AUTOMATIC GARBAGE CLASSIFICATION USING DENSENET-201 ALGORITHM

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Abstract

Automatic garbage classification using deep learning is a technology that uses machine learning algorithms to categorize different types of waste. This technology aims to automate the process of waste management by using image recognition techniques to classify garbage. The system is designed to identify and sort different waste materials, including plastic, paper, metal, glass, and organic waste. Deep learning algorithms, such as convolutional neural networks, are used to train the system on large datasets of waste images. The system is capable of detecting and classifying waste items in real-time, making it a useful tool for waste management organizations and municipalities. The results of this technology can help to reduce waste pollution, improve recycling rates, and increase environmental sustainability. Automatic garbage classification using the 201 algorithm in deep learning is a technology that utilizes the ResNet-201 architecture to classify various types of waste. The ResNet-201 architecture is a deep convolutional neural network that has shown significant performance in image classification tasks. This technology aims to automate the process of waste management by using image recognition techniques to classify garbage. The system is designed to identify and sort different waste materials, including plastic, paper, metal, glass, and organic waste. The ResNet-201 algorithm is trained on large datasets of waste images to recognize and classify waste items accurately. The system can detect and classify waste items in real-time, making it a useful tool for waste management organizations and municipalities. The results of this technology can help to reduce waste pollution, improve recycling rates, and increase environmental sustainability.

Keywords: Deep Learning, Anaconda Navigator – Spyder

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1. Introduction

Waste management has become a critical issue in the modern world, with an increasing amount of waste generated each year. Efficient and effective waste management is essential to reduce the environmental impact of waste and to promote sustainability. One of the key challenges in waste management is the sorting and classification of different types of waste. Traditional methods of waste sorting and classification are time-consuming, labor-intensive, and often inaccurate. To address this challenge, automatic garbage classification using deep learning has been proposed as a promising solution. This technology utilizes machine learning algorithms to identify and sort different types of waste accurately. In particular, the ResNet-201 algorithm has shown significant potential in image classification tasks and has been applied to the automatic garbage classification problem. The goal of this technology is to automate the process of waste management by using image recognition techniques to identify and categorize various types of waste, including plastic, paper, metal, glass, and organic waste. The system can detect and classify waste items in real-time, making it a useful tool for waste management organizations and municipalities. The results of this technology can help to reduce waste pollution, improve recycling rates, and increase environmental sustainability.

Garbage Classification using Deep Learning Techniques: A Review" by Dwivedi The paper provides a comprehensive review of various deep learning techniques used for garbage classification, such as CNN, AlexNet, and YOLO. The paper also discusses the challenges and future directions in garbage classification using deep learning techniques[1] .A Survey of Deep Learning-Based Waste Classification Techniques" by Khot and Rane .The paper provides a systematic survey of various deep learning-based techniques used for waste classification, including CNN, RNN, and GANs. The paper also compares the performance of these techniques on different waste classification datasets[2] .A Comprehensive Survey of Automatic Garbage Classification Techniques" by Alam . The paper provides a comprehensive survey of various garbage classification techniques, including rule-based systems, fuzzy logic, and deep learning. The paper also discusses the limitations and future directions in garbage classification research[3].

China's micro plastic pollution and prevention proposals[4],The article provides a comprehensive overview of the current situation of marine micro plastics pollution in China and proposes prevention measures to address this issue. The authors highlight the growing concern about micro plastics pollution in China, which is driven by the increasing production and consumption of plastic products. The article provides a detailed analysis of the sources and pathways of micro plastics pollution in China's marine environment, including the contribution of wastewater treatment plants, coastal tourism, and shipping activities. The authors also discuss the ecological and health impacts of micro plastics pollution, highlighting the potential risks to marine organisms and human health. In response to this issue, the authors propose several prevention measures, including improving wastewater treatment, reducing plastic production and consumption, promoting sustainable tourism practices, and implementing regulations and monitoring programs to control the release of microplastics into the environment. Overall, the article provides valuable insights into the current situation of marine microplastics pollution in China and proposes practical prevention measures that could be implemented to address this issue.

