

Waste Classification System based on Web Application using Deep Learning Techniques

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Abstract - Recycling is already a significant work for all countries. Among the work needed for recycling, garbage classification is the most fundamental step to enable cost-efficient recycling. In this paper, we attempt to identify single garbage object in images and classify it into one of the recycling categories. We study several approaches and provide comprehensive evaluation. The models we used include simple convolutional neural network (CNN), and CNN with residual blocks. According to the evaluation results. Thanks to deep learning techniques, the garbage classification problem for the target database can be effectively solved.

Key Words: Convolutional Neural Network, Transfer learning, Artificial intelligence, Deep learning, image classification, neural networks.

1. INTRODUCTION

Garbage classification has always been an important issue in environmental protection, resource recycling and social livelihood. In order to improve the efficiency of front-end garbage collection, an automatic garbage classification system is proposed based on deep learning. Firstly, the overall system of the garbage bin is designed, including the hardware structure and the mobile app. Secondly, the proposed garbage classification algorithm is based on CNN algorithm, and its network structure is further optimized by three aspects, including the multi feature fusion of input images, the feature reuse of the residual unit, and the design of a new activation function. Finally, the superiority of the proposed classification algorithm is verified with the constructed garbage data. Conventional treatment and recycling methods of organic solid waste contain inherent flaws, such as low efficiency, low accuracy, high cost, and potential environmental risks. In the past decade, machine learning has gradually attracted increasing

attention in solving the complex problems of organic solid waste treatment. Although significant research has been carried out, there is a lack of a systematic review of the research findings in this field. This study sorts the research studies published between 2003 and 2020, summarizes the specific application fields, characteristics, and suitability of different machine learning models, and discusses the relevant application limitations and future prospects. It can be concluded that studies mostly focused on municipal solid waste management, followed by anaerobic digestion, thermal treatment, composting, and landfill. The most widely used model is the artificial neural network, which has been successfully applied to various complicated non-linear organic solid waste related problems. A new regulation of trash management, which obtains a series of achievements in managing trash. In order to implement this regulation further and help citizens understand clearer about trash classification, we decided to develop a deep learning dataset and models to classify waste automatically. The object of this study is to take an image as input and identify the category of trash. We write a web crawler to capture images. After pre-processing, we gain about 7605 images in total. We compare models including CNN, and a VGG16 model on the dataset. Our experiments show that the VGG16 model perform better than the others.



2. LITERATURE SURVEY

To study the application of deep learning in the field of environmental protection, the convolutional neural network VGG16 model is used to solve the problem of identification and classification of domestic garbage. This solution first used the Tensorflow Deep Learning library to locate library to locate and select the identified objects and preprocessed the images into 224×224 pixel RGB images accepted by the VGG16 network. Then after RGB images accepted by the VGG16 network. Then after data enhancement, a VGG16 convolutional neural network based on the TensorFlow framework is built, by using the softmax activation function and adding BN layer to accelerate the model's convergence speed, while ensuring recognition accuracy. This project Finally classifies domestic garbage into recyclable garbage, hazardous garbage, kitchen waste and other garbage. After actual test, the correct classification rate of the garbage classification system based on VGG16 network proposed in this paper is 81.1%, the result meets the needs of daily use.

3. EXISTING METHODOLOGY

3.1 Introduction

The world generates at least 3.5 million tons of waste per day and this number is still increasing day by day that's why we need to aware about waste.

This web application can classify waste with different types of waste materials and it will show you the details of that particular waste materials and also will show you the waste materials related videos. This will help to raise awareness for people to reduce and recycle waste.

4. IMPLEMENTATION

4.1 Proposed Work

The garbage collection in India still depends on unorganized collection of waste. The segregation process is still handled by mankind which has many health issues, time consuming, costly and less effective. In the existing system, all the garbage collected from households and industries was

dumped on the outskirts of towns and cities. Due to uncontrolled dumping of waste, it gave rise to the problems like overflowing landfills but also contributed a huge amount in terms of ground waste pollution and Global Warming. A new concept uses deep learning algorithms to segregate the waste at initial level thus making waste management more powerful. The designed method sorts the waste into different categories with higher accuracy. This study reviews the best and effective approach to segregate the garbage into different types. The proposed method mainly focuses on identification and segregation of waste by using deep learning algorithms like convolution neural networks (CNN) Usually, all the toxic wastes are dumped with recyclable waste which causes huge damage to land. This project proposes an idea where to segregate the toxic waste with higher accuracy.

- This method work in different phrases which are as follows:

A. Capturing of images

B. Collection of datasets

C. Pre-processing of images

D. Training data

E. Testing data

F. Evaluation of model

G. Model Deployment

A. Capturing of images

- Waste objects :- In this step , we are considering different local areas or bins for collection of waste images.

- Stereo camera :- Stereo camera provides a Large-scale High-resolution Outdoor Stereo Dataset. So, In order to get clean and proper images for the dataset . We used a stereo camera to capture images of different types of wastes.

