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Waste Classification with CNN

V Bhavani,

Koneru Lakshmaiah Education Foundation, Department of Computer Science and Engineering, vaddeswaram, Guntur, 5220302, India

A.Roshini

Koneru Lakshmaiah Education Foundation, Department of Computer Science and Engineering, vaddeswaram, Guntur, 5220302, India

Abstract

Waste is a serious global problem. As the world's population and living standards rise, so will the amount of waste produced. People are thinking about waste generation and its consequences, and they are finding for solutions.

The process of transforming garbage into new materials and items is known as recycling. Energy recovery from waste products is commonly included in this notion. Recyclability is determined by a material's ability to restore the attributes it had in its original state. Recyclability is determined by a material's ability to regain the properties it had in its original state. It is a substitute to "traditional" waste disposal that can help to save while also minimisng greenhouse gas emissions. Recycling can help reduction of waste such as spoiled food, fresh juice, and coffee, as well as helping to reduce air miles and air pollutants from incinerators and the dump waste from landfilling. In this article, we are using CNN for classifying the data which is in the form of images into Organic waste and Recyclable waste.

Keywords Convolutional Neural Network, CNN, Waste Classification, Image Classification, Organic, Recyclable

1.Introduction

DELHI and MUMBAI stand out not only as India's most populous urban centers but also as the most heavily burdened by pollution. Based on estimates from the Central Pollution Control Board (CPCB), Mumbai and Delhi produce around 11,000 and 7,500 tonnes of solid waste daily, respectively. The Ministry of Housing and Urban Affairs (MoHUA) data, submitted to the Union Environment Ministry, indicates that Maharashtra consistently ranked as the leading generator of municipal solid waste for two consecutive years in 2018.

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According to the Brihan-Mumbai Municipal Corporation (BMC), Mumbai alone contributes 7,500 million tonnes of waste per day, equivalent to 27.37 lakh MT annually, constituting one-third of Maharashtra's total waste output.

In India, over 377 million urban residents inhabit 7,935 cities and towns, collectively producing an average 62 million tonnes of municipal solid waste annually. Regrettably, only 43 million tonnes are collected, with 11.9 MT undergoing treatment and 31 MT ending up in landfill sites[1]–[4]. A critical aspect is the management solid waste, an essential service provided by municipal jurisdictions nationwide to maintain cleanliness in these urban and metropolitan areas. Despite this, most municipal authorities haphazardly deposit solid waste in dump yards within or outside the city. Experts argue that India's waste disposal and management system is fundamentally flawed[5]–[7].

Waste can be categorized into two main types:

(a) Organic waste

(b) Recyclable waste

Organic waste decomposes slowly, primarily facilitated by various types of microorganisms. Composting, the transformation of organic waste into reusable materials, plays a crucial role[8]–[10]. Encouraging composting at both community and household levels is imperative for effective waste management. Citizens must ensure proper segregation, storage, and disposal of solid waste in accordance with provided guidelines[11]–[13]. Containers provided by authorities facilitate the handling and storage of different types of waste. For instance, biodegradable waste goes in a green container, recyclable waste in a white container, and hazardous or inorganic waste in a black container. Biodegradable waste can be decomposed or repurposed as agricultural manure.

Integrating machine learning and neural networks into waste classification processes, even on a large scale, can significantly enhance efficiency. This advancement not only aids in reducing pollution stemming from the current waste crisis in the country but also benefits municipal workers by simplifying their tasks. Computer Vision, specifically convolutional neural networks (CNN), emerges as a potential solution to empower BMC workers handling waste. CNN, a deep learning artificial neural network, excels in object recognition, image classification, and clustering. Our research delves into the application of Convolutional Neural Networks (CNN) for solid waste classification, with the primary objective of evaluating the model's performance.

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BACKGROUND AND RELATED WORK

A considerable number of individuals and scholars are actively engaged in the field of image recognition, with a significant focus on convolutional neural networks (CNN). Convolutional neural networks have played a pivotal role in advancing image recognition, making them a central element in this domain. Object detection has become a prominent subject of exploration in the scientific community, with applications in motion detection, image and video recognition, classification, and semantic segmentation experiencing notable improvements through the utilization of CNN[14]–[16]. In contrast to traditional methods, computer vision has now become a fundamental tool in addressing a wide array of global challenges. Notably, when CNN models were applied to categorize over a million photos within the ImageNet dataset, researchers observed a substantial improvement in performance[17]. Several studies have delved into the evaluation of various pre-trained CNN architecture models, determining the most effective ones. Concurrently, investigations comparing the waste classification performance of CNN-based frameworks such as Vgg-16 and Resnet with older classifiers revealed that CNN-based classifiers consistently outperformed their predecessors.

PROPOSED SYSTEM

A. Dataset

From the Kaggle website, we gathered dataset named Waste classification Dataset. The dataset indulges waste from three major categories: household waste, plastic waste, and other waste. These wastes are classified as organic or recyclable. The dataset contains 22500 coloured images, which is enough to effectively train a neural network. The data sources were Google and ImageNet, but because the dimensions of the images varied, they were normalised for the experiment. The dataset have 22500 images, of which 22564 images are used for train the model and 2513 images are used for test the model. Furthermore, the validation set uses 20% of the training data to validate the neural network.

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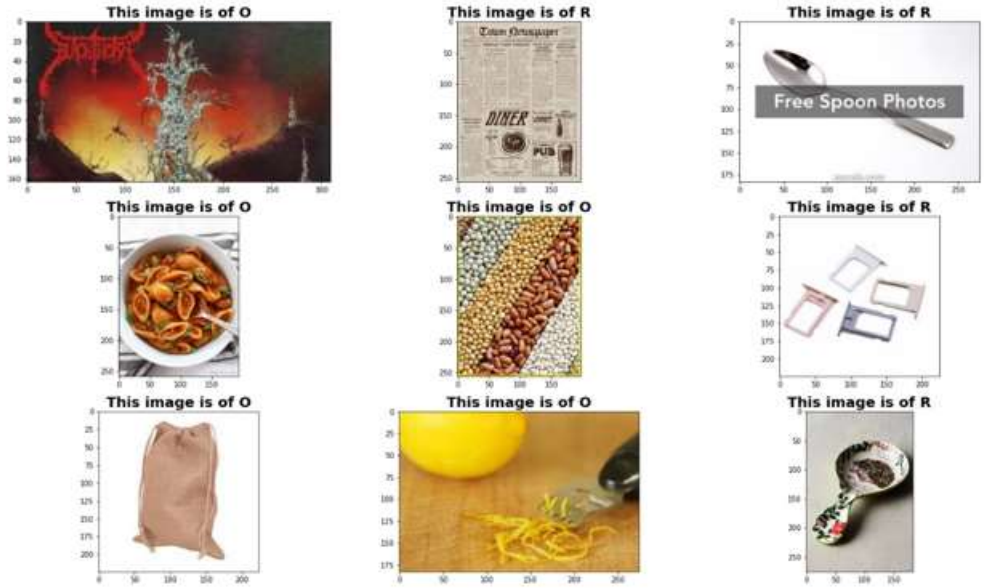

Figure 1 Sample Data after Classification

B. Pre-processing

The dataset comprises images from various sources, with dimensions ranging from 150x120 pixels to 120x120 pixels. To facilitate computation, all images were normalized to a consistent size of 100x100 pixels, maintaining uniformity across the dataset. Subsequently, an array representing the images was constructed with three parameters: image height, width, and channel. Given that colored images utilize the RGB format, the channel was set at 3. This array was converted to float32 and divided by 255 to standardize the values within the 0 to 1 range, optimizing image computation speed and efficiency. Augmentation and dataset expansion were achieved using Imagedatagenerator, incorporating image zoom by 0.1, height shift by 0.2, and width shift by 0.2. The height_shift and width_shift functions randomly adjust the image by a fraction.

C. CNN Model Architecture

The CNN model is structured sequentially, allowing for the stacking of layers. Comprising five major layers, the first four involve two convolutions, one batch normalization, and one max-pooling operation. The activation function for all layers is Relu (Rectified Linear Unit). The initial layer, being a tensor, declares the input shape of the image. In the first layer, 32 feature maps were generated using a 3x3 pixel filter/kernel, with a stride of 1. The subsequent convolutions reduce the image size, following the formula [(n-f)+1], resulting in a 98x98 pixel dimension after the first convolution. The second convolution further reduces the size to 96x96, aiding in feature identification. Batch normalization mitigates internal covariate shift

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during backpropagation and accelerates training. A 2x2 pool size retains features while halving the image dimension. The dropout layer, removing 20% of neurons, prevents overfitting. This process is replicated in the next three major layers, with an increase in feature maps to 64, 128, and 256 in the second, third, and fourth layers, respectively. The image size continually diminishes to capture detailed features. The flatten method in the final layer prepares input for the dense layers, which play a pivotal role in distinguishing organic from recyclable items. Three dense layers with sizes of 512, 256, and 128 were employed, ultimately connecting to a layer with a size of 2 to determine whether the image is Organic or Ecological. The 'adam' optimizer, known for its adaptive learning rate, was selected, and model compilation metrics

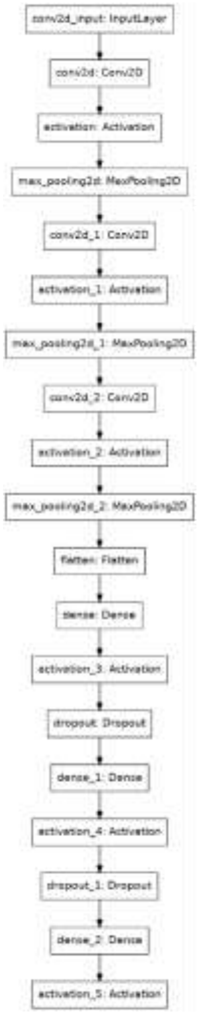

Figure 2 CNN Model

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were based on accuracy. To mitigate overfitting, there are 1,862,498 trainable parameters and 960 non-trainable parameters.

Convolutional Neural Networks consist of various layers.. Some of them are Convolution layer, Pooling Layer, ReLU correction layer, Padding Layer and Fully Connected Layers.

We use this formula to calculate the convolution layer:

$$W_{out} = \frac{W - F + 2P}{S} + 1$$

We use this formula to calculate the Pooling layer:

$$Wout = \frac{w - F}{s} + 1$$

We use this formula to calculate the ReLU correction layer formula:

$$f(x) = max(0, x)$$

For padding layer,

For a 2D image H and 2D Filter(kernel) F,

(1) Convolution Operation : G $= H * F$

$$G[i,j] = \sum_{u=-k}^{k} \sum_{u=-k}^{k} H[u,v]F[i-u, j-v]$$

(2) Correlation Operation : G $= H \oslash F$

$$G[i,j] = \sum_{u=-k}^{k} \sum_{u=-k}^{k} H[u,v]F[i+u, j+v]$$

Figure 3 Formula For padding layer

2. PERFORMANCES AND OUTPUT

A. Performance

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Because there had been no improvement in validation loss since the previous fifteen epochs, the model stopped training at the 38th epoch and considered the epoch with the highest accuracy for weights.

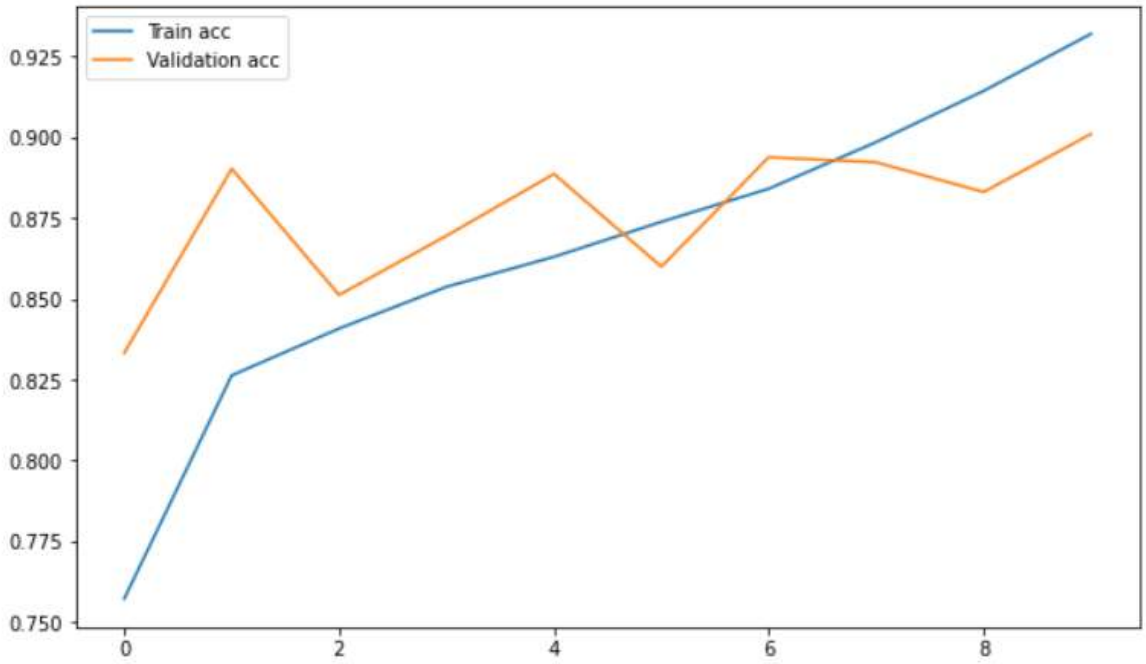

Figure 4 Accuracy for the model

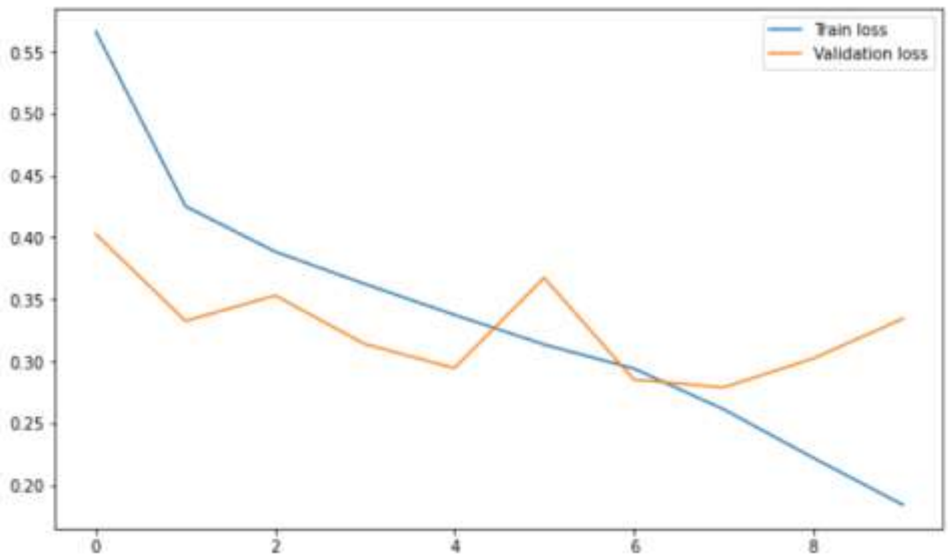

Figure 5 Model Loss

There is a steep drop in the validation set's accuracy because the model encountered many different types of images with different features but belonging to the same category right up until the 5th epoch, after which there is a huge increase in the accuracy because almost all of

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the features are recognised and the model can predict correctly. The model loss in Fig 4 there is a steep increase in the validation loss as it kept guessing the wrong classification for a first epoch as the model was not familiar with total images that belong to the same class as there are

lot many images from various types of waste some of which are household waste and some of which are industrial but after the third epoch, there is a steep drop in the loss from almost 0.75 to 0.2 later it remained almost equal to the model became accurate.

B. Output

On the testing dataset, the model accuracy was found to be a staggering 90.66% percent. The test loss is 0.24441 and the error rate is 9.44% percent.

Test Loss	0.24411
Test Accuracy	0.90688

Table 1 Model Acuuracy and Loss

The experiment's results can be understood using a Pie plot, in which the green colour represent organic.1350 recyclable waste images were correctly identified, but 51 recyclable images were incorrectly identified as organic. In the second row, 127 organic images were incorrectly identified as Recyclable images, while 985 organic images were correctly identified.

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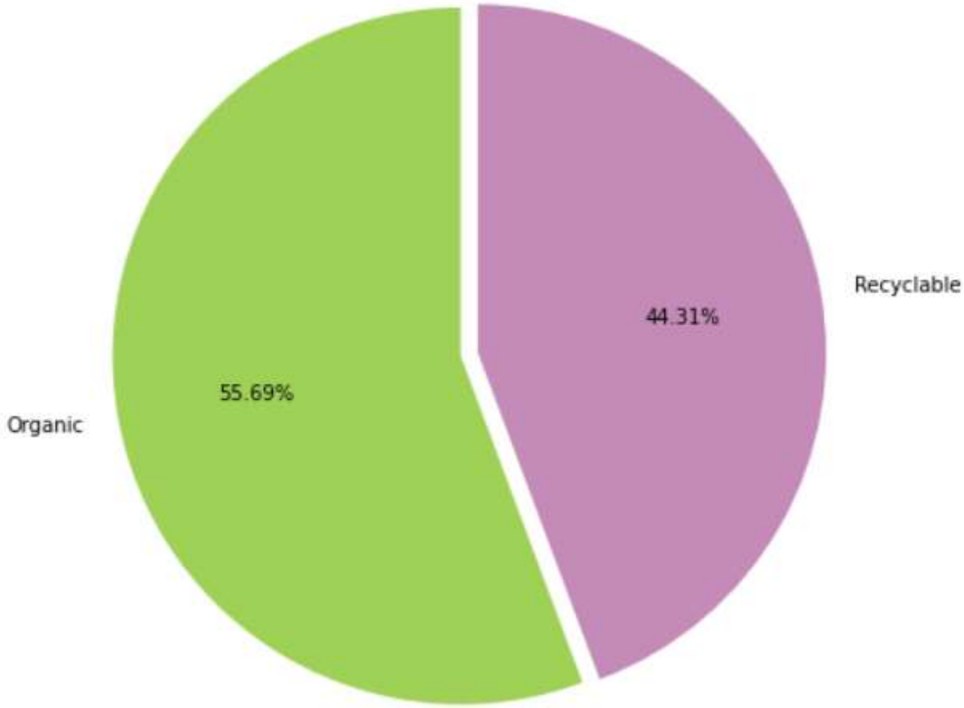

Figure 6 Pie Representation

CONCLUSION

Here, we show a model that can recognise and classify images as Organic or Recyclable waste. Later, the waste can be more specific, such as plastic, lead, industrial, and so on.

Object detection can also determine the amount of toxic material or plastic contained within a waste. It is assumed that using the VGG-16 or Resnet model will improve the accuracy by 3-4 percent. These models were trained on a massive dataset of over 10000 images. Image recognition is a fantastic way to learn about neural networks and develop deep learning techniques for solving problems. In the future, we hope to create an app that can take pictures of waste and then classify it.

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