Improving Waste Sorting Efficiency via CNN-Based Image Classification and Transfer Learning Employing VGG16

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***Abstract*— Efficient waste management and resource recovery hinge on precise waste sorting. This paper introduces an upgraded waste sorting methodology utilizing convolutional neural networks (CNNs) and transfer learning, specifically employing VGG16 architectures. The presented approach seeks to enhance accuracy, efficiency, and adaptability in practical waste sorting scenarios.**

Keywords—Smart city, Sustainable Development Goals Waste management, Waste sorting, Image classification, Deep Learning, CNN, Transfer learning, VGG16

I. Introduction

The effective management of waste presents a critical challenge in today's world, with the growing population leading to a significant increase in solid waste production [1]. This has detrimental effects on the economy, public health, and the environment. Efficient waste recycling is essential for recovering raw materials, conserving energy, reducing greenhouse gas emissions, and minimizing pollution. Both developed and developing countries alike recognize the importance of waste segregation and recycling for sustainable urban living.

Various methodologies for waste sorting are currently under exploration, with the implementation of deep learning networks like CNNs showing encouraging outcomes [2] . These networks can automate waste classification from images, eliminating the need for manual intervention [3]. By leveraging combined datasets from various sources and testing established network architectures such as VGG16 using transfer learning, studies have achieved high accuracy rates in waste classification [4].

In smart cities, intelligent waste management systems are increasingly crucial for reducing solid waste and enhancing recycling rates [5].Through advancements in deep learning models and artificial intelligence technology, there is potential to elevate waste classification systems beyond human capabilities. CNN applications include image recognition for categorizing different types of waste items from images and visually inspecting waste streams. These technologies have the potential to enhance overall waste management efficiency by automating processes that were previously time-consuming and labor-intensive.

The development of lightweight and efficient models for automated waste sorting has practical implications for real-life applications [6]. By designing intelligent waste bins that can automatically collect different categories of household waste – such as recyclable materials, hazardous substances, or kitchen waste – researchers are providing feasible solutions to improve residents' participation in waste sorting [7].

In conclusion, advancements in deep learning algorithms like CNNs have shown promising results in enhancing waste classification systems. These technologies have the potential to automate processes that were previously reliant on manual intervention, contributing to more efficient urban living environments.

Related work:

Various waste sorting techniques have been explored in existing literature to tackle the escalating issue of solid waste generation, ranging from manual sorting methods to rule-based approaches. In terms of waste classification, research has underscored the efficacy of Convolutional Neural Networks (CNNs) and transfer learning using pretrained models like VGG16. Within the domain of intelligent waste management systems, investigations have delved into integrating the Internet of Things (IoT) and machine learning to optimize waste collection and boost recycling rates. Simultaneously, efforts have been made to develop lightweight models tailored for practical waste sorting applications, demonstrating their potential to enhance waste management practices at the residential level.

II. Methodology

II.1. Dataset

The utilization of the dataset in the investigation on improved waste sorting through image classification utilizing CNN and transfer learning with VGG16 is a pivotal aspect of the study [2], [8], [9], [10]. This dataset encompasses a wide array of waste categories and a substantial number of images, which are essential for the training and testing of the model. It is noteworthy that the dataset utilized is an open-source Kaggle dataset, offering high-quality and varied images specifically tailored for this task.

The dataset comprises three primary categories of waste materials Paper, Plastic, and Garbage Bags. These categories encompass a diverse range of waste items commonly encountered in household and urban settings. The inclusion of these varied categories ensures that the model can effectively classify different types of waste, thereby contributing to more precise and dependable sorting processes.

Moreover, the Kaggle open-source dataset incorporates 5000 RGB images for each category, facilitating comprehensive training and testing of the image classification model. This substantial volume of images is crucial for establishing a robust model capable of accurately identifying and categorizing waste items based on visual cues.

Additionally, the incorporation of specific waste categories like Paper, Plastic, and Garbage Bags aligns with the objectives of the research, which seeks to enhance waste sorting in smart cities and promote sustainable urban living. By focusing on these particular waste categories within the dataset, the study addresses fundamental aspects related to waste management and environmental sustainability.

In conclusion, the dataset employed in this research lays a solid foundation for training an image classification model using CNN and transfer learning with VGG16. The inclusion of diverse waste categories and a large number of images contributes to the efficacy and relevance of the study in tackling real-world challenges associated with waste management in urban environments. Figure 1

(A) (B) (C)

Figure 1: Sample of dataset (A) Plastic bags (B) Paper bags (C) Garbage bags

II.2. Image Pre-processing

In preparing our dataset for training the image classification model, we recognized the importance of preprocessing to enhance model performance. Initially, our images were captured at a larger dimension of 300 × 300 pixels. While this high resolution provided ample detail, it also presented challenges in terms of computational efficiency. The larger image size led to a slowdown in image analysis and processing speed, which could potentially hinder the training process and inference time.