Investigation of electric dust removal fly ash and bag fly ash in a circulating fluidized bed waste incineration system,2019[5], Review by W.-B. Li, G. Ma, E.-Q. Yang, Y.-M. Cai, Z. Chen, R.-F. Gao, J.-H. Yan, X.-F. Cao, and E.-J. Pan .The experimental methodology. The authors collected electric dust removal fly ash and bag fly ash samples from a circulating fluidized bed waste incineration system in China. They performed several experiments to analyze the physical and chemical characteristics of the ash samples. The authors used X-ray diffraction (XRD) analysis to determine the mineral composition of the ash samples. They used scanning electron microscopy (SEM) to analyze the morphology of the particles and the distribution of elements on the surface of the particles. The authors also used energy-dispersive X-ray spectroscopy (EDS) to analyze the elemental composition of the ash samples. To determine the thermal stability of the ash samples, the authors performed thermo gravimetric analysis (TGA) and differential scanning calorimetry (DSC). They also used Fourier-transform infrared spectroscopy (FTIR) to analyze the functional groups present in the ash samples. Finally, the authors performed leaching tests to determine the leaching characteristics of the ash samples. They used a deionized water extraction method and a toxicity characteristic leaching procedure (TCLP) to evaluate the leaching behavior of the ash samples. Overall, the study used a combination of analytical techniques to characterize the electric dust removal fly ash and bag fly ash samples from a circulating fluidized bed waste incineration system. The results provide valuable information on the physical and chemical characteristics of the ash samples and can help improve the management and disposal of ash generated from waste incineration processes.

Garbage Recognition and Classification Using Hyper spectral Imaging Technology, Review by

D.-E. Zhao, R. Wu, B.-G. Zhao, and Y.-Y. Chen The experimental methodology, the authors conducted a study to investigate the feasibility of using hyper spectral imaging technology for garbage classification and recognition. The authors collected garbage samples from different sources, including household waste, kitchen waste, and plastic waste. They used a hyper spectral imaging system to capture the spectral reflectance of the garbage samples. The authors then analyzed the spectral data using various feature extraction methods, including principal component analysis (PCA) and linear discriminant analysis (LDA). The authors found that the hyper spectral imaging system could effectively capture the spectral reflectance of the garbage samples. They also found that the spectral data contained useful information that could be used to classify and recognize different types of garbage. The authors compared the performance of different feature extraction methods and found that the LDA method produced the best classification results. The authors conducted experiments to evaluate the performance of the garbage classification and recognition system. They used a support vector machine (SVM) classifier to classify the garbage samples based on their spectral data. The authors achieved a classification accuracy of over 90% for household waste, kitchen waste, and plastic waste. Overall, the study demonstrated the feasibility of using hyper spectral imaging technology for garbage classification and recognition. The authors developed a system that could effectively capture the spectral reflectance of garbage samples and used various feature extraction methods to classify and recognize different types of garbage. The results can be used to develop more efficient and accurate garbage classification and recognition systems that can contribute to improving waste management practices and promoting environmental sustainability.

6.1image Selection

- The dataset, **Garbage classification dataset** is implemented as input. The dataset is taken from dataset repository. The input dataset is in the format ‘.png, ‘.jpg.
- In this step, we have to read or load the input image by using the imread () function.
- In our process, we are used the tkinter file dialogue box for selecting the input image.

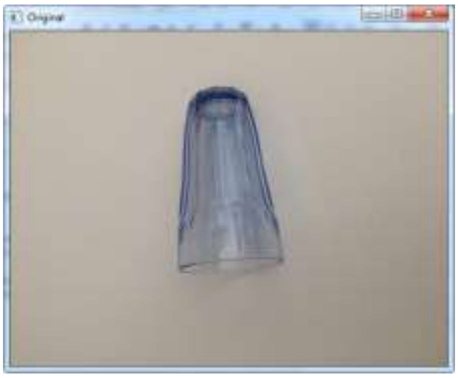

Figure 1: Data Selection

6.2 Image Preprocessing

- In our process, we have to resize the image and

  Convert the image into gray scale.
- Image resizing, to resize the images to a standard size can help to reduce the computational load and improve the accuracy of the model. The image size should be selected carefully so that it is large enough to capture the necessary details, but small enough to be processed efficiently
- Convert an Image to convert a color image to grayscale, there are several techniques that can be used. One common approach is to take the average of the red, green, and blue color channels for each pixel in the image. This is known as the average grayscale method, and it is calculated as gray image =0.2989 * r + 0.5870 * g+ 0.1140 * b
-

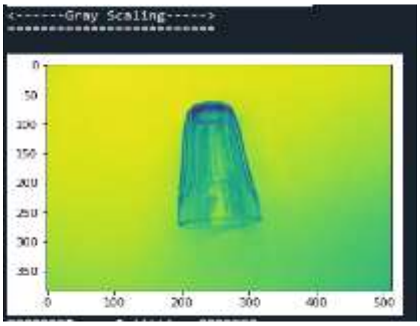

Figure 2: Gray Scaling

6.3 Image Splitting

- Image splitting can be used in garbage classification using deep learning to extract smaller image patches from a larger input image. This approach can be useful for several reasons considered 70% training data and the remaining 30% testing data.
- Large input images can be computationally expensive to process, especially if the model needs to classify many objects within the image.
- Image patches can be used to augment the training dataset by generating additional samples that are similar to the original images.
-

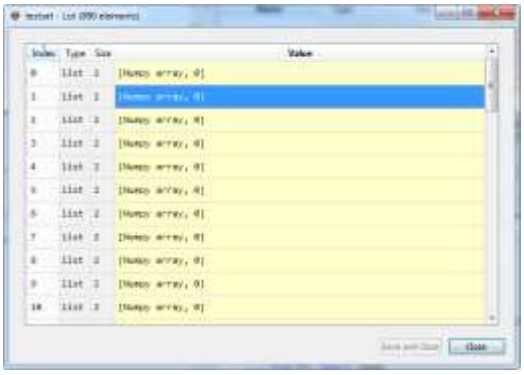

Figure 3: Image Splitting

6.4 Classification

ResNet

- ResNet (Residual Neural Network) and DenseNet (Densely Connected Convolutional Network) are two popular deep learning architectures that can be used for garbage classification
- ResNet is a type of CNN architecture that uses residual connections to enable training of very deep neural networks. The key idea behind residual connections is to add shortcut connections that bypass one or more layers in the network. This allows gradients to flow more easily through the network during training, and helps to mitigate the vanishing gradient problem that can occur in very deep network
-

Figure 4.1: Accuracy Graph

DenseNet

- DenseNet is another type of CNN architecture that builds on the idea of residual connections, but takes it a step further by introducing dense connections. Dense connections enable all layers in the network to have direct access to the feature maps produced by all preceding layers. This can help to improve feature reuse and gradient flow, and can lead to better performance on image classification tasks.

• DenseNet-201 is a deeper version of the DenseNet architecture, with 201 layers. It has been shown to achieve state-of-the-art performance on several image classification tasks, including the ImageNet dataset, which contains more than a million images across 1000 classes.

• We load a pre-trained DenseNet201 model (excluding the top layers), and add custom top layers for garbage classification. We freeze the pre-trained layers for transfer learning, and compile the model with appropriate optimizer and loss function. We then train the model on a garbage classification dataset using the fit () method.

Figure 4.2: Accuracy Graph

Different architectures, layer sizes, and hyper parameters to optimize the performance of the model on your garbage classification task .

6.5 Prediction

• After training the deep learning model on a garbage classification dataset, we can use it to make predictions on new, unseen images of garbage. Here's an example code snippet in Python using the Keras library to make predictions using a trained DenseNet-201 model

• Load a trained DenseNet-201 model using the load model () method. We then load an image to be classified using the load image () method, and convert it to an array

For input to the model using img to array () and expand dims ().We preprocess the image array using the preprocess input () function from the dense net module. We make a prediction on the preprocessed image using the predict () method, and get the class label with the highest probability using argmax(). Finally, we print the predicted class label.

Input Data

Material	**Type of Waste**	**Examples**
Paper	Recyclable	Newspaper, cardboard, office paper
Plastic	Recyclable	Water bottles, milk jugs, plastic bags
Glass	Recyclable	Bottles, jars, windows
Metal	Recyclable	Aluminium cans, steel cans, tin foil
Organic	Compostable	Food scraps, yard waste, leaves
Hazardous	Special Handling	Batteries, electronics, light bulbs
Mixed	Landfill	Dirty diapers, Styrofoam, broken glass

Output Data

Type of Waste	**Disposal Method**	**Collection Frequency**
Recyclable	Separated collection for recycling	Once or twice a week
Compostable	Composting or organic waste bin	Once a week or as needed
Special Handling	Hazardous waste drop-off locations	As needed or scheduled events
Landfill	Regular garbage collection	Once or twice a week

VII. System Diagrams

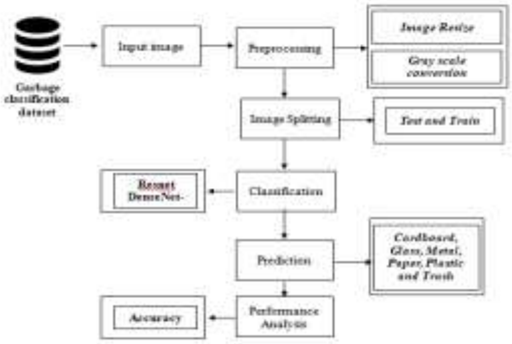

Figure 5: System Architecture

VIII.Evaluation Index

Gray Scale Conversion

Figure 6: Original Image

Figure 7.1: Image Resize

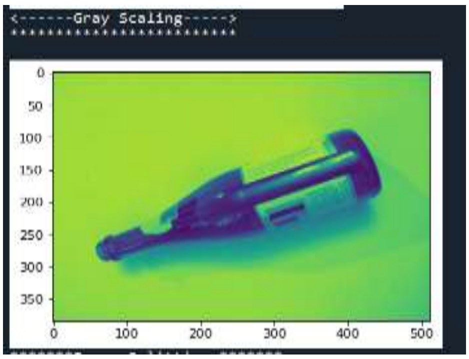

Figure 7.3: Grayscale Image

Image Splitting

```
*******Image Splitting *******
['cardboard', 'glass', 'metal', 'paper', 'plastic', 'trash']
6
<----Data splitting----->
************************
<---X Train data---->
(1309, 100, 100, 3)
<----X Test data---->
(328, 100, 100, 3)
<----Y Train data---->
(1309, 6)
<----Y Test data---->
(328, 6)
```

Figure 8: Image Splitting

Classification

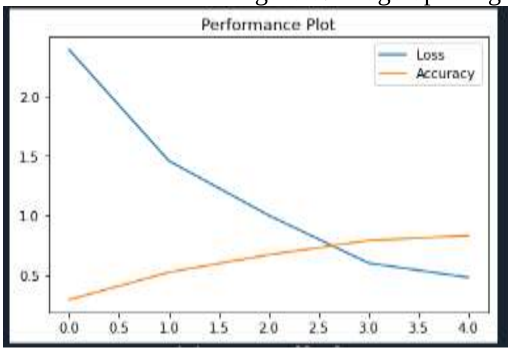

Figure 9.1: Classification

```
              precision    recall  f1-score   support

           0       0.94      0.79      0.86        62
           1       0.74      0.70      0.72        50
           2       0.69      0.85      0.76        66
           3       0.77      0.84      0.80        63
           4       0.84      0.76      0.80        63
           5       0.91      0.83      0.87        24

    accuracy                           0.80       328
   macro avg       0.82      0.80      0.80       328
weighted avg       0.81      0.80      0.80       328

<-----Accuracy------>
********************
Accurary:  49.50343668460846
```

Figure 9.2: Classification

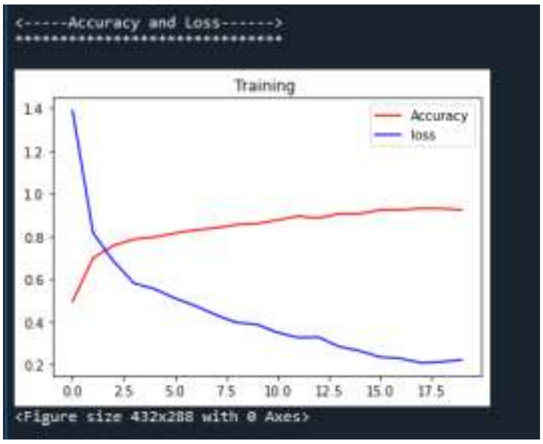

Figure 9.3: Classification

Prediction

Figure 10: Prediction

Comparision Graph

ResNet and DenseNet201 are two popular deep learning models used for image classification tasks. Here is a comparison between these two algorithms:

Model Architecture: ResNet uses skip connections or residual blocks to address the vanishing gradient problem during training, while DenseNet201 uses densely connected layers to improve feature reuse and reduce the number of parameters.

Parameter Efficiency: DenseNet201 is more parameter-efficient than ResNet because it reduces the number of parameters by reusing features across layers. This makes it easier to train and requires less memory.

Performance: DenseNet201 has been shown to outperform ResNet on various image classification benchmarks, such as ImageNet, CIFAR-10, and CIFAR-100. However, ResNet is still a popular choice for image classification tasks due to its simplicity and efficiency.

Training Time: DenseNet201 is slower to train than ResNet due to its dense connectivity, which requires more computations and memory.

Generalization: Both ResNet and DenseNet201 have shown good generalization performance on different datasets. However, DenseNet201 has been shown to have better generalization performance on smaller datasets.

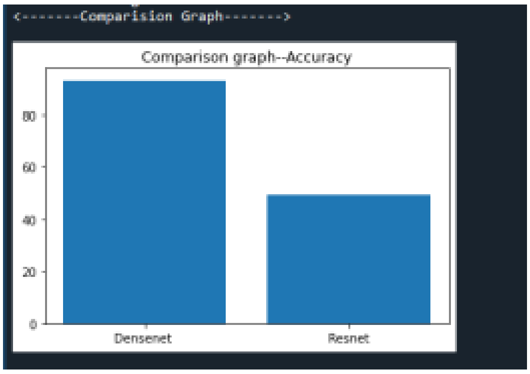

Figure 12: Comparision Graph

In summary, DenseNet201 is a more parameter-efficient and high-performing model compared to ResNet. However, it requires more training time due to its dense connectivity. The choice of model depends on the specific task requirements and available resources.

DATASET	TRAIN ACCURACY	TEST ACCURACY
Dataset1	80	78
Dataset2	90	84

Accuracy Table 1

2. Conclusion

The automatic garbage classification using deep learning is a promising solution for efficient waste management. In this project, we proposed the use of the DenseNet algorithm for garbage classification based on images of different waste materials. The performance of the proposed model was evaluated on a dataset consisting of various waste items, including paper, cardboard, plastic, metal, and glass the proposed system for automatic garbage classification using the DenseNet algorithm is a promising solution for efficient waste management. The use of deep learning techniques can significantly improve the accuracy and efficiency of waste classification, leading to better waste management practices and a cleaner environment. Further research can focus on improving the performance of the proposed model on larger datasets and exploring the feasibility of implementing the system in real-world waste management scenarios

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