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A Method for Waste Segregation using Convolutional Neural Networks

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***Abstract*—Segregation of garbage is a primary concern in many nations across the world. In spite of being in the modern era, many people still do not know how to distinguish between organic and recyclable waste. It is because of this that the world is facing a major crisis of waste disposal. In this paper, deep learning algorithms have been used to help solve this problem of waste classification. The waste is classified into two categories like organic and recyclable. Our proposed model achieves an accuracy of 94.9%. Although the other two models also show promising results, the Proposed Model stands out with the greatest accuracy. With the help of deep learning, one of the greatest obstacles to efficient waste management can finally be removed.**

***Keywords*—Waste classification, convolutional neural networks, transfer learning, deep learning, machine learning**

I. Introduction

The garbage and recycling businesses are being overwhelmed by the ever-increasing volume of global garbage. As a result, the demand for smart solutions for environmental monitoring and recycling process improvement is stronger than ever [1]. Human life and the environment are both affected by waste disposal, whether directly or indirectly. The negative consequences of waste materials can be mitigated with the use of a competent waste management system [2].As of now, waste is separated and classified in two ways that are manually or by automation using multiple techniques. Manual way can be accomplished with power and human intelligence, whereas the second entails the automatic search for appropriate waste classification techniques [3].

Recycling is quickly gaining traction as a necessary component of a sustainable society. However, a hidden cost is attached to the entire recycling process. This happens as a result of the recycling materials' selection, categorization, and processing. Even while many customers nowadays are able to perform their own garbage sorting, they may be puzzled about how to select the correct waste category when disposing of a wide range of items. Finding an automated approach to recycling is currently extremely valuable in today's industrial and information-based world since it offers both environmental and economic benefits [4].

Dumping organic wastes in landfills is a big concern, not because of the resources lost in the process, but because the organic waste undergoes anaerobic decomposition in the landfill, resulting in methane production. Methane has a greater greenhouse gas effect than carbon dioxide when discharged into the atmosphere. Organic waste, on the other hand, has its own set of issues, since it may be a source of greenhouse gases, methane, and pollution. If organic waste is not properly cleaned or controlled, it can infiltrate water sources and feed bacteria, resulting in the formation of fungus, which can be hazardous to society.

As most of municipal trash is not separated at the source and gets dumped in sanitary landfills. This is the reason for requirement of a more efficient system for distinguishing materials that are recyclable, and this is where machine learning can help. Machine learning techniques can identify, filter, and sort those items on a conveyor using computer vision and machine learning. Most of today's high performing object detection networks use the characteristics of CNN (convolutional neural networks). An approach that supports automation helps ship fewer recyclables to landfills. In this paper, three models have been built, namely ResNet-34, VGG16 and a proposed deep neural network for image classification, segmentation, and detection and compared the results that were obtained. The categorization of recyclable and organic materials is a difficult topic that necessitates the use of advanced approaches. A worldwide strategy for industrial applications is required, in addition to dataset gathering. A more accurate and optimum waste categorization approach is offered in this study.

II. Literature Survey

In paper [5], OpenCV was used for carrying out data improvement and image preparation on the waste images gathered. A VGG16 neural network is created using TensorFlow, with the RELU activation function and the introduction of a batch normalisation layer to improve the rate of convergence of model and recognition accuracy rate. The accuracy on test is found out to be 75.6 percent. The approach followed in this paper can classify domestic waste into toxic waste, other waste, kitchen waste and recyclable waste, meeting the needs of practical applications.

Paper [6] suggests using a Convolutional Neural Network and a Support Vector Machine algorithm for better waste classification. They have used ResNet-50 as the transfer learning model as the dataset was small. They segregate waste into six categories: cardboard, metal, paper, trash, glass, plastic and trash. By this approach, they have achieved an accuracy of 87% on epoch number 12.

