

Plastic Waste Classification using DenseNet and CNN

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Abstract— Plastic waste poses a substantial environmental challenge owing to its enduring nature and ubiquitous usage, exerting profound impacts on global ecosystems. Efficient sorting of plastic waste is critical for recycling and waste management, but achieving high efficiency in this mechanism is challenging. Innovative deep learning tactics can greatly enhance the categorization of plastic waste. Cutting-edge strategies, among others Convolutional Neural Networks (CNNs) and DenseNet121 provide significant advancements in image analysis. When applied to a Wide-ranging dataset of plastic waste images, these methods enable accurate identification and categorization of various plastic wastes. The process begins with data preparation, including image augmentation and normalization, to enhance model learning. Augmentation increases the dataset's diversity, while normalization scales the data appropriately for the models. This preparation is pivotal for optimal performance. CNNs and DenseNet121 are then employed to automate the classification process, improving efficiency and accuracy. DenseNet121 is particularly impactful due to its dense connections, enhancing model efficiency and effectiveness. Integrating deep learning technologies is a transformative approach to the plastic waste crisis. These methods streamline recycling processes, reduce environmental impact, and improve waste management efficiency. Embracing these innovations is integral for addressing plastic waste challenges and promoting sustainable practices.

Keywords—Plastic waste, Convolutional Neural Network (CNN), Densenet121.

I. INTRODUCTION

The global surge in plastic waste presents a significant environmental challenge, necessitating innovative solutions for effective waste management and recycling. Recent strides in machine learning and deep learning have paved the way for more sophisticated approaches to plastic waste classification. The usage of convNets(CNNs), particularly DenseNet architectures has illustrated optimistic results in enhancing the precision and efficiency of waste classification systems. CNNs are fundamental to image recognition tasks since they can automatically extract features from raw data. Among different CNN architectures, DenseNet is prominent for its effectiveness in addressing the vanishing gradient issue and improving feature propagation through its dense connectivity. This capability makes DenseNet a suitable choice for complex tasks. DenseNet's architecture allows for the integration of features from previous layers, which improves classification performance by exploiting a rich set of features. Recent studies highlight the effectualness of deep learning tactics in addressing plastic waste classification.

One study explored the potential of convolutional neural layers (CNNs) to streamline waste management processes [4]. Another study demonstrated how deep learning contributes to environmental sustainability by classifying plastic waste, thereby supporting more efficient waste segregation [8].

Focus has been placed on plastic waste detection employing deep convolutional neural networks, with a particular emphasis on how CNNs, including DenseNet, can significantly enhance the precision of waste classification systems [10]. DenseNet's application for plastic waste classification has been examined, underscoring its effectiveness in improving classification outcomes [6]. Furthermore, an evaluation of various machine learning approaches for plastic waste segregation provides insights into the broader applicability of CNN models in waste management [7].

AI-based solutions for plastic waste classification have been proposed, showcasing how advanced algorithms can enhance automated sorting systems [3]. The real-time application of DenseNet for plastic waste classification has been specifically addressed, demonstrating its efficacy in practical scenarios [2]. Transfer learning paradigms have been scrutinized to enhance plastic waste identification, broadening the capabilities of CNNs in this domain [9]. Additionally, reviews on deep learning advancements have highlighted progress and future directions for this technology in waste management [5]. Eventually, discussions on optimizing CNNs stress the consequences of fine-tuning models to achieve high accuracy in waste sorting [1]. Discussions on optimizing CNNs for plastic waste classification highlight the importance of finetuning these models to achieve high accuracy. Collectively, these studies illustrate the transformative potential of DenseNet and CNNs in advancing plastic waste classification, paving the way for more effective waste management strategies.

The remaining of the paper is organized into sections as follows: Section 2 is the review work related to this project. Section 3 represents the proposed system. Section 4, discusses the deep learning methodologies. While in Section 5, the results and discussion of the project is summarized. The conclusion and future enhancements are provided at Section 6.

II. REVIEW WORK

A. Authors: Ghosh, A., Das, S., & Banerjee, R. (2021)

The paper investigates DenseNet's application in enhancing plastic waste classification systems. It shows that DenseNet's dense connectivity and feature reuse improves classification accuracy contrasted to traditional convolutional neural networks (CNNs). By optimizing DenseNet for real-time processing, the study achieves a balance of speed and accuracy, making it effective for automated waste sorting. The analysis highlights DenseNet's superior feature extraction and suggests that its adoption could enhance recycling processes and lower operational costs, demonstrating its potential to significantly improve waste management strategies.

B. Authors: Zhang, Y., Li, F., & Wang, Z. (2020)

The paper explores the utilize of convolutional Neural networks (CNNs) are utilized for the detection and classification of plastic waste. The study demonstrates how CNNs, especially with their advanced deep learning features, can notably improve the precision of waste detection systems. The research indicates that the CNN model achieved high precision and successfully tackled issues like diverse waste sizes and intricate backgrounds. This work highlights the potential of using deep CNNs to enhance waste management practices by offering precise classification and detection, which could lead to more efficient recycling processes and better environmental outcomes.