● **Object Detector :-** Object detector is a technology which relates to computer types of application and image processing that detects and defines various objects such as humans, buildings and cars from images. The technology has power to identify once or various types of objects within a d image at one. So , we used this technology to classify images into different categories like glass, paper, plastic, metal , Clothes, Organic, Light Bulbs, E-Waste, Batteries.

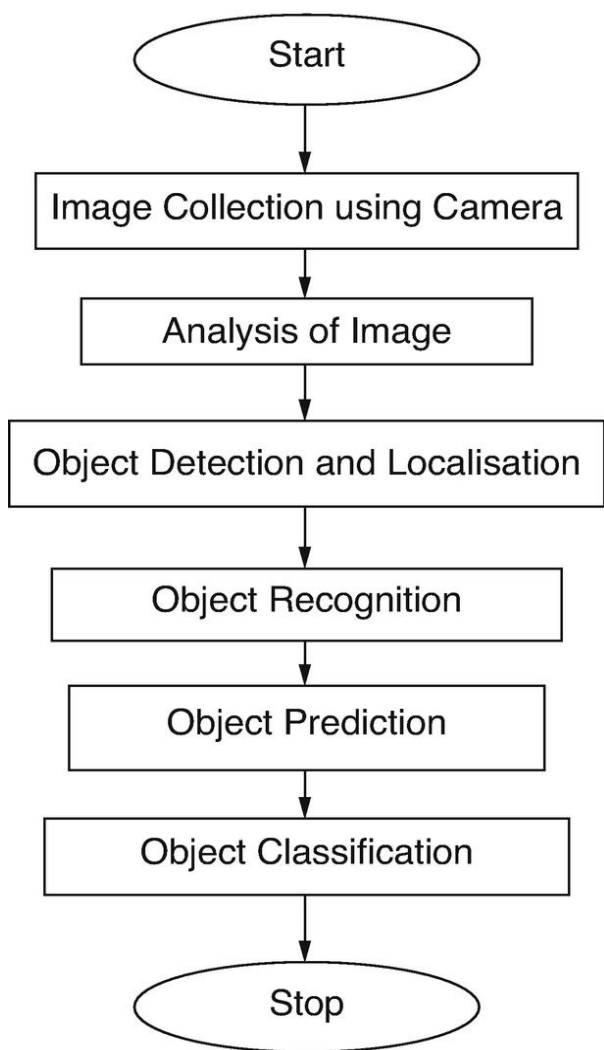


Fig. 1., Automatic Classification of Solid Waste Using Deep Learning

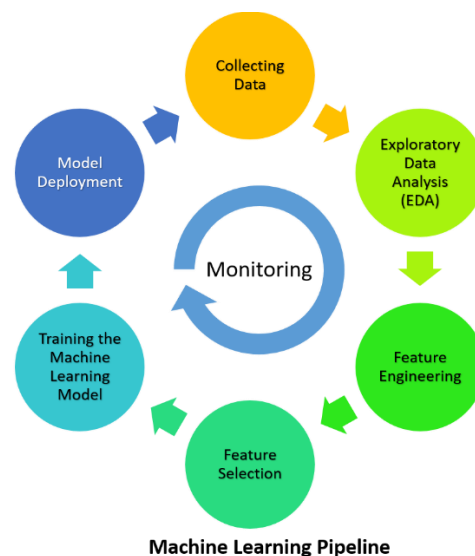


Fig. 2., Machine Learning Pipeline

B. Collection of datasets

I. Garbage Dataset

A lot of image data involving garbage is available and present on the internet and government based datasets. This data is present in variety with different types according to different class labels/target labels. We have explored 2-3 different datasets given below: Garbage Classification Dataset we have collected and filtered data by our self from google images, dreamstime.com and Kaggle. It has almost 7605 images of garbage which has target labels given as Light Bulbs, Organic, Batteries, Clothes, E-Waste, glass, metal, Paper and Plastic. This amount of data is still not enough to be fed to any state-of-the-art CNN algorithm. The images in the dataset are of the certain object related to its target label which are kept in a clean background. Second Data set is the Garbage in Images (GINI) Dataset. The dataset contains images with and without garbage in it. The maximum of the dataset is annotated and has the label and bounding box parameters in a Comma Separated file. The target labels are given as 1 (Garbage Present) and 2 (Garbage Not Present).

Sr No.	Category	Number of Images Present	Annotated
1	Light Bulbs	650	yes
2	Batteries	355	yes
3	Clothes	729	yes
4	E-Waste	624	yes
5	Glass	773	yes
6	Metal	1092	yes
7	Paper	1467	yes
8	Plastic	1244	yes
	Total	7605	

Table I: A Summary of Existing Garbage Datasets

II. Dataset Description

I] Categories : There are four main categories, as we mentioned earlier. There are 60 sub-classes under the four main categories too, as shown in Table II.

II] Web Crawler : In order to gather adequate training samples from websites, we write a web crawler to help us capture images from Baidu Image and Google Image. For each sub-classes, we set the web crawler to download up to 300 images, both from Baidu and Google. We add filter conditions including the white background and a resolution requirement higher than 200×200. However, some websites are expired, and we totally collected near 7605 images. While these images cannot be directly used as they have different resolutions and formats and some of them are not closely related to the keywords as garbage types, we have to select and clean the images manually, as we did in the dataset preprocessing step.

III] Dataset Preprocessing : We find out there are many irrelevant images contained in the dataset after browsing the downloaded raw images. To achieve a better training dataset, we deleted some irrelevant or inappropriate images, which are unhelpful in classification and could not convey correct information. Next, we develop a simple program to transform the size of images to a united size of 224×224. Thirdly, we filter the images which are not in a jpg format.

IV] Dataset Statistics : After preprocessing, we annotate and collect 7605 images in total for the purpose of training and testing. Specifically, there are more images for recyclable waste, more images for hazardous waste, more images for household food waste, and more images for residual waste. For some specific classes with no or few images, we directly remove this kind of classes. In the next section, we use 234 classes selected from a total number of 240 sub-classes.

Main Categories	Sub-Classes
Household food waste	egg shell, shrimp shell, cookies, bread, etc.
Recyclable waste	milk box, plastic, glass bottle, clothes, etc.
Hazardous waste	medicine, battery, roll firm, spray, etc.
Residual waste	hair, gum, tissue, lib-stick, etc.

Table II: Four Main Categories and Their Sub-Classes

Main categories Sub-classes household food waste egg shell, shrimp shell, cookies, bread, etc. recyclable waste milk box, plastic, glass bottle, clothes, etc. hazardous waste medicine, battery, roll firm, spray, etc. residual waste hair, gum, tissue, lib-stick, etc. We show an example of the household food waste in

Fig. 3., which is the mix food.



Fig. 3., The example of the household food waste

We show an example of the recyclable waste in

Fig. 4., which is the glass.



Fig. 4., The example of the recyclable waste.

We show an example of the household food waste in

Fig. 5., which is the battery.



Fig. 5., The example of the hazardous waste.

We show an example of the Residual waste in

Fig. 6., which is the tissue.



Fig. 6., The example of the Residual waste

C. Pre-processing of images

I. Image Processing Techniques

The images need to be pre-processed using Deep Learning techniques so as to make them easy to understand for the computer so it can make a prediction on it. Basically the image needs to be brought in the format necessary for the model it

needs to be fed in. This whole process is quite tedious when dealing with multiple images of different types and categories. The main aim for image pre-processing is the improvement of image data that suppresses undesired distortions or enhances some image features relevant for further processing and analysis tasks.

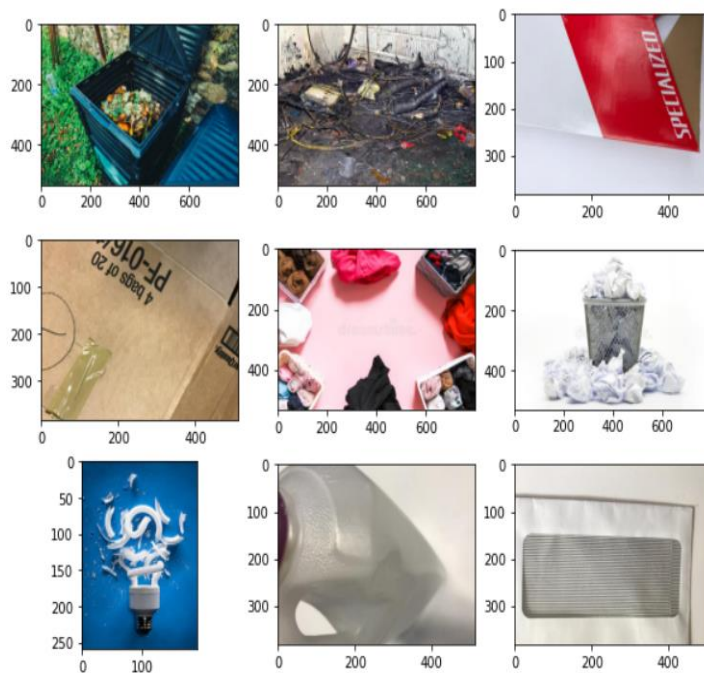


Fig. 7., Images from the dataset

Before doing image pre-processing it is important to understand the images that we are dealing with. What steps should be taken, what image preprocessing techniques should be used depending on "how strong is your image data?" is and "what operations are you going to perform on it?". One important necessary step before feeding the data to a model is to standardize the images. Image standardization refers to resizing of images in a dataset to a unified dimension which is suitable for the particular model it is fed to. Second important step is Data Augmentation which is the process of scaling, rotating and performing other affine transformations (Denoising using Gaussian Blur, Segmentation, Morphological Operations) on the existing images from existing dataset. This is mainly done to enlarge the size of the dataset and expose the model to a wide variety of variations of the images.

D. Training data

It's a set of data samples used to fit the parameters of a machine learning model to training it by example. Training data is also known as training dataset, learning set, and training set. It's an essential component of every machine learning model and helps them make accurate predictions or perform a desired task.

E. Testing data

Test Dataset: The sample of data used to provide an unbiased evaluation of a final model fit on the training dataset. Test data is the data that is used in the test of a software system. Specifically identified data is known as test data. Test data can be generated by automation tools and we can also generate test data by testers. Mainly in regression testing data test is used as the same data can be used again and again.

F. Evaluation of model

In this section, we implement classifiers based on our dataset. We build a CNN model from scratch and compare it with pre-trained models from the transfer learning approach. We design two classification problems, classifying the four main classes and classifying the 234 sub-classes. We want to evaluate the accuracies on both problems. Convolutional neural network is a feedforward neural network, whose artificial neuron can respond to the surrounding units in a partial coverage range, and has excellent performance for large-scale image processing, with the convolutional and pooling operations. And CNN possesses three main advantages. Firstly, the size of the convolution kernel is generally equal or smaller than the size of the input image, so the features extracted by the convolution layer will pay more attention to local areas which is very consistent with the image processing we are exposed to in daily life. In fact, each neuron does not need to perceive the global image, just only needs to focus on the local information, and then integration of the local information will be constructed at the higher level to obtain the global information. Secondly, CNN can reduce the computation through parameter sharing. Thirdly, we will not use only one convolution operation to filter the input images generally, because the parameters of a kernel are fixed, and the

extracted features will be simplified. It's kind of like how we look at things physically in the really world, you have to look at things from multiple perspectives to try to avoid bias as much as possible. We also need multiple convolution checks to convolve the input images. So CNN is good at feature extraction and classification. As for this problem, we divided dataset with a ratio of 64%:16%:20% for training, validation, and testing. Then we normalization data to the range between 0 to 1, to train the model easily. After normalization, we build a classic CNN architecture for this research in Fig. 10.

The specific layers include:

Layer 0: Input images of size 224×224 with 3 color channels

Layer 1: Convolution with 64 filters which have size as 3×3 and relu as the activation function, stride and padding as default value.

Layer 2: Convolution with 64 filters which have size as 3×3 and relu as the activation function.

Layer 3: Max-Pooling with a size 2×2 filter.

Layer 4: As for the output pooling layer, probability equal to 0.25 Dropout is adopted.

Layer 5: Flatten all the pixels.

Layer 6: Fully connected with 128 neurons in which the nonlinear activation function is used with the relu function.

Layer 7: As for the fully connection layer, probability equal to 0.5 Dropout is adopted.

Layer 8: The last layer is a fully connection layer, the amount of neurons depends on the number of classes, and we use non-normalized log softmax scores as activation function. We also use the transfer learning approach. Transfer learning is a machine learning technique that a model trained on one task which is re-purposed on other related task. Based on the extraordinary portability of transfer learning, it has been widely used in deep learning tasks which do not have a large amount of training dataset and need to be supported by the pre-trained models. In this study, the images we collected are not enough for training a deeper model with large numbers of parameters. Instead, we use a model, namely, VGG16, trained on the ImageNet dataset and fine-tune these models on our dataset.

Layer	VGG16
Size of Layer	41
Image Input Size	224x224 pixel
Convolutional Layer	13
Filter Size	64 & 128
ReLU	5
Max Pooling	5
FCL	3
Drop Out	0.5
Softmax	1

Model: "model"

Layer (type)	Output Shape	Param #
input_1 (InputLayer)	[(None, 224, 224, 3)]	0
block1_conv1 (Conv2D)	(None, 224, 224, 64)	1792
block1_conv2 (Conv2D)	(None, 224, 224, 64)	36928
block1_pool1 (MaxPooling2D)	(None, 112, 112, 64)	0
block2_conv1 (Conv2D)	(None, 112, 112, 128)	73856
block2_conv2 (Conv2D)	(None, 112, 112, 128)	147584
block2_pool1 (MaxPooling2D)	(None, 56, 56, 128)	0
block3_conv1 (Conv2D)	(None, 56, 56, 256)	295168
block3_conv2 (Conv2D)	(None, 56, 56, 256)	590080
block3_conv3 (Conv2D)	(None, 56, 56, 256)	590080
block3_pool1 (MaxPooling2D)	(None, 28, 28, 256)	0
block4_conv1 (Conv2D)	(None, 28, 28, 512)	1180160
block4_conv2 (Conv2D)	(None, 28, 28, 512)	2359808
block4_conv3 (Conv2D)	(None, 28, 28, 512)	2359808
block4_pool1 (MaxPooling2D)	(None, 14, 14, 512)	0
block5_conv1 (Conv2D)	(None, 14, 14, 512)	2359808
block5_conv2 (Conv2D)	(None, 14, 14, 512)	2359808
block5_conv3 (Conv2D)	(None, 14, 14, 512)	2359808
block5_pool1 (MaxPooling2D)	(None, 7, 7, 512)	0
flatten (Flatten)	(None, 25088)	0
dense (Dense)	(None, 9)	225801

Total params: 14,940,489

Trainable params: 225,801

Non-trainable params: 14,714,688

Fig. 8., CNN architecture model with a simple layers

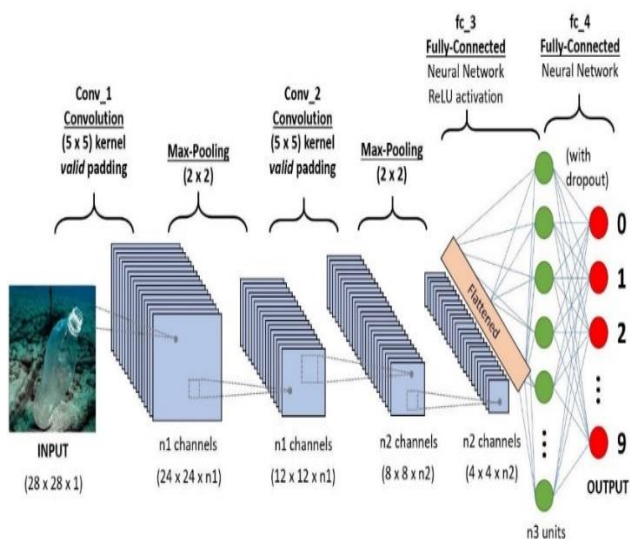


Fig. 9., Waste Classification using Convolutional Neural Network Structure

Fig. 10., The structure of the CNN model

The structure of VGG16 used in this study is shown in Fig. 11. Proposed by the Oxford visual geometry group, VGG demonstrates that increasing network depth can optimize network performance to a certain extent. VGG has two variants, namely, VGG16 and VGG19. The former has 13 convolutional layers and the latter has 16 convolutional layers, both of which contain three fully

connected layers. For a given receiving field, it is better to use multiple small convolutional kernels than a single large convolutional kernel because multiple nonlinear layers can increase the network depth to ensure more complex learning patterns with fewer parameters.

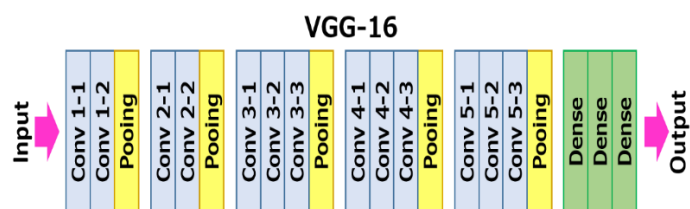


Fig. 11., The structure of the VGG16 model

4.2. Implementation of the models

The implementation of the models is conducted on a computer with Windows 10 OS, which is equipped with an Intel i5-9600K CPU (which has six 3.7GHz processors), and a NVIDIA GeForce GTX 2070 GPU with 16GB DDR4 RAM for acceleration of the convolutional operations in the deep learning models. The loss function is the categorical cross entropy, and Adam is used as the optimizer. The batch training size is set to be 16. For each model, we train for 30 epochs. The best parameter with the highest validation accuracy is saved and further used for the evaluation on the testing set.

5. RESULT ANALYSIS AND DISCUSSION

5.1. Result Analysis

We show the experiment results in Table III

Model	Training loss	Training Accuracy	Validation loss	Validation Accuracy	Testing loss	Testing Accuracy
VGG16	0.7946	0.7198	2.1471	0.4522	2.1471	0.4522

Table III: The Performance of VGG16 Model

From Table III, we can compare the models both horizontally and vertically. We discovered that the accuracy of pre-trained models is better than using a

CNN directly is even better than VGG16 horizontally. We believe the main reason leading to this result is that the size of dataset is too small, and we cannot obtain an accurate parameter from such a simple dataset. And the results are strongly affected by the number of layers, CNN model only has 8 layers, and VGG16 has 16 layers. With the vertical comparison, we found that model barely learned from architecture in the case of CNN and transfer learning base on VGG16 model, because the difference among training accuracy, validation accuracy and testing accuracy are too small. Based on the analysis, we believe that expanding the size of dataset and increasing the training layer will be very helpful for the problem of garbage classification.

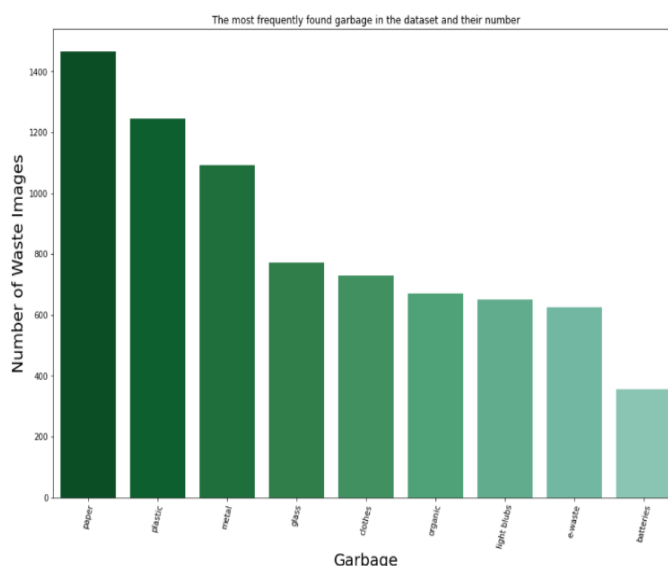


Fig. 12., The Most Frequently Found Garbage in The Dataset and Their Numbers

This fig.12 shows that visualisation of garbage images and how many numbers of Garbage images in dataset? we are found that most of the Garbage images of Paper waste and their number is 1467, Plastic waste number is 1244, Metal waste number is 1092, Glass waste number is 773, Clothes waste number is 729, Organic waste number is 671, Light Bulbs waste number is 650, E-Waste number is 624, Batteries waste number is 355.

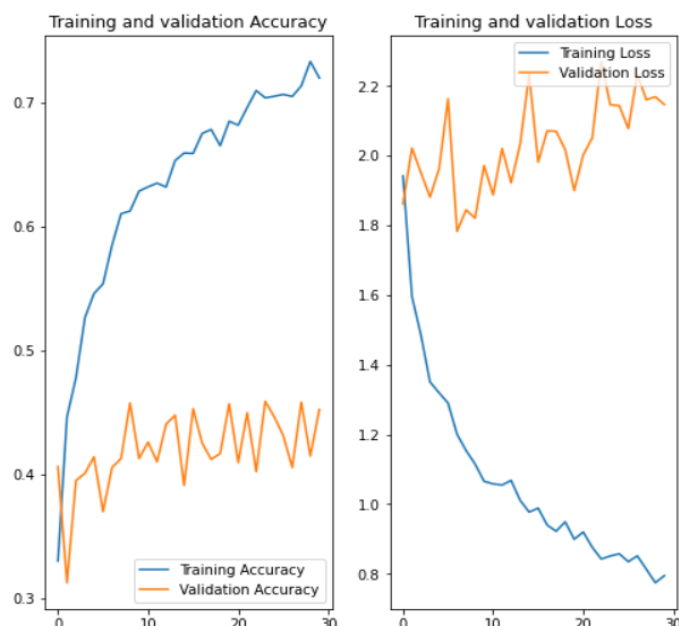


Fig. 13., Loss and Accuracy of The VGG16 Model

To further explain our results, we show the training/validation loss of VGG16 in Fig. 13. As we can tell from Fig. 13 both the training and validation losses keep decreasing with the epochs. However, the change of the training loss is more smooth because we are fitting on the training data. We show the training/validation accuracy of VGG16 in Fig. 13. Similarly, we can observe that both the training and validation accuracies are increasing.

5.2. Model Deployment

I. Machine Learning Model Deployment on Heroku Using Flask

The post consists of three parts, they are:

1. Setting up a Flask web application
2. Creating a Machine Learning model
3. Deploy the app on Heroku

II. Heroku using Flask

Heroku is a Platform-as-a-Service tool by Salesforce. Heroku is backed by AWS and all Heroku applications/services are hosted on AWS. AWS provides the infrastructure and handles all the load-balancing, resource utilization, networking, logging, monitoring and Heroku acts as a middle-man to provide a scalable, automated rapid deployment platform with all cloud capabilities. Using Flask will provide UI to test and it can be integrated with enterprise-level applications.

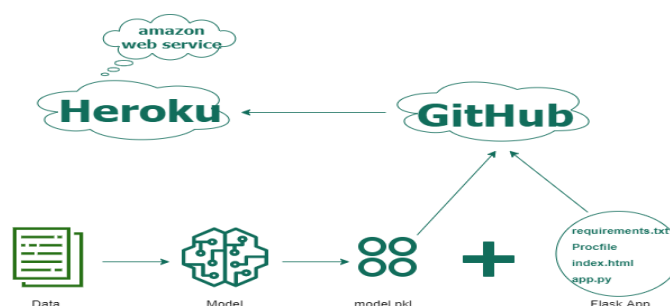


Fig. 14., Machine Learning Model Deployment on Heroku Using Flask

Steps for deployment on Heroku using Flask

Deployment on Heroku using Flask has 7 steps from creating a machine learning model to deployment. These steps are the same for all machine learning models and you can deploy any ML model on Heroku using these steps.

1. Create ML Model and save (pickle) it
2. Create Flask files for UI and python main file (app.py) that can unpickle the machine learning model from step 1 and do predictions
3. Create requirements.txt to setup Flask web app with all python dependencies
4. Create Procfile to initiate Flask app command
5. Commit files from Step 1, 2, 3 & 4 in the Git hub repo
6. Create account/Login on Heroku, create an

app, connect with Github repo, and select branch

Select manual deploy (or enable Automatic deploys) on Heroku

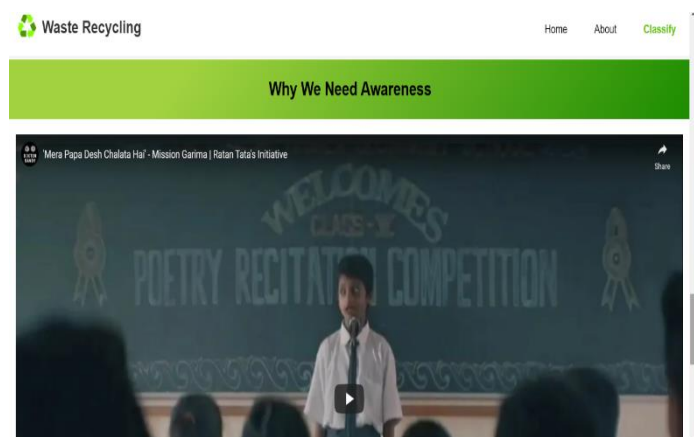
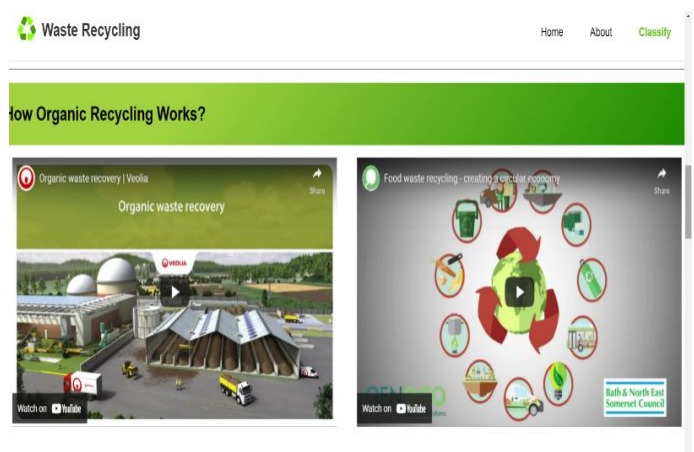
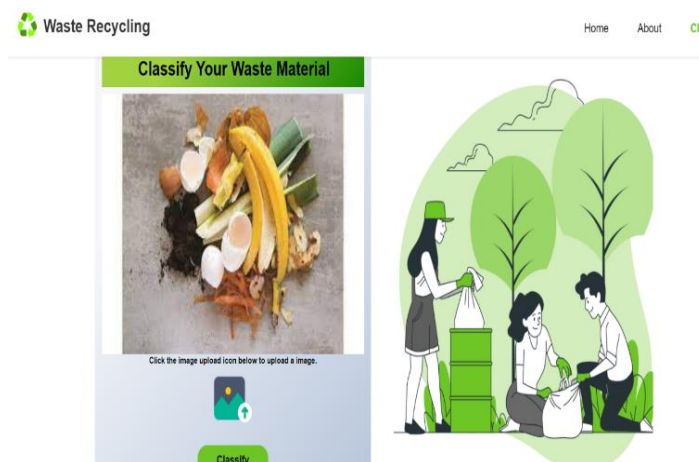
III. Output of Deployed Machine Learning Model

We have deployed this on Heroku platform.

Home Page



Classify Page



6. BNEFITS OF RECYCLING

- Reduces the amount of waste sent to landfills and incinerators.
- Conserves natural resources such as timber, water and minerals.
- Increases economic security by tapping a domestic source of materials.
- Prevents pollution by reducing the need to collect new raw materials.
- Saves energy.

7. ADVANTAGES OF RECYCLING

I. Recycling minimizes pollution

All forms of pollution in the modern world emanate from industrial waste. Recycling of these industrial wastes such as plastics, cans, and chemicals go a long way towards considerably cutting back on levels of pollution because these waste products are reused rather than just being thrown away recklessly.

II. Protects the environment

The great benefit of recycling waste material is that it plays a big part in protecting Mother Nature in the most balanced way. While many trees are felled every day, recycled paper manufactured from specific trees is continually utilized to reduce deforestation.

This classic example demonstrates that other natural resources can be recycled and made useful this way to conserve the environment.

III. Recycling minimizes global warming

It is perfectly true that recycling minimizes global warming and its grave impacts. During waste disposal, huge amounts of waste have combusted that lead to the emission of vast greenhouse gases such as carbon dioxide, sulfur, and nitrogen, which contribute to climate change and global warming.

The recycling process involves minimal combustion and waste is transformed into reusable materials with zero or minimal harmful impact on the environment.

The whole process of processing and manufacturing products from waste materials emits few greenhouse gases because the waste recycling industries burn little fossil fuels.

IV. Conserves natural resources

If the process of recycling used and old materials was not there, it means new products will be manufactured by the extraction of fresh raw materials underneath the earth through the process of mining and extraction.

Recycling is a surefire way of conserving existing raw materials and protecting them for future use. Taking steps to conserve natural resources like minerals, water, and wood ensure sustainable and optimal use.

V. Recycling cuts down the amount of waste in landfill sites

Recycling old and used materials into reusable products enormously reduces the possibility of choking of landfill sites. This is beneficial because it helps minimize land and water pollution.

Since landfills contribute mightily to environmental degradation, less landfill and waste littering ensures the less erosion of the topmost fertile soil. As wastes are saved from being dumped in the ocean, aquatic biodiversity is also maintained.

VI. Recycling ensures sustainable use of resources

Recycling guarantees that existing resources will be used sensibly and sustainably. The recycling process alleviates the possibility of discriminate use of raw materials when they are obtainable in huge supply.

Governments these days have stepped in to encourage recycling from lower levels, for instance, schools, small-sized organizations and also at global levels.

This means that manufacturing industries can leave existing natural resources for exploitation by our children in the future without affecting current production.

VII. Recycling contributes to the creation of jobs

To add to the benefits it brings to the environment, recycling opens up job opportunities. Recycling means many recycling plants will be set up, thus, leading to a long chain of collection and delivery. All these activities are performed by humans, so this will also trigger an explosion of opportunities.

VIII. Reduces energy consumption

A lot of energy is used to process raw materials in the course of manufacture. Recycling plays a big role in reducing energy consumption, which is vital for large-scale production, for instance, mining and refining.

Recycling also renders the whole process of production less expensive, which is a great victory for manufacturers.

IX. Recycling helps to make and to save money

Electronics, old water bottles, and other trash can be sold for cash. So if you sell trash, you not only save the environment but make money in exchange.

If you buy recycled materials, they are less expensive, and you will also save money. If you reuse some of the trash that your home produces, you will make and save more money.

X. Recycling spreads environmental awareness

Recycling is just the beginning of a revolution that will help preserve the planet for our future generations. With calls for sorting waste into biodegradable, non-biodegradable and recyclable, people become aware of recycling while reducing environmental impact.

When everyone becomes accustomed to recycling, people will be more eco-conscious and will participate in more eco-friendly activities.

XI. Recycling can reduce allied activities needed for the production of fresh products

Industries are the biggest producers of greenhouse gases and pollution. If the need for fresh materials is lessened due to recycling, there will be a lesser need for allied activities that usually make huge environmental impacts like mining and transportation.

XII. Recycling of organic matter

Recycling of organic matter leads to the generation of valuable compost, which serves as plant fertilizer.

“Even when all actions have been taken to use your wasted food, certain inedible parts will still remain and can be turned into compost to feed and nourish the soil,” the EPA says with regards to food waste scraps and yard waste. “Composting these wastes creates a product that can be used to help improve soils, grow the next generation of crops, and improve water quality.”

XIII. Innovations drive scientific advancements

Scientific advances are producing less natural resource-intensive products making it easier to recycle numerous products. New sorting technologies can identify grade and type of plastic, automatically speeding up the process of the work to reduce landfill content.

A new polymer can be added to both polyethylene and polypropylene that creates a tough new plastic to recycle the second time easily.

8. FUTURE SCOPE

This project indeed has a very vast scope not only in India but Globally too because the project is very effective in segregating the waste this segregation will finally lead to protecting our environment and people's health which is major problem in today's world

- Project can be further improved in many ways

A: It is obvious that after a certain period of time the bin will get full. Using modules such as wifi and proximity sensors etc. the data that bin is filled completely can be sent to the concerned authority who can then be alerted to see and empty the bin.

B: Work can also be extended in introducing a robot in the bin which automatically dumps the bin when it finds it to be full.

9. CONCLUSIONS

In this study, we write a crawler and use it to capture images from the Internet for garbage classification. We also investigate the possibility of implementing deep learning models for automatic waste classification. We implement two different models in this research including a CNN model and VGG16 models, which are pre-trained on the ImageNet dataset. We find the superiority of the VGG16, which we attribute to the contribution of the pre-trained parameters and the complex structure with deeper layers. We plan to release our dataset for future research and expand our dataset for achieving a better classification accuracy. We also pointed out several future research directions that would inspire the following research.



Your waste material is paper with 99.97 % accuracy



Your waste material is e-waste with 100.0 % accuracy

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