The paper [7] proposes a neural network for waste classification into following categories: organic, non-recyclable and recyclable waste, with an accuracy of 81.22%. The paper also compares other models like VGG16, Inception-Net, Dense-Net and Mobile-Net. Out of all these transfer learning models, Mobile-Net showed the highest accuracy of 92.65%.

In paper [8], a comparison is made between a proposed model that is WasteNet and various other models like VGG, AlexNet, ResNet, DenseNet and SqueezeNet on four different metrics. The waste is categorised into six different categories. It was found that the proposed model performed better on all four metrics and had an accuracy of 97%. Hence, it was then used to make a smart dustbin that classifies the waste that comes into the dustbin.

Trashnet datasets were utilized to conduct this [9] study. The performance of the Support Vector Machine (SVM) classifier using the SIFT is compared to the performance of the same technique using the SIFT-PCA combined feature. The outcome of the experiments indicate that categorization using SIFT feature extraction achieves a 62 per cent accuracy.

The authors of [10] look at a variety of approaches and give a thorough assessment. SVM using features of HOG, basic CNN, and CNN with residual blocks were among models they used. The authors concluded that both the basic CNN networks that are with or without residual blocks perform well, based on the results of the study.

The critical component of the system mentioned in [11] is a garbage container that will automatically sort waste using the Internet of Things and Machine Learning technologies. The bin is linked to the cloud, which aids in the waste collection by recording and uploading numerous data points for each bin. This study describes two versions of the system, the first of which achieves a 75 per cent accuracy in categorising garbage as wet or dry, and the second of which achieves a 90 per cent accuracy in sorting waste into six unique categories.

In paper [12], four CNN-based models, namely ResNet50, VGG16, MobileNet-V2 and DenseNet 121 were studied. The garbage was categorized into four categories like hazardous waste, general waste, recyclable waste and compostable waste. The highest accuracy of 94.8 per cent was obtained for ResNet-50.

Using a deep learning technique, the paper [13] examines a unique approach for waste sorting for successful recycling and disposal. The YOLOv3 method was used to train a self-made dataset in the Darknet framework. The network has been taught to recognise six different categories of objects. The detection test was also done using YOLOv3-tiny for comparative assessment to evaluate the competency of the YOLOv3 algorithm.

The authors in paper [14] have classified the waste into four classes like cardboard, paper, metal and plastic. They designed a Convolutional Neural Network, which attained the highest testing accuracy of 76 per cent for 100 epochs for 50x50 size images.

III. Dataset

Kaggle provided the dataset for the transfer learning model and the proposed CNN model. It is waste classification data, which comprises approximately 25,077 waste images split into two categories: organic and recyclable. Table I indicates images contained in each class, whereas Fig. 1 depicts the same in a pie chart. Fig. 2 shows some sample images in the input dataset.

TABLE I
Number of waste images in the dataset.

	Organic	Recyclable
Training data	12565	9999
Testing data	1401	1112
Total	13966	11111

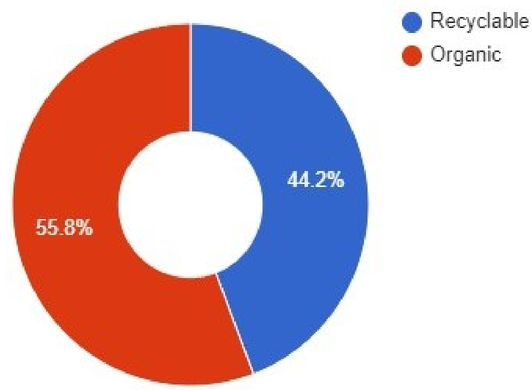

Fig. 1. Distribution of waste images in data set.

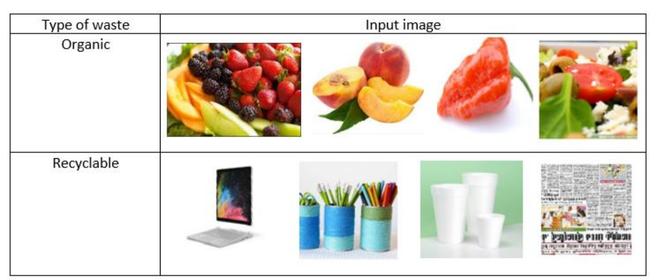

Fig. 2. Types of waste images in data set.