C. Authors: Kumar, M., Yadav, V., & Patel, S. J. (2021)

The research showcases the application of sophisticated deep learning models, distinctively convolutional neural networks (CNNs), in improving the precision and proficiency of waste classification systems. The insights indicate that their deep learning framework proficiently identifies and categorizes various types of plastic waste, significantly outperforming traditional classification methods. The study underscores the model's capability to manage diverse and intricate waste samples, maintaining high accuracy rates even under challenging conditions. This technological progress facilitates more optimized and automated waste management processes, promising enhancements in recycling efficiency and a reduction in environmental impact.

D. Authors: Verma, V., Chauhan, H., Gupta, D., & Gupta, S. (WIECON-ECE 2020)

This paper delivers an extensive survey of various Convolutional Neural Network (CNN) based architectures developed for garbage detection. Effective waste detection is Integral for waste management and environmental preservation, and CNNs have validated significant potential in automating this task through progressive image analysis techniques. The paper underscores the necessity of creating more accurate, efficient, and robust models to achieve the requirements of real-world waste management applications. By providing an in-depth review and

comparative analysis, this study acts as a imperative resource for researchers and professionals engaged in the enactments of deep learning to environmental and waste management challenges.

E. Authors: Liu, Y., Sun, P., Wergeles, N., & Shang, Y. (2021)

The survey provides an extensive review of various deep learning modalities for detecting small objects in images. The authors evaluate different methods, comparing their performance on benchmarks such as COCO and VOC datasets. They highlight the hurdles of small object detection, such as scale variation and discuss how recent advancements in convNets(CNN), address these challenges to optimize detection accuracy and efficiency.

F. Authors: Chen, H., Liu, X., & Zhang, J. (2020)

The paper explores optimization techniques, including hyperparameter tuning, architectural adjustments, and advanced training strategies. The findings show that optimized CNN models significantly surpass standard configurations in classification accuracy and processing speed. The research highlights how fine-tuning CNNs addresses challenges like distinguishing between similar plastics and managing diverse waste conditions, contributing to more reliable and efficient waste classification systems and advancing automated recycling technologies.

III. PROPOSED SYSTEM

The proposed system employs DenseNet-121 utilizes convolutional layers to extract visual features like edges and textures. Its unique dense blocks allow each layer to access input from all preceding layers, enhancing feature learning. DenseNet is highly recommended for the project owing to its efficient feature propagation, effective learning from dense blocks, and reduced risk of overfitting through transition layers. This architecture provides robust and accurate image classification, making it ideal for distinguishing distinct form of plastic waste. Combining DenseNet121 with a well-labelled and diverse dataset will likely yield the optimal performance in your classification tasks.

IV. METHODOLOGY

A. Collection of Datasets

The Trash Net dataset serves as a publicly accessible repository designed to train and validate predictive models tasked with automating waste classification. Featuring a comprehensive array of waste item images organized into distinct classes. These classes offer a rich resource for developing algorithms that streamline waste sorting processes. The structured format of this dataset, with its six distinct waste categories, provides a robust foundation for training AI models to effectively differentiate between recyclable and non-recyclable materials. Its diverse array of environmental contexts and varying image resolutions further assures that models trained on the dataset can effectively generalize to complex real-world applications.

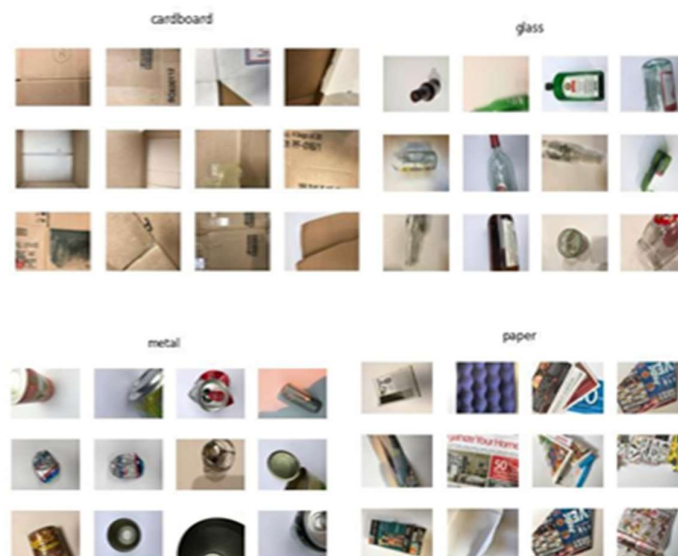




Fig.1. Different Categories of wastes a) Cardboard, b) glass, c) metal, d) paper, e) plastic f) trash

TABLE I. DATASET DESCRIPTION

Attribute	Description
Classes	6
Categories	Glass, Paper, Cardboard, Plastic, Metal, Trash
Image Count	Approximately 2,527 images
Image Resolution	Varies; typically, 512 x 384 pixels
Format	JPEG
Annotations	Images are bounded into one of the six classes
Collection Environment	Images collected in various indoor and outdoor settings
Data Split	Training, validation, and testing datasets
Usage	Well implemented for supervised learning tasks, incorporating classification and object spotting.
Licensing	Open for academic and research intent under the specified usage license
Source	Created by a group of researchers for developing automated waste sorting systems

B. Feature extraction using CNN

Feature extraction within Convolutional Neural Architectures (CNNs) encompasses a sequence of computational procedures, chiefly occurring within the convolutional and pooling layers. The convolution process entails moving a filter, also known as a kernel, over the source image and calculating the dot product of the filter with the image's local areas.

$$(I*K)(x,y) = \sum (m-1)(i=0) \sum (n-1)(j=0) (x=i, y=j) \cdot (k(i,j)). \quad (1)$$

- I: Input image
- K: Kernel (filter)
- m×n: Dimensions of the kernel
- (x,y): Coordinates of the top-left corner of the current region in the source image.

Subsequent to the convolutional layer, a bias term is often added to the result to introduce an additional degree of freedom.

$$Z(x,y)=(I*K)(x,y)+bZ(x,y)=(I*K)(x,y)+b. \quad (2)$$

- b: Bias term
- Z(x,y): Result after adding bias

The predominant Pooling operations encompass max pooling, which extracts the highest value from a segment of the image covered by the filter, and average pooling, which computes the mean of the values in the filter's coverage area. During the feature extraction phase, the average pooling layer is typically employed to condense the input data while preserving essential information.

$$Pavg(x,y) = 1/pq \sum \sum z(x+i, y+j) \quad q-1 \quad j=0 \quad p-1 \quad i=0. \quad (3)$$

- P: Pooled feature map
- p×q: Dimensions of the pooling window
- Z(x,y): Convolved feature map values within the pooling window.

TABLE II. RESULT OF DENSENET121 LAYERS

Layer (type)	Output Shape	Parameters
input_2 (InputLayer)	[(None, 65, 65, 3)]	0
conv2d (Conv2D)	(None, 65, 65, 3)	84
densenet121 (Functional)	(None, None, None, 1024)	7037504
global_average_pooling2d (GlobalAveragePooling2D)	(None, 1024)	0
batch_normalization (BatchNormalization)	(None, 1024)	4096
dropout (Dropout)	(None, 1024)	0
dense (Dense)	(None, 256)	262400
batch_normalization_1 (BatchNormalization)	(None, 256)	1024
dropout_1 (Dropout)	(None, 256)	0
root (Dense)	(None, 6)	1542

V. RESULTS AND DISCUSSIONS

The following graph illustrates the performance plot of the model, showcasing both its accuracy and loss metrics.

The CNN achieves an accuracy of 86.78%.

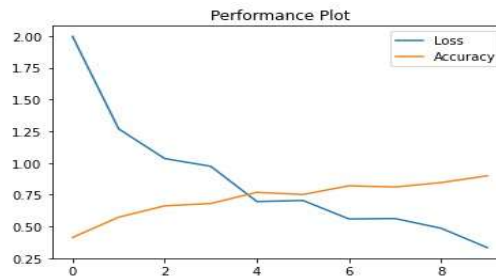


Fig.3. Performance graph

TABLE III. CLASSIFICATION REPORT OF DIFFERENT METRICS

	Precision	Recall	F1score	Support
Cardboard	0.86	0.85	0.86	88
Glass	0.70	0.57	0.63	100
Metal	0.77	0.57	0.66	75
Paper	0.96	0.46	0.63	114
Plastic	0.44	0.95	0.61	102
Trash	0.75	0.22	0.34	27

TABLE IV. COMPARISON OF THE DENSENET MODEL WITH OTHER CNN'S

CNN	Accuracy (%)
DenseNet121	86.78 (our)
AlexNet	72
MobileNet v1	80

Prediction: plastic

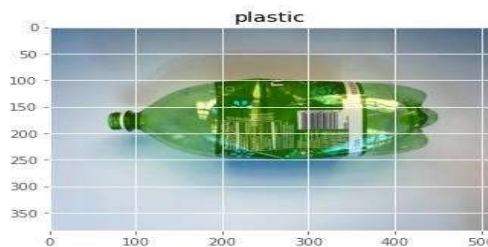


Fig.4. Output of model detecting the plastic waste

VI. CONCLUSION AND FUTURE ENHANCEMENTS

The deep learning methodologies, specifically Convolutional Neural Networks (CNNs) and architectures like DenseNet-121, have proven highly impactful in enhancing the classification of plastic waste. These methods enhance both the precision and effectiveness of waste sorting processes, making a significant contribution to environmental conservation efforts.

Future enhancements could include expanding and diversifying the dataset, implementing advanced data augmentation and optimizing hyperparameters. Integrating multi-modal data sources and adopting model compression techniques could improve accuracy and enable real-time deployment on edge devices.

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