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DenseNet201-Based Waste Material Classification Using Transfer Learning Approach

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ABSTRACT

This paper explores the application of deep learning models in waste material classification, motivated by the need for efficient waste management practices to address environmental sustainability concerns. Drawing parallels with the success of deep learning in healthcare domains, the study investigates the effectiveness of various deep learning architectures for waste material classification. The DenseNet201 model is proposed and compared with various deep learning models such as ResNet, MobileNetV2, AlexNet, and GoogleNet. Experimental results demonstrate that DenseNet201 achieves superior accuracy, average recall, and average precision, making it the most effective model for waste material classification. The dense connectivity and feature aggregation capabilities of DenseNet201 contribute to its outstanding performance, showcasing its potential for enhancing waste management processes.

Keywords: waste material classification, deep learning, computer vision, convolutional neural networks, image processing.

1 INTRODUCTION

In recent years, the utilization of deep learning models has witnessed widespread adoption across various fields, marking a significant shift in how complex problems are approached and solved. Among these domains, waste material classification has emerged as a focal point, driven by escalating concerns surrounding environmental sustainability and waste management. With the imperative need for efficient methods to classify and segregate waste materials, deep learning models have been increasingly relied upon.

Deep learning's application in waste material classification mirrors its success in critical healthcare domains, such as brain tumor detection [1] and diabetic retinopathy detection [2]–[5]. In medical imaging, deep learning algorithms have been shown to achieve remarkable accuracy in analyzing complex patterns within images, facilitating early disease diagnosis and treatment planning by clinicians. Analogously, in waste material classification, these models leverage their capacity to discern intricate features from diverse waste compositions, thereby enabling automated sorting processes with unprecedented accuracy and efficiency.

Drawing insights from the successes of deep learning models in healthcare applications illuminates the immense potential they hold in waste material classification. This introductory perspective lays the groundwork for further exploration into the methodologies, challenges, and prospects of employing deep learning in the sustainable management of waste materials.

Until now, the search for an accurate deep learning model for waste material classification remains a challenge. To date, the best model for waste material classification remains unknown. This paper aims to address this research gap by analyzing various deep learning models to assess their effectiveness in categorizing waste materials.

The remainder of this paper is divided into several subsections. Section 2 presents the related works of this study. Section 3 discusses the methodology of this study. Section 4 presents the results obtained from the experiment. Finally, Section 5 concludes this paper.

2 RELATED WORKS

Several studies have explored the use of deep learning models to classify waste materials, addressing global environmental concerns and the need for efficient waste management practices. For example, Faria et al. [6] developed a method to automatically categorize waste into four main types (organic, glass, metal, and plastic) using the OrgalidWaste dataset, comprising approximately 5600 images from various sources. They trained several convolutional neural network (CNN) architectures, including VGG16, Inception-V3, and ResNet50, with VGG16 achieving the highest accuracy of 88.42%. This automated classification system offers significant benefits for waste management.

Lin et al. [7] focused on sorting recyclable waste using deep learning techniques to support the transition towards a circular economy. They tested several ResNet architectures, including ResNet18 and ResNet34. Moreover, they introduced RWNet models based on ResNet structures, achieving an overall accuracy of around 88%, with RWNet-152 performing the best at 88.8%. Their approach, utilizing evaluation metrics such as precision, recall, and F1 score, demonstrates the effectiveness of deep learning in improving waste sorting processes.

Noh et al. [8] proposed a recycled clothing classification system leveraging IoT devices and deep learning technology to address challenges in clothing recycling. By integrating IoT devices with AI, specifically using transfer learned AlexNet, they developed a system capable of accurately classifying recycled clothing types, thus streamlining the recycling process and reducing manual labor.

Yong et al. [9] tackled waste separation using deep learning techniques, particularly focusing on domestic waste classification. They trained a garbage classification model using MobileNetV2, achieving an accuracy of 82.92% and surpassing traditional CNN models by 15.42%. The lightweight nature of their model makes it suitable for mobile applications, promising cost and time savings in waste classification.

Al-Mashhadani et al. [10] emphasized the importance of waste classification for efficient waste management and highlighted various deep learning models' performance in this domain. They tested several models including GoogleNet, InceptionV3, and ResNet50. Their results showed that the ResNet50 model exhibited impressive results with 95% accuracy, while InceptionV3 achieved perfect accuracy across all classes. Their study underscores the significance of deep learning in improving waste sorting and recycling practices for a more sustainable future.

Based on the reviewed papers, most researchers utilized deep learning models for waste material detection. They applied transfer learning techniques to detect waste materials. However, one of the most powerful deep learning models, DenseNet201, has not been investigated. This has led to a gap in knowledge regarding whether DenseNet201 can outperform the deep learning models implemented by other researchers. This paper aims to address this concern by filling the gap and testing DenseNet201 to evaluate its efficacy in waste material detection.

3 METHODOLOGY

This study suggests the DenseNet201 [11] deep learning model for waste material classification. The deep learning model is implemented using transfer learning for waste material detection. The proposed model consists of 201 weight layers, which are highly complex and robust for accurate image classification tasks. Moreover, the proposed model connects each layer to every other layer in a feed-forward fashion. This connectivity pattern leads to a dense feature map, reducing the number of parameters compared to traditional architectures like VGG [12] or ResNet [13]. Additionally, the proposed model encourages feature reuse throughout the network by concatenating feature maps from different layers. This helps mitigate the vanishing-gradient problem and enables better flow of gradients during training. Therefore, employing the DenseNet201 architecture is advantageous. Figure 1 shows the flowchart of this study.

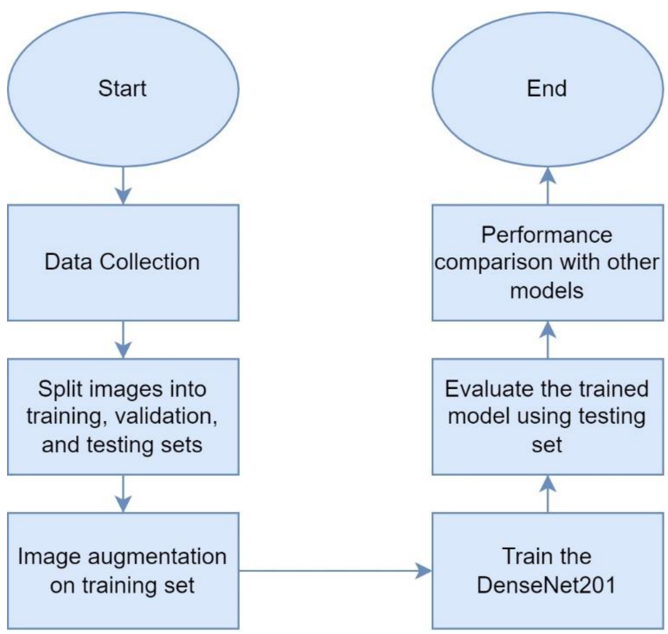

Figure 1: The flowchart of this study.

The dataset of waste materials was obtained from Kaggle [14]. This dataset contains six classes: Cardboard, glass, metal, paper, plastic, and trash. There are 403 images of cardboard, 501 images of glass, 410 images of metal, 594 images of paper, 482 images of plastic, and 137 images of trash. The dataset is split into a training set, a validation set, and a testing set. Fifty percent of the images are allocated to the training set, 25% to the validation set, and the remaining 25% to the testing set. Figure 2 shows some of the images obtained from the dataset. Table 1 shows the summary of the number of images present in the dataset.

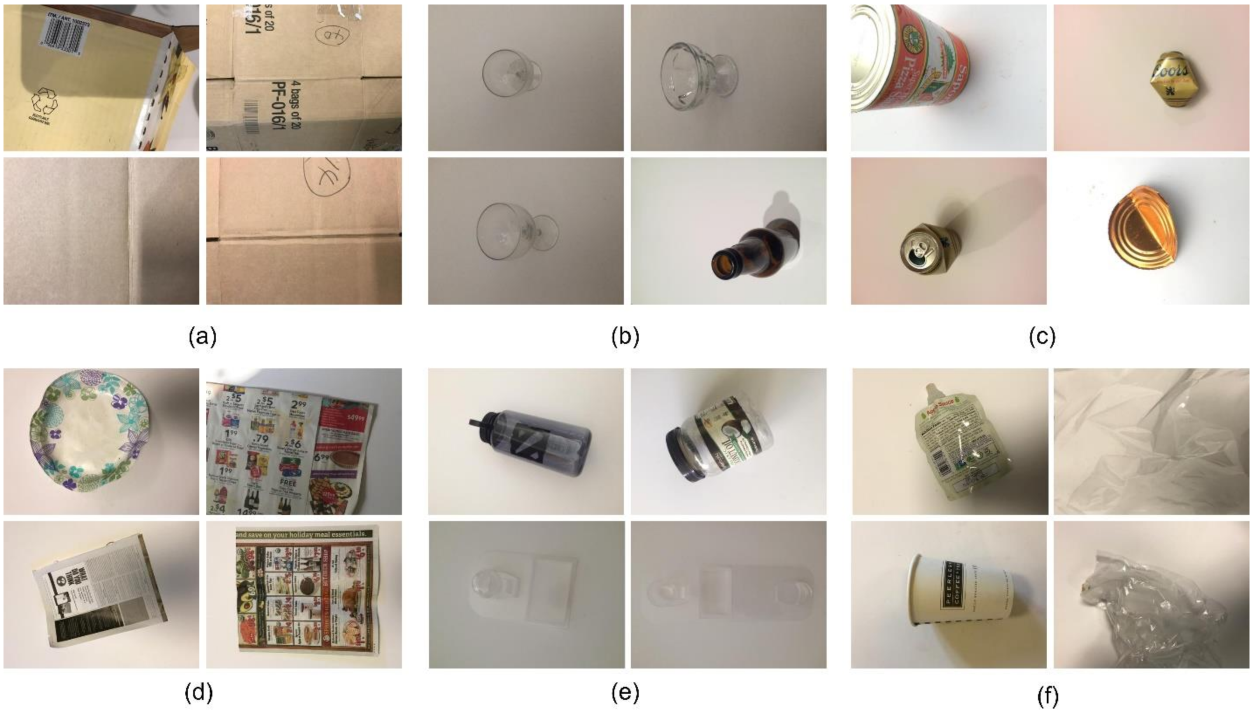

Figure 2: Several images obtained from the dataset [14]. (a) Cardboard. (b) Glass. (c) Metal. (d) Paper. (e) Plastic. (f) Trash.

Table 1: Summary of number of images in the dataset.

Portion	Number of Images	Percentage
Training	1263	50
Validation	632	25
Testing	632	25

Image augmentation is performed on the training set by flipping the images horizontally and vertically. The validation set and the testing set images are not augmented because those images need to represent the reality of how waste materials will be encountered in real-life situations. Subsequently, the training set and the validation set were used to train the model. Stochastic gradient descent with momentum was used to update the weights in the model. The gradient of each weight is calculated using backpropagation, and the weight is then adjusted to minimize the loss. The loss function used is the cross-entropy loss function, which calculates the difference between the actual class and the predicted class. This function is chosen because it is widely used for image classification in deep learning models [6][7][8].

The batch size used was 32, which is a standard batch size used by many researchers [6][7][8]. The learning rate used was 0.001, determining the magnitude of the gradient, or how much the weight will be changed during each iteration of training. The learning rate of 0.001 is used because it can give better convergence than bigger learning rates, such as 0.1 and 0.01. The patience used was 10, meaning that if the validation loss is higher than the previous lowest loss by 10 times, the training is automatically stopped since the model is no longer improving. This is done to eliminate unnecessary epochs needed to train the model. The best model is chosen by determining which epoch has the lowest validation loss, and that model with the lowest validation loss is used for performance evaluation on the testing set later.

After the model has finished training, it is evaluated using the testing set, containing images that the model has never seen before during training. These images are fed into the model, and each image is classified into the classes of materials. The classified images are then compared to the ground truth to see if the model correctly classifies the images. Based on the testing set images, the number of correctly classified images is calculated. The number of correctly classified images divided by the total number of images is referred to as accuracy. For each class, the number of correctly classified images for that specific class is referred to as recall. The average recall is the average of all recall values across the classes. For each class, the number of true classes divided by the total number of images the model classified as such class is referred to as precision. The average of these precisions across the classes is referred to as average precision.

The calculated accuracy, average recall, and average precision are then used to compare with other deep learning models, such as ResNet18 [13], ResNet34 [13], ResNet50 [13], AlexNet [15], GoogleNet [16], and MobileNetV2 [17]. These deep learning models were also trained using the dataset used in this study, and the same testing set is used to evaluate these models. This ensures a fair performance comparison, ensuring all the models are tested using the same testing set and trained using the same images. The deep learning models were compared to the proposed model in this study because previous researchers had tested those deep learning models for waste material detection. This study aims to determine if DenseNet201 can outperform those deep learning models.

4 RESULTS AND DISCUSSIONS

The tested models include DenseNet201, the proposed model in this study, as well as ResNet50, ResNet34, ResNet18, MobileNetV2, AlexNet, and GoogleNet. These models were evaluated using the same images from the testing set. Table 2 presents the results obtained from various deep learning models for waste material classification.

Table 2: Results obtained from various deep learning models for waste material classification.

Model	Accuracy	Average Recall	Average Precision
Proposed (DenseNet201)	**0.9793**	**0.9781**	**0.9787**
Faria et al. [6] using ResNet50	0.9555	0.9461	0.9604
Lin et al. [7] using ResNet34	0.9459	0.9389	0.9456
Lin et al. [7] using ResNet18	0.9380	0.9316	0.9381
Yong et al. [9] using MobileNetV2	0.9300	0.9259	0.9177
Noh et al. [8] using AlexNet	0.9126	0.9095	0.9010
Al-Mashhadani et al. [10] using GoogleNet	0.9062	0.9039	0.8957

Each row of the table corresponds to a different deep learning model. These models are evaluated based on three key performance metrics: Accuracy, Average Recall, and Average Precision.

Accuracy, as indicated in the table, represents the overall effectiveness of each model in correctly classifying instances. It is computed as the ratio of the number of correct predictions to the total number of predictions made by the model. A higher accuracy score signifies better performance in accurately predicting the correct classes for the given dataset. Average Recall, also known as sensitivity, measures the ability of each model to correctly identify positive instances from the dataset. This metric is particularly crucial in scenarios where the identification of all positive instances is vital. The reported values in the table represent the average recall across different classes or instances, providing insights into the models' performance in capturing true positives. Average Precision, on the other hand, evaluates the precision of each model's predictions, focusing on the proportion of true positive predictions out of all positive predictions made. A higher average precision score implies that the model has a lower rate of false positives and is more precise in its classifications.

Upon analyzing the table, it's evident that the proposed model based on DenseNet201 achieves the highest accuracy of 0.9793, accompanied by impressive average recall and average precision scores of 0.9781 and 0.9787, respectively. In comparison, other models such as ResNet50, ResNet34, and ResNet18 also demonstrate strong performance across these metrics, albeit with slightly lower scores. MobileNetV2, AlexNet, and GoogleNet, while still achieving respectable results, exhibit comparatively lower performance in terms of accuracy, average recall, and average precision.

Overall, DenseNet201 achieved the best results, and therefore, it is the best model for classifying waste materials. The remarkable performance of DenseNet201, as observed in the provided table, can be attributed to a combination of architectural features and design principles unique to the DenseNet framework. DenseNet stands out among the deep learning models due to its dense connectivity pattern, where each layer receives direct input from all preceding layers. This connectivity scheme fosters extensive information flow throughout the network, facilitating effective feature reuse and gradient propagation during training.

One of the key advantages of DenseNet201 lies in its parameter efficiency, achieved through the dense connections between layers. By leveraging feature concatenation across all preceding layers, DenseNet reduces redundancy in parameter usage while maximizing information flow. This parameter-efficient design not only enables DenseNet201 to effectively learn from limited data but also helps mitigate overfitting, leading to improved generalization performance.

Furthermore, DenseNet201 excels in feature aggregation, leveraging its dense connectivity to aggregate features from multiple network depths. This enables the model to capture intricate patterns and dependencies across different spatial scales, empowering it to learn rich and discriminative representations from input images. Such hierarchical feature learning is crucial for tackling complex tasks with diverse datasets, where robust representations are essential for accurate classification.

5 CONCLUSIONS

In conclusion, this study highlights the pivotal role of deep learning in revolutionizing waste material classification for sustainable waste management practices. Through comprehensive experimentation and performance evaluation, DenseNet201 emerges as the optimal choice for accurately categorizing waste materials. Its exceptional accuracy, average recall, and average precision underscore its superiority over other deep learning models, showcasing its efficacy in handling complex classification tasks. The findings of this study contribute to advancing the field of waste management by providing a robust framework for automating waste classification processes, thereby promoting environmental sustainability and resource conservation. Further research can explore the integration of advanced deep learning techniques to address evolving challenges in waste management and enhance the efficiency of waste classification systems.

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