and Production Patterns, Climate Action, Life Below Water, and Life on Land, respectively.

The next sections of this research paper detail relevant past studies regarding classifying waste and discovering different possible approaches used to create deep learning models. This paper also details the process of developing the deep learning model to classify seven types of plastic, *PET*, *HDPE*, *PVC*, *LDPE*, *PP*, *PS,* and *Other* using CNN with ResNet50 in the methodology section. After clarification of the steps needed for modeling, results will be discussed followed by the conclusion as well as future work to end this research paper.

## II. Related Work

Lots of different algorithms have been developed for the classification problem such as Support Vector Machine (SVM), Logistic Regression, K-Nearest Neighbors, etc. Recent models based on the Convolutional Neural Networks outperform most of the previous algorithms with the revival of deep neural networks. CNNs have massively contributed to solving highly complex recognition tasks by utilizing the deep learning neural network architecture. With deep learning neural network, CNNs has the ability to learn autonomously without human intervention and the model can be further developed with the availability of new data. Ever since 2012, various types of CNN architecture have been introduced to solve image classification problems [8]. A lot of studies have been conducted to solve varieties of classification problems. As CNN algorithms are widely used, many researchers have done exhaustive research using various techniques and combinations of a few algorithms to provide an optimistic result on a classification problem.

A study was found where the researchers implemented a multilayer hybrid deep-learning (MHS) to automatically sort waste disposed of by people who are living in the urban public area [9]. The proposed system is equipped with a high-resolution camera to capture the images of the waste and sensors to detect the feature of the waste image. The MHS is based on CNN algorithms and Multilayer Perceptron (MLP) that are able to extract the useful features from the images to classify them into their respective classes. The model consists of three interdependent sub-systems, namely; an image processing system, a numerical system, and an MLP system. AlexNet CNN was used in the image processing to extract the information and acted as input for the MLP. Meanwhile, the sensor was created to measure the waste feature to pass that value as numerical input for MLP. The researchers tested the model under two different testing scenarios, namely; MHS and CNN models that only take images as input. The model was tested with 50 waste items and achieved the overall performance accuracies of 98.2% and 91.6%.

Additionally, research conducted by [10] proposed a solution to classify PET waste and created a plastic waste database consisting of the various municipal waste. The authors also presented the method of plastic waste selection by using histogram analysis. The main aim of the study was to develop an automatic sorting waste that uses the methods of pattern recognition in computer vision. The researchers wanted to explore the new methods of pattern recognition by providing free access to the database of images.

The study by [11] successfully built an intelligent waste material classification system using CNN and Support Vector Machine (SVM) with an accuracy of 87% on their dataset. Their dataset however does not include plastic materials only but includes glasses, paper, and metal. After 12 epochs, their accuracy rate reached peak performance of an average training accuracy of 94.5% when plotted against value loss epoch.

Another study by [12] claimed that their multilayer hybrid convolutional neural network method (MLH-CNN) can provide the best classification performance. After extensive research on comparing multiple optimizers, the authors adopted stochastic gradient descent with momentum (SGDM) with Nesterov as it proved to show high accuracy prediction with good performance. To boot, the authors also measured the precision, recall, and F1-score of their model with AlexNet, ResNet50, and Vgg16 and presented each of these methods' performance using confusion matrix analysis as well as heat map analysis. The classification accuracy of the MLH-CNN model reached up to 92.6% which is higher than pre-existing models as well as traditional methods [12].

Similar to other related works, the study in [13] attempted to develop a deep learning model that is capable of classifying waste. However, in addition to classifying household solid waste (HSW) into their common material categories such as glasses, paper, plastic, cardboard, metal, and trash. They also classified them according to the four states of the waste, namely dry waste, wet waste, recyclables, and harmful waste. The authors attempted to compare multiple CNN models and their model equipped with an unequal precision measurement weighting strategy (EnCNN-UPMWS), showing that their newly developed model surpasses its predecessors in terms of performance [13].

## III. Methodology

For this study, current deep learning techniques such as data augmentation, optimal learning rate finder, and fine-tuning were utilized to build the model. The proposed CNN model is based on ResNet50 to classify plastic wastes. ResNet50 is a CNNs with 50 layers that have been pre-trained on the ImageNet database. The pre-trained model was trained on ImageNet images with a size of 256 x 256 and classified into 1000 classes [11]. The architecture model of ResNet-50 deep networks is shown in Fig. 1 which was used for feature extraction. ResNet-50 is discussed in the next subsection.

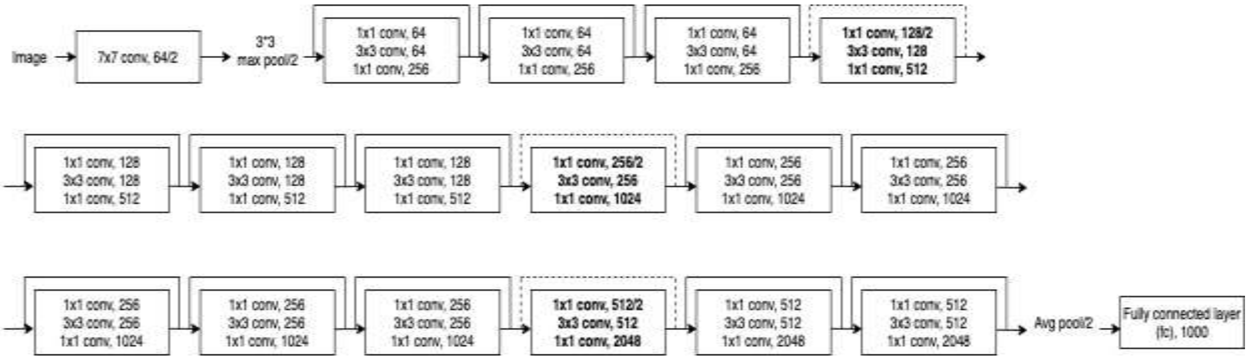


Fig. 1 ResNet-50 Architecture

### A) *ResNet-50*

ResNet-50 is a variant model which has 48 Convolution layers along with 1 MaxPool and 1 Average Pool layer. The architecture of this model managed to achieve high performance by making the ultra-deep learning neural network possible. This model solved the degradation problem that has been faced by previous CNN architecture because of the increasing network depth that led to higher training error, thus, affecting the accuracy of the model. ResNet introduces the concept of shortcut connection by adding the original input to the output of each convolution block. In the traditional method, the input travelled layer by layer and returned as the outputs of the stacked layers. Meanwhile, ResNet uses shortcut connection and performs identity mapping to solve the degradation that can lead to better performance and reduce complexity. As a result, the training will be faster and computationally less expensive than the conventional CNN [14].

### B) *Convolutional Layer*

This study used ResNet-50 to extract the features from the given dataset. The plastic images dataset needs to undergo preprocessing before feeding it into the model. This is further discussed in the *dataset* section. The ResNet-50 is designed with five convolutional blocks that are stacked on top of each other as shown in Fig. 2. The notation of $k \times k, n$ in every block represents a filter size of *k* and n channels of the convolutional layer. FC represents a fully connected layer with 1000 neurons. The multiplier at the top of the blocks represents the number of repetitions of each unit and nClasses represents the number of output classes. The preprocessed plastic images are then passed through the first convolutional layer with $7 \times 7$, 64 channel and operate on a stride value of 2. Then, the second convolutional layer takes as input from the output of the first convolutional layer and filters it. This operation continues until it reaches the last convolutional layer where its output is utilised as input for the FC-1000 layer.

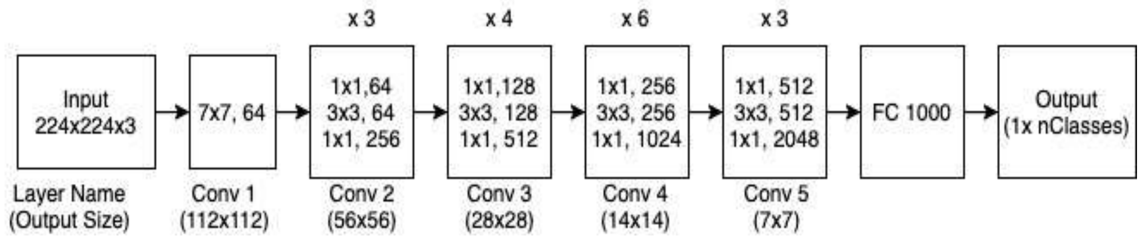


Fig. 2 Residual units of ResNet-50 depict the size of the filters and the output of each convolution block

It is necessary to note here that after every convolutional layer, rectified linear function (ReLU) is performed to treat the model as non-linearity since the image per se is non-linear. ReLU is applied as the activation function for this model. This process improves the performance of the model as it converges faster than other non-linear functions. Fig. 3 depicts ReLU graph where it cancels out all negative values and linear for all positive values. In other words, it returns zero output when the input is negative and gives the same value as input when the input is positive.

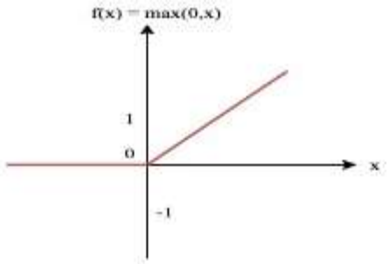


Fig. 3 ReLU Activation Function

### C) *Pooling Layer*

After the input passes through the first convolutional layer, the pooling takes place to down-sample the feature maps into submatrices and select one value to represent each submatrix. Two types of pooling layers have been applied in this model which are the max pooling and the average pooling layers. In ResNet-50, the output of the initial convolution will be encountered max pooling and average pooling will be taken place after the last convolution before it passes through the fully connected layer. In max pooling, it returns the maximum value in the submatrix while the average pooling returns the average of the submatrix. This model performs initial max pooling with the size of $3 \times 3$ on a stride of 2 while the average global pooling function is used to reduce the number of parameters that have been passed throughout the layers.

### D) *Residual Connections*

The introduction of shortcut connections in ResNet is the main difference between ResNet and those of the traditional CNNs as it adds a new path from the input to the output of each block. This is the ultimate solution for the vanishing or exploding gradients encountered using previous CNN architectures. Fig. 4 illustrates the shortcut connection between the building blocks.

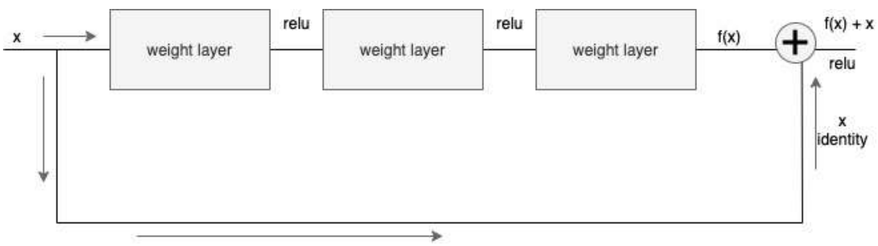


Fig. 4 Residual building block: Identity Block

The residual blocks are designed to maintain the original size of the input before it is transformed into some layers by skipping weight layers and performing summation [15]. It uses a shortcut connection and adds input to the function $f(x)$ element-wise. This shortcut is also known as identity shortcut or skip connection. Overall mapping of the block can be perceived by the equation below where $x$ is the input, $f(x)$ is the residual mapping, and $h(x)$ is the desired output.

$$f(x) = h(x) - x \tag{1}$$

Based on the above learning block, we inserted a shortcut connection that makes the input size equal to the output size thus becoming the counterpart residual version. The identity shortcuts will be used when the input and output sizes are in the same dimensions. The equation can be redefined as

$$h(x) = f(x) + x \quad (2)$$

It is worth noticing that the dimensions of $f(x)$ and $x$ should be equal. If the dimensions are different at summation, we can consider two options to match the output size. The first option to be considered is padding the input volume. The shortcuts will perform identity mapping with the additional zero entries padded and no extra parameter to increase the size dimensions. This can be represented by the equation below

$$y = F(x, \{W_i\}) + x \quad (3)$$

Meanwhile, the other option is performing a linear projection. $1 \times 1$ convolutions will be added at the shortcut path to match the output's dimensions as shown in Fig. 5. This can be defined by the equation below where we introduce linear projection in the Eqn. (3) and it is denoted as $W_S$.

$$y = F(x, \{W_i\}) + W_S x \quad (4)$$

This operation can be visualized in Fig. 1 where there is a solid line shortcut to represent the same size dimension while the dotted line shortcut is presented when the dimensions are different. Both options are performed with a stride of 2 when they go through across the layers of two sizes [16].

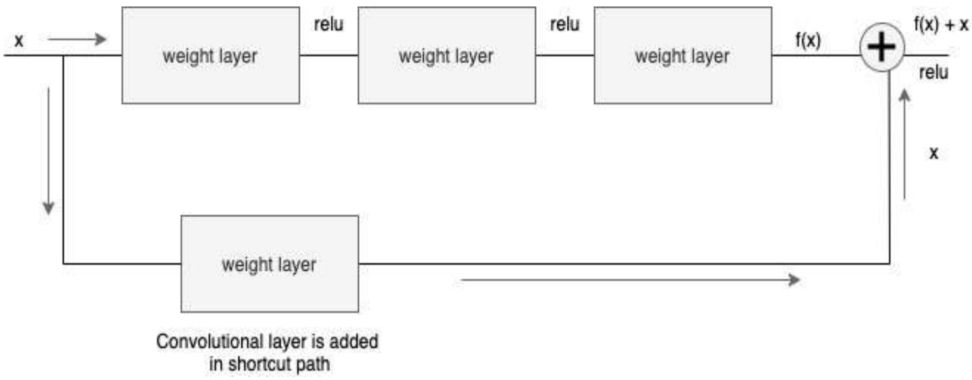


Fig. 5 Residual building block: Convolutional Block

*E) Fully Connected Layer*

After passing Conv5 block, the output encountered global average pooling before it passes through the fully connected layer which consists of 1000 neurons. The fully connected layer resides at the end of the network and gives superior classification performance as compared to the extracted features from previous layers. This is where the actual classification takes place as the extracted features have been passed through the deeper layers encoded with specific class properties such as shape, texture, and color [14]. The output from the last convolution acts as the input to the fully connected layer where it will be flattened and then passes into the fully connected layer. The flattening process is necessary before the input is fed into the fully connected layer because the output from the last convolution is in a form of a dimensional matrix. Flattening will take place by turning all the values from the matrix into a vector. After passing the fully connected layers, the SoftMax operation is applied to the last layer to compute the probabilities of the input being in a particular class to determine the final classification of the objects. This operation can be defined as

$$Softmax(x_i) = \frac{\mathrm{EXP}(x_i)}{\sum_j \mathrm{EXP}(x_j)} \quad (5)$$

For this study, the input will be classified into the seven classes of plastic that have been mentioned previously according to the probability of the object in the classes.

*F) Dataset*

For the experiment with deep neural networks, it is important to gather a lot of data for each labelled class. The images in the dataset have been collected from different sources such as online image databases, research publications [17] and manually taken using a 12 MP phone camera. After filtrations, the images that can be used for this model are 2110 images. Then, the collected images are divided into groups based on the type of materials which are commonly known as Resin Identification Code (RIC). The seven RIC symbols are PET, HDPE, PVC, LDPE, PP, PS, and Other. The descriptions of the seven different plastics can be seen in Table 1 [18] and a few samples of the images are shown in Fig. 6.

TABLE I
PLASTIC TYPE CLASSIFICATION

| Plastic Type | Common Name | Chemical Name | Main end-use | Example products |
|---|---|---|---|---|
| 1 PETE | PET | Polyethylene Terephthalate | Used primarily for food and drink packaging |  |
| 2 HDPE | HDPE | High-Density Polyethylene | Commonly used for milk and juice containers, shampoo bottles, and medicine bottles |  |
| 3 PVC | PVC | Polyvinyl Chloride | Commonly used for toys, blister wraps, cling-wraps, detergent bottles, and household pipes |  |
| 4 LDPE | LDPE | Low-Density Polyethylene | Grocery bags, dry cleaning bags, plastic wraps |  |
| 5 PP | PP | Polypropylene | Hot food containers, vehicle parts, bottle caps |  |
| 6 PS | PS | Polystyrene | Food containers and packaging |  |
| 7 OTHER | Others | Commonly a layer or a mix of multiple plastic types | Baby bottles, multi-layer individual packaging sachets, CDs |  |

Adapted from *Study on Extended Producer Responsibility (EPR) Scheme Assessment for Packaging Waste in Malaysia* [Press release], by WWF-Malaysia, 2020 (https://www.wwf.org.my/?28886/Study-on-Extended-Producer-Responsibility-EPR-Scheme-Assessment-for-Packaging-Waste-in-Malaysia)


FIG. 6 IMAGES FROM DATASET

After labelling the images into their respective classes, the images were split to evaluate the performance of the model. The labelled images were split into training, validation, and testing set with 50-25-25 split. This process is highly important to prevent the model from overfitting and to accurately evaluate our model. Then, we apply data augmentation for our dataset to improve the downstream performance of our model by creating more variants. Essentially, the model can be prevented from learning unnecessary patterns by performing augmentation, hence, boosting overall performance. This is crucial as a deep learning neural network model is highly dependent on the quantity and diversity of the data. The process of data augmentation used in this model includes transforming the data by flipping all the images vertically and resizing the images into a size of 224.

Resizing the image is compulsory in training a convolutional neural network as it is required for trained images to be of the same size.

TABLE II

DISTRIBUTION OF PLASTICS DATASET

| Plastic Type | Train | Valid | Test | Total |
|---|---|---|---|---|
| PET | 211 | 107 | 106 | 424 |
| HDPE | 309 | 158 | 153 | 620 |
| PVC | 100 | 50 | 50 | 200 |
| LDPE | 93 | 48 | 45 | 186 |
| PP | 195 | 78 | 94 | 367 |
| PS | 106 | 54 | 53 | 213 |
| Others | 50 | 25 | 25 | 100 |
| Total | 1064 | 520 | 526 | 2110 |

In our model, we used get_transforms() function, a library from FastAi to augment our data. Next, we specify the batchsize for our dataset. The batchsize indicates how many images would be trained at a time. 16 batchsize was chosen consequently training 16 images in one iteration.

### G) *Finding learning rate*

Finding an optimal learning rate is very crucial for training neural networks to ensure that it converges rationally quickly without missing the optimal error. The learning rate needs to be selected wisely to minimize the network's loss function. The training will progress slowly if we set the learning rate below the optimal as they are updating the weight regularly before reaching the minimum point. To put it simply, the small learning rate will cause many updates on the weights in the network and affects the training progress. On the flip side, if the learning rate is set above the optimal, it can cause unwanted divergent behavior in the loss function as it drastically updates the weights. For this study, we are using FastAi library to find the optimal learning rate by calling learn.lr_find() function. Upon completing the operation, it states the learning rate that can be used for the model. The learning rate finder suggests a learning rate of $5.13e^{-3}$. This process can be visualized in Fig. 7 where it plots the learning rate for gradient descent.

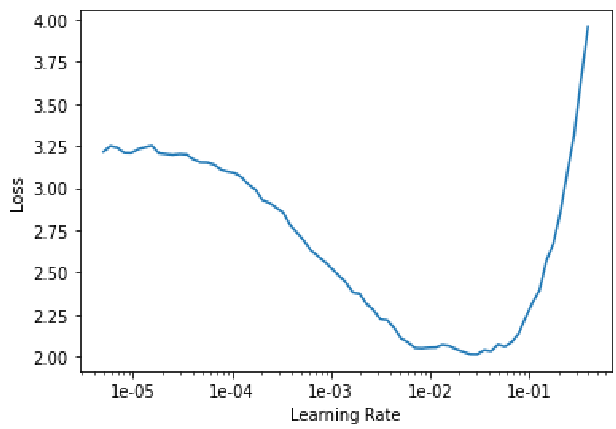


Fig. 7 Learning Rate Finder Graph

### A) *Fine-tuning*

Training a deep neural network model can be very gruesome and expensive because it requires an enormous amount of training dataset to yield high accuracy results. Despite the exhausting process, the deep neural network stands at the centre of classification and recognition tasks and continue to rise with their significant role in developing advanced applications for various domains. Due to its capability of learning independently and autonomously without human intervention, the transfer learning method has been introduced to overcome the problem of training with the limited dataset. It works by fine-tuning the deep network models where it utilizes the pre-trained models on a large dataset of a similar domain and adapts it to another task [19]. Fine-tuning helps by simplifying the learning process of the new deep learning algorithm and decreases the time for coding and programming as it contains some visual features and can transfer that knowledge over. The transfer learning from the pre-trained model will make the new model more reliable as it has already captured the overall shape of the object within the region of interest. Fine-tuning starts at the beginning of the learning process where we have a pre-trained network (ResNet-50) as initialization for parameters. The very first step for fine-tuning is replacing the final layer to fit the new task. The available data that has been fed into the network will be used to identify the relative importance of initial weight [20]. When new categories are found, the network architecture must adapt to the changes by replacing the previous output layer with a new output variable. It is important to note that some layers might need to be removed or added depending on the similarities of the two models.

## IV. RESULTS AND DISCUSSION

After pre-processing the dataset, the ResNet-50 CNN pre-trained model was applied to train the dataset. The weight assignment of the model was derived from the previous model that have been pre-trained. In addition, the last layer of the model was designed to classify the seven classes of plastic, which required the original output to be removed and replaced with a new layer with random weight.

The new assignment was made to ensure the model works as it was intended to be which in this case, plastic classifier. Then, the prominent Adam optimizer was utilised as our learning rate optimizer. After creating the learning model, it was run for 20 epochs with a learning rate of $5.13e^{-3}$. For the performance metrics, fitting methods were applied to see how well the model's performance was for training data. the training loss, validation loss, and error rate were recorded in a table for each iteration as shown in table 1. Training loss indicates the error on the training set of data. Based on the result, it can be seen how the model was fit with the training data.

TABLE III
RESULTS OF TRAINING ON VALIDATION SET

| Epoch | Train_loss | Valid_loss | Error_rate | Time |
|---|---|---|---|---|
| 1 | 1.341081 | 0.430949 | 0.123077 | 00:52 |
| 2 | 0.827533 | 0.388225 | 0.101923 | 00:49 |
| 3 | 0.793229 | 0.456794 | 0.098077 | 00:48 |
| 4 | 0.635198 | 0.517827 | 0.140385 | 00:48 |
| 5 | 0.736985 | 0.779986 | 0.246154 | 00:48 |
| 6 | 0.775418 | 0.735139 | 0.219231 | 00:48 |
| 7 | 0.807474 | 0.410223 | 0.103846 | 00:48 |
| 8 | 0.707015 | 0.626140 | 0.175000 | 00:48 |
| 9 | 0.574476 | 0.421171 | 0.126923 | 00:49 |
| 10 | 0.479178 | 0.508349 | 0.144231 | 00:48 |
| 11 | 0.394792 | 0.347851 | 0.098077 | 00:50 |
| 12 | 0.415412 | 0.281033 | 0.073077 | 00:50 |
| 13 | 0.421746 | 0.377367 | 0.098077 | 00:50 |
| 14 | 0.312220 | 0.272956 | 0.080769 | 00:49 |
| 15 | 0.229074 | 0.279345 | 0.076923 | 00:50 |
| 16 | 0.187869 | 0.281438 | 0.065385 | 00:50 |
| 17 | 0.158487 | 0.266359 | 0.073077 | 00:50 |
| 18 | 0.110003 | 0.266030 | 0.067308 | 00:49 |
| 19 | 0.107568 | 0.272383 | 0.063462 | 00:50 |
| 20 | 0.082808 | 0.239888 | 0.059615 | 00:50 |

Meanwhile, the validation loss indicates the error after conducting a validation set of data through the trained network to see how well the model fits new data. The error rate is defined as the proportion of patterns that are incorrectly classified by a model. It is calculated by dividing the number of incorrect predictions by the total number of data points in the dataset. From the table, it can be observed that the learning rate decreases with each epoch. It demonstrates that our model is attaining closer to the optimum with a 5.9% error rate. Before testing the model, efforts were made to identify which images were the most incorrectly classified. This can be done by visualizing the most incorrect images as depicted in Figure 8. It was observed that the incorrectly classified images are relevant because some products may be made from different types of plastic. For instance, the highest loss for our model is 10.91 as it incorrectly classified the PP bottle as HDPE. This is indeed plausible because the design and the structure of the bottle usually can be perceived as HDPE. The other incorrect images are also facing the same problem where many identical products can be made from different types of plastic depending on their functionality. For our model, the highest classes that were incorrectly classified are HDPE and PP.


Fig. 8 Most incorrect images

After interpreting the training result, the new recognitions on the test data were attempted to evaluate the performance of this model. As can be seen in the confusion matrix in Fig. 9, to visualize the classification of seven classes of plastic as shown in Fig. 9. Out of 153 HDPE plastic images, over 150 were correctly classified while the other 3 images were wrongly classified into PP and PS. For LDPE type, 43 out of 45 images were correctly classified and the other 2 were wrongly classified as PET and PP. Next for Other categories of plastic, 22 images were correctly classified while the other 3 images were falsely classified as PP and PS. Meanwhile, there were 103 PET plastic images rightly classified to its classes while another 3 images were wrongly classified as PP and PS. Other than that, 83 plastic images were correctly classified into PP type while the other 11 images were falsely classified as HDPE, PET, and PS. As for PS, 8 images failed to be classified correctly while the remaining 45 images were successfully classified. Lastly, this model managed to classify correctly for 49 images as PVC but falsely classified 1 image as HDPE. This model managed to achieve a very decent accuracy of 94.1% despite its high loss probability. From the result, we also evaluated our model for each plastic type. We calculated the accuracy, precision, recall, specificity, and F1 score to see the performance of our model. This is summarized in Table 2 to compare the performance results for every type of plastic.

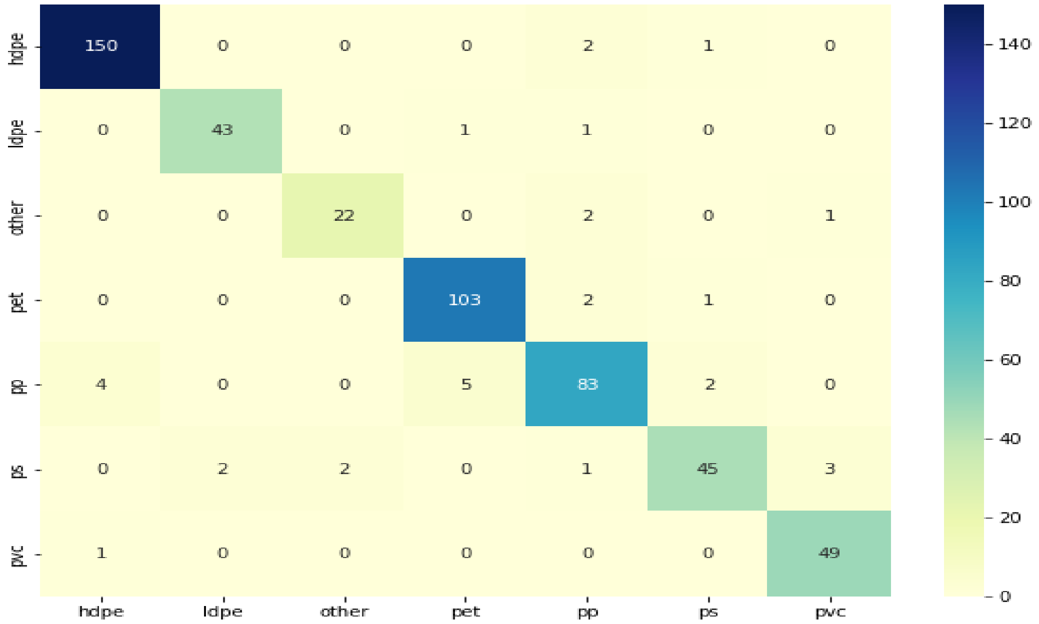


Fig. 9 Confusion Matrix

The proposed model performance is compared in terms of accuracy with other models taken from related works mentioned in this paper. Overall, the CNN with ResNet-50 classification model showed considerable superior performance when set side by side with other models. The proposed model achieved an accuracy of 94.1%, slightly higher than the SVM model with ResNet-50 [11]. Multilayer Hybrid Convolutional Neural Network method (MLH-CNN) [9], and a CNN ensemble using the UPM Weighting Strategy (EnCNN-UPMWS)[13], each with an accuracy of 87%, 92.6% and 92.85% respectively. It also slightly outperforms Multilayer Hybrid System (MHS) with CNN and Multilayer Perceptron (MLP) in their final overall test performance result of 92.6% [12].

TABLE IV
Performance Metrics

| Plastic Type | Accuracy | True Positive | False Positive | True Negative | False Negative | Precision | Recall | Specificity | F1 Score |
|---|---|---|---|---|---|---|---|---|---|
| PET | 0.97 | 103 | 6 | 414 | 3 | 0.94 | 0.97 | 0.98 | 0.95 |
| HDPE | 0.98 | 150 | 5 | 368 | 3 | 0.97 | 0.98 | 0.99 | 0.97 |
| PVC | 0.98 | 49 | 4 | 471 | 1 | 0.92 | 0.98 | 0.99 | 0.95 |
| LDPE | 0.96 | 43 | 2 | 479 | 2 | 0.96 | 0.99 | 0.99 | 0.95 |
| PP | 0.88 | 83 | 8 | 432 | 11 | 0.91 | 0.88 | 0.98 | 0.89 |
| PS | 0.85 | 45 | 4 | 469 | 8 | 0.91 | 0.89 | 0.99 | 0.88 |
| OTHER | 0.88 | 22 | 2 | 414 | 3 | 0.91 | 0.88 | 0.99 | 0.89 |

TABLE V
MODEL PERFORMANCE COMPARISON

| Methodology | Model Performance |
|---|---|
| CNN with ResNet -50 | 94.1% accuracy |
| MHS with CNN and MLP | 98.2% and 91.6% accuracy under two different testing scenarios |
| SVM with ResNet-50 | 87% accuracy |
| MLH-CNN | 92.6% accuracy |
| EnCNN-UPMWS | 92.85% accuracy |

## V. CONCLUSION

After intense training and testing with the preprocessed dataset, a plastic waste classifier model using Convolutional Neural Networks (CNNs) with 50-layer residual net pre-train (ResNet50) architecture was developed at the end of this research. The dataset used for the model development is a combination of self-collected images while some are taken from other research papers and public online dataset repositories such as Kaggle. These images first went through pre-processing to ease data interpretation by the algorithm afterwards. This step is then followed by the application of the ResNet50 pre-train model and fine-tuning. Using Adam optimizer as learning rate optimizer, the model learner is finalized at this stage. From the result, the model achieved 94.1% accuracy when the model was tested with the testing data set. Furthermore, the separation of plastic waste will become faster and more efficient as it is working autonomously and reducing human involvement during the separation process. The feature extraction technique can be improved in the future to cater to the above-stated problem regarding the different types of plastic of identical products. To enhance the model's performance, it may need an extensive collection of data to retrain and fine-tune the model. A considerably large dataset will have more variations and patterns to be learned by the model thus, attaining a better accuracy than this present model. The improvement for the recognition level of plastics can be made by improving the feature extraction technique and tuning some of the parameters used. However, exploring another architectural model structure and evaluation techniques may also seem feasible as alternatives and can be compared for efficiency and effectiveness.

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