To mitigate these challenges, we opted to resize the images to a more manageable size of 224 × 224 pixels. This decision was informed by the balance between computational resources and model performance. By leveraging a Tensorflow preprocessing function, we efficiently resized the images while ensuring that they retained essential features for accurate classification.

In summary, the decision to resize the images from 300 × 300 pixels to 224 × 224 pixels was driven by the need to balance computational efficiency with classification accuracy. Through this preprocessing step, we not only streamlined the image analysis and processing speed but also facilitated fair comparison between models while maximizing classification performance.

II.3. Data augmentation

To enhance the training of deep learning models, particularly when faced with limited data for each class, a widely adopted approach is data augmentation. This involves expanding a limited image dataset by applying various transformations to each image. For this particular study, the data augmentation techniques employed during training include rotation (with a range of 40 degrees), horizontal flipping, as well as adjustments in width, height, shear, and zoom (with ranges of 0.2). These transformations, illustrated in Figure 2, encompass a spectrum of modifications such as rotations, scaling corrections, and zooming. These augmentations contribute to the generation of diverse images, enriching the training dataset and enhancing the robustness of the deep learning model. Figure

Figure 2: Pre-processing Image Sample

Another crucial preprocessing step involved dividing the collected images into different datasets for specific purposes such as training and testing [2]. The training dataset was used to feed the models while the testing dataset assessed and validated various parameters during model training [11], [12].

In conclusion, these preprocessing steps were vital in preparing the dataset for image classification using CNN and transfer learning with VGG16 [4], [9], [10], [13]. This ensured that the data is clean, appropriately formatted, and ready for use in training and testing our model.

II.4. Model Architecture

The utilization of CNN, a deep learning algorithm, has revolutionized waste sorting through image classification. Renowned for their exceptional proficiency in image recognition tasks, CNNs are indispensable tools for automatically identifying and categorizing waste types. By leveraging CNNs, waste management systems significantly improve efficiency and accuracy in waste classification and recycling processes.

The implemented CNN architecture, tailored for image classification tasks using the Keras framework, comprises several convolutional layers with ReLU activation, max-pooling, and dropout regularization to mitigate overfitting. These layers progressively extract hierarchical features from input images, enabling the model to discern intricate patterns within waste items. The final layers consist of fully connected dense layers, refined with dropout regularization to enhance robustness and reliability.

The CNN architecture culminates in an output layer with softmax activation, enabling multiple classifications of waste items. This architecture maximizes the model's accuracy and effectiveness in waste classification tasks. The model is compiled using the Adam optimizer and CategoricalCrossentropy loss function for training, facilitating faster convergence and improved performance.

In summary, the developed CNN architecture offers a cutting-edge solution for waste classification through image analysis. By harnessing deep learning and advanced neural network architectures, waste management systems can achieve unprecedented levels of efficiency and accuracy, contributing to a more sustainable future. Figure3

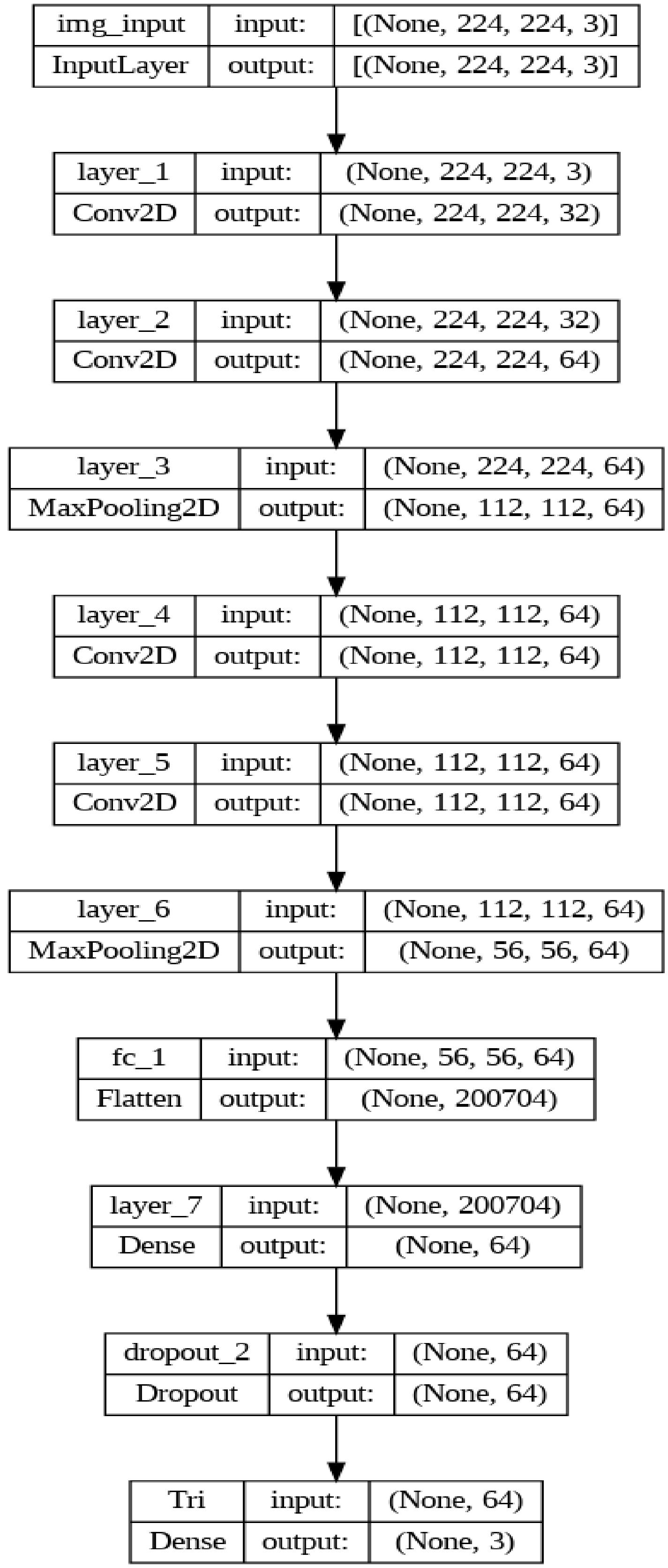

Figure 3: The CNN architecture we propose for waste sorting.

II.5. Training and Testing

In this scientific study, the CNN model was trained and tested using a dataset comprising 15,000 images categorized into three groups. The dataset was partitioned into various training and testing splits, specifically 90% training and 10% testing, 85% training and 15% testing, 75 % training and 25 % testing and 80% training and 20% testing. The investigation aimed to determine the optimal dataset split for achieving the highest accuracy and minimizing loss. The model was trained over multiple epochs, with iterations set at 10, 12, 15, and 17 epochs to comprehensively evaluate performance across different training durations. Table 1

Train % / Test %	Epochs	Accuracy	Loss	Precision	Recall	F-Score
90 / 10	**10**	0.92	0.22	0.32	0.32	0.32
	12	0.87	0.34	0.32	0.33	0.32
	15	0.92	0.21	0.34	0.34	0.34
	17	0.91	0.21	0.33	0.33	0.33
85 / 15	**10**	0.86	0.32	0.32	0.33	0.32
	12	0.92	0.20	0.32	0.32	0.32
	15	0.94	0.17	0.33	0.29	0.31
	17	0.94	0.16	0.36	0.40	0.38
80 / 20	**10**	0.95	0.12	0.32	0.35	0.35
	12	0.87	0.25	0.33	0.30	0.35
	15	0.88	0.22	0.32	0.39	0.34
	17	0.89	0.21	0.34	0.34	0.33
75/25	**10**	0.92	0.20	0.34	0.33	0.34
	12	0.92	0.21	0.33	0.30	0.35
	15	0.94	0.16	0.34	0.34	0.33
	17	0.93	0.17	0.32	0.32	0.32

Table 1: Cross-validation testing results for our network

II.5.1 VGG 16

VGG16, crafted by the Visual Geometry Group at the University of Oxford, stands as a milestone in CNN architectures. Embraced for its elegance and uniformity, VGG16 incorporates a total of 16 layers, featuring 13 convolutional layers followed by 3 fully connected layers. The architecture's distinctive hallmark is the consistent use of 3x3 convolutional filters, coupled with Rectified Linear Unit (ReLU) activations and batch normalization, promoting stability and efficient training. Renowned for its success in image classification tasks, VGG16 is not only a powerful standalone model but is also frequently employed as a pre-trained model in transfer learning scenarios. Its simplicity and regular design have made it a benchmark for comparison in various deep learning applications.