IV. Methodology

A. VGG16

In 2014, Zisserman and Simonyan suggested the VGG16 network structure as one of the VGG networks [15]. VGG16 is an improvised version of the AlexNet network. While recognising and categorising pictures, it can convey the features of the data collected in a better way. Large-scale datasets and complicated backdrop recognition tasks get advantage from this. Thirteen convolutional layers, three fully connected layers, and five pool layers form the model's structure. The convolution kernel in the thirteen convolutional layers in VGG16 is a medium-sized 3 x 3 matrix having a moving step of one compared to other networks. The number of convolution kernels slowly grew from 64, followed by 128, 256, and ultimately 512 in the final layer. The convolutional kernel of the pooling layer has a size of 2 x 2, and a step size of 2. It performs better on the retrieved features than other networks with a convolution kernel size of 5 x 5. VGG model offers superior processing capabilities for datasets used for training with tiny amounts of data, and it becomes easier for deployment and has greater recognition accuracy than other deep convolutional neural networks [16].

The VGG16 model has both advantages and downsides in terms of precise identification. The number of model parameters and the complexity of computations during training has risen as the network structure has been deepened, resulting in a long training period and low training efficiency. The following approaches are utilised to enhance the VGG16 model in this work in order to maintain the key features of the model extraction without lowering the accuracy of recognition while also improving the pace of model training and minimising the time it takes to train the model. The Relu function is used to activate the VGG 16 network in the VGG network, and the formula is:

$$f(x) = \begin{cases} x & \text{if } x \geq 0 \\ 0 & \text{if } x < 0 \end{cases} \tag{1}$$

Where: x is the input of the Relu function; f(x) is the function's output. The loss function is used to measure the difference between the predicted and actual values throughout the model training process. In the VGG 16 network, use the CrossEntropyLoss loss function, which has the following formula:

$$E(t, y) = -\sum_j t_j \log y_j \tag{2}$$

Among them: t and y represent the target label and output of the neural network, respectively, and represents the softmax loss function:

$$y_j = e^{z_j} / \sum_k e^{z_k} \tag{3}$$

B. ResNet - 34 (FastAI)

ResNet-34 is a 34-layer convolutional neural network image categorization model that is state-of-the-art. ResNet model has been pre-trained using the ImageNet dataset, that contains more than 100,000 images sorted into 200 categories [17]. It varies from standard neural networks in that the successive linked layers employ the residuals from each layer.

The infrastructure of the ResNet-34 is actually the residual building component, and it makes up the majority of the network. The residual building block used a shortcut connection to skip the convolutional layers, effectively alleviating the problem of gradient disappearance or explosion characterized by increasing depth in neural networks and allowing to build CNN structures more freely and improving the rate of recognition [18].

ResNet has one convolution and pooling step, the four layers of identical behaviour. Each layer follows a similar pattern. They execute 3x3 convolution with a fixed feature map dimension (F) of [64, 128, 256, 512] and skip the input after every two convolutions. Furthermore, the width (W) and height (H) of the layer stay consistent throughout. [19]

C. Proposed Model

1) Convolutional Layer: The input image is first passed via a convolutional layer of the CNN. These convolutional layers use convolution to extract high-level characteristics from an image. A convolution is a linear procedure in which the input is multiplied by a set of filters. The convolutional neural network, unlike previous algorithms, learns the filters from the training dataset. The earlier convolutional layers generally capture the lower-level features such as gradient orientation, edges, and so on. Increasing the number of convolutional layers enhances the capability to encode features of higher-level. [20]

2) Pooling Layer: The dimensions of the output from the ReLu function are then reduced in the pooling layer. To extract the salient characteristics important in the feature maps, the pooling layer uses a max-pooling method. The maximum pooling layer's output is invariant to both rotation and translation. Max pooling can also be used to filter out noisy and minor activations, lowering the number of computing resources required.

3) Fully Connected Layer: The features are flattened and sent into the fully connected layer after going through the above stages. The fully connected layer receives the features from the previous layers and uses the backpropagation technique to learn the non-linear functions of the features. The last fully-connected layer uses a softmax function to calculate each class's probability. All of the classes' probabilities will add up to one.

4) Activation Layer: The output from the convolutional layer is activated by a ReLU activation function before being sent to the next layer. When compared to the commonly used sigmoid and tanh functions, the ReLU function has the advantage of just activating non-negative neurons, making it more computationally efficient.

In this work, the desired shape of input images is 224x224 with an RGB color scheme. The CNN used in this work contains 6 Conv2D layers, 3 MaxPool2D layers and three fully connected Dense layers. ReLU acts as the activation function in the fully connected layers. The output layer contains only a single neuron which will contain values as 0 or 1, where 0 stands for class ('Organic') and 1 for class ('Recycled').

V. Results

After training the ResNet-34 model for seven epochs at a learning rate of 0.002, a training accuracy of 93.1%, test accuracy of 91.8%, and training loss of 0.3158 were achieved.

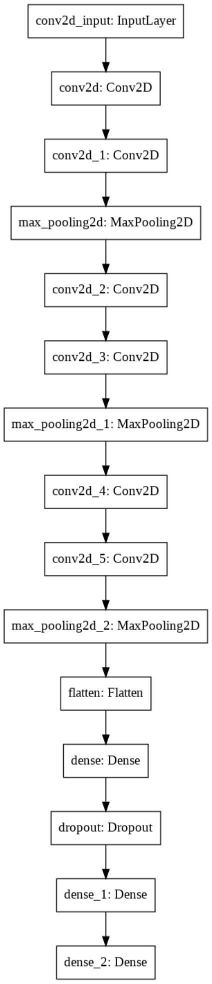

Fig. 3. Architecture of proposed CNN model.

On training the VGG16 model for five epochs at a learning rate of 0.001, an accuracy of 94.62% on the training set and accuracy of 93.37% on the test set was obtained. At the end of the fifth epoch, the training loss for the VGG16 model was 0.2765.

TABLE II
CLASSIFICATION REPORT ON TEST DATA.

	VGG16		ResNet-34		Proposed model	
	Organic	Recyclable	Organic	Recyclable	Organic	Recyclable
Precision	0.86	0.89	0.94	0.92	0.96	0.95
Recall	0.92	0.81	0.93	0.91	0.94	0.96
f1-score	0.89	0.85	0.94	0.93	0.95	0.94

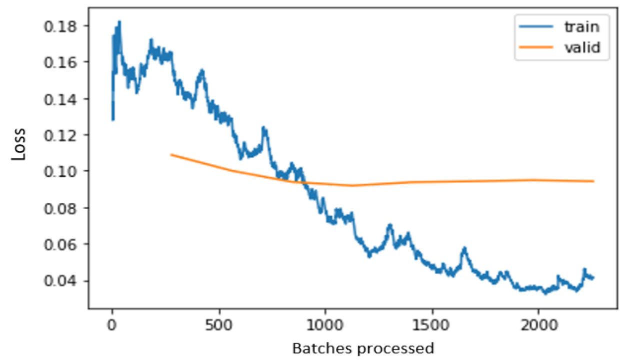

Fig. 4. Evaluation of loss function of ResNet-34 model.

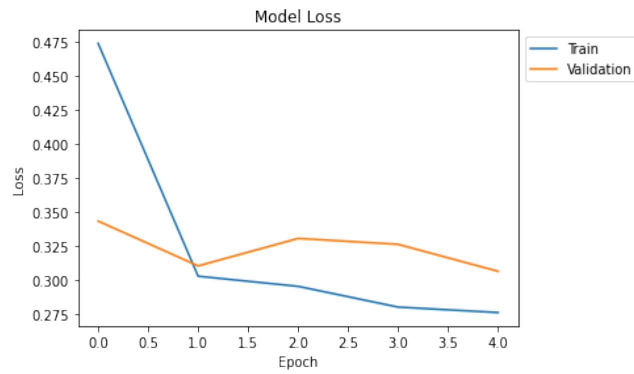

Fig. 5. Evaluation of loss function of VGG16 model.

In the proposed model, the batch size was set to 64, and the number of epochs was kept at ten, but it was observed that the accuracy of the model was not improving after epoch number seven, which had a loss of 0.1781 and hence, an early stopping method was applied. The proposed model was trained using Root Mean Squared Propagation (RMSProp) optimizer at a learning rate of 0.001, and training accuracy of 95.8% and test accuracy of 94.96% was attained.

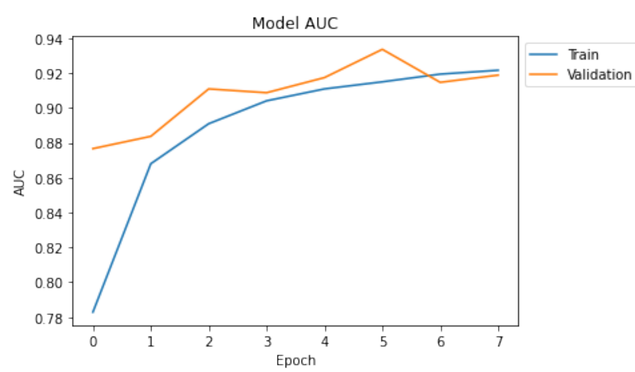

Fig. 6. Evaluation of accuracy for proposed CNN model.

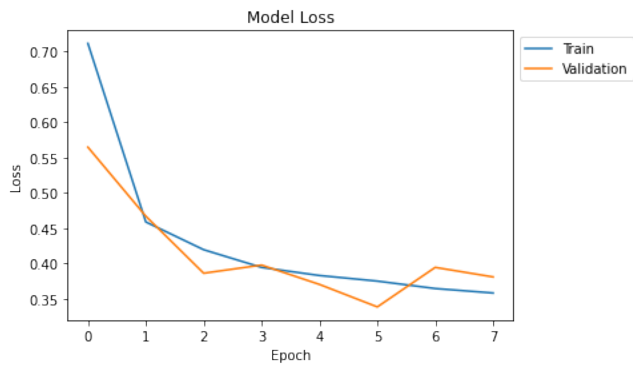

Fig. 7. Evaluation of loss function for proposed CNN model.

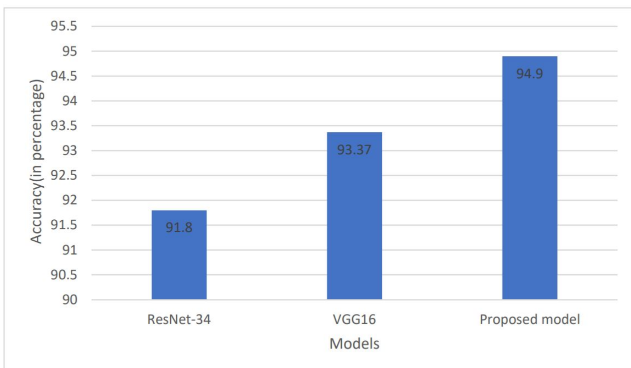

Fig. 8. Bar chart representation of accuracies of various models.

VI. Conclusion

Segregation and management of waste have been a long-standing issue that has impacted a vast percentage of the ecosystem. It is easier to manage waste using today's technology if they are applied properly.

As it can be see from the findings of this study, the problem of waste image categorization can be tackled with deep learning algorithms with a high degree of accuracy. It can thus be seen from the comparison of accuracies of the three deep learning models the proposed has the highest accuracy of 94.9%. Though the accuracy of other models doesn't come at par with the proposed model, still these models can be considered for further improvement since the accuracy of those architectures is above 90%.

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