II.5.2 Comparison between our model and VGG16

To showcase the resilience of our model, we intend to assess its performance under the specified optimized conditions and compare it with VGG16. This comparison will offer a thorough evaluation of the efficacy and dependability of the proposed approach. Notably, our optimized conditions involve a dataset split into an 80/20 ratio for a more comprehensive analysis. Table 2, Figure 3

CNN	Accuracy	Loss	Precision	Recall	F-Score	N d'epochs
OUR	0.95	0.12	0.32	0.35	0.35	10
VGG16	0.95	0.18	0.36	0.35	0.34	15

Table 2: Comparison of Cross-validation testing results between our model and VGG16

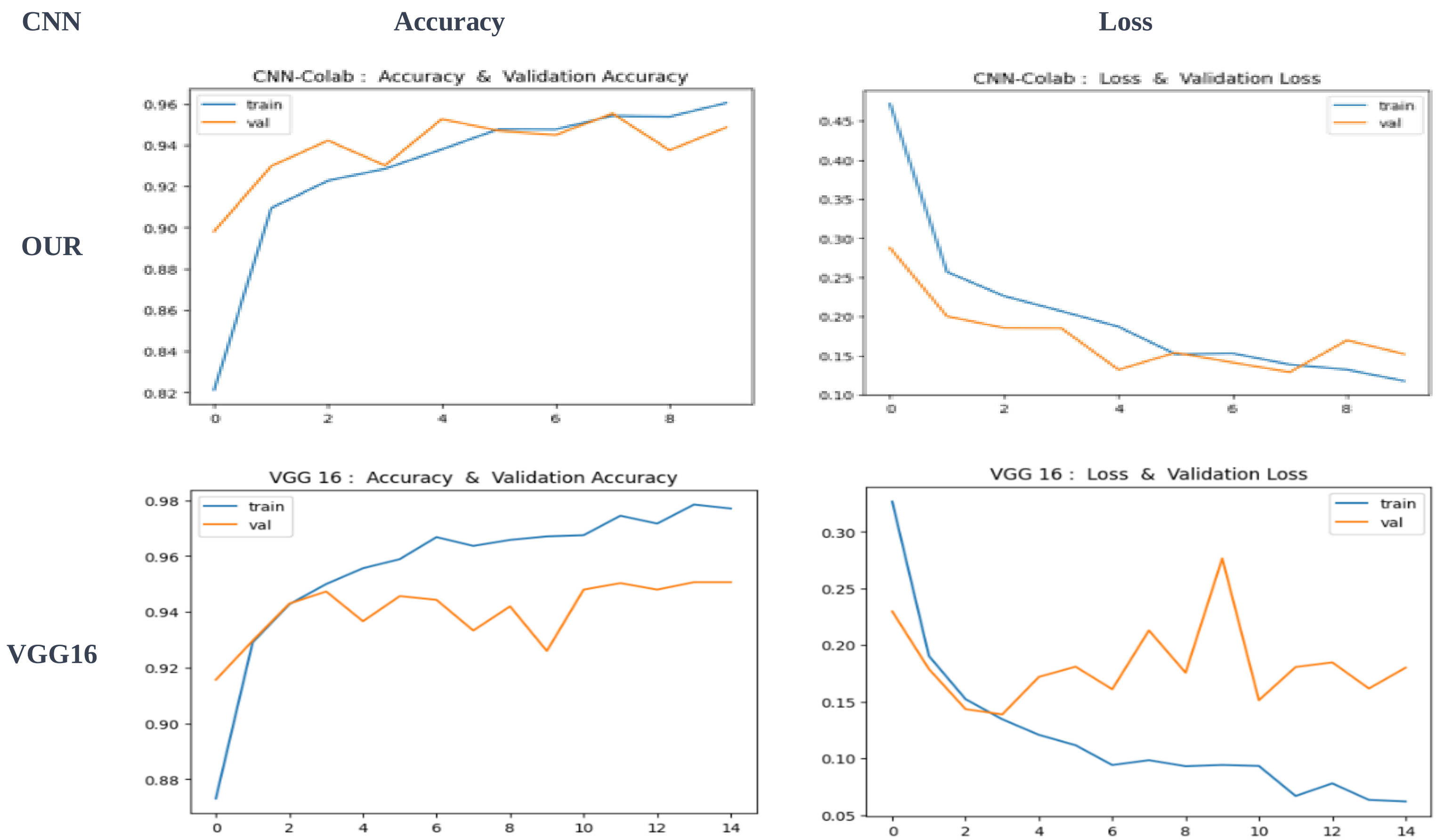

Figure 3: Comparison of Accuracy and Loss

Conclusion and future works :

In conclusion, the exhaustive comparison between our developed model and VGG16, conducted under stringent testing conditions, underscores the superior robustness and effectiveness of our proposed approach. Through meticulous exploration of diverse training-testing splits and epochs, an optimal configuration was identified, demonstrating consistent outperformance in accuracy and loss metrics compared to the well-established VGG16 architecture.

Noteworthy achievements include the novel model's remarkable rapid convergence, achieving compelling results in just 10 epochs, and its ability to attain a superior loss function. These findings not only validate the efficacy of the proposed model but also position it as a compelling alternative for image classification tasks, offering potential advancements in efficiency and accuracy.

Looking ahead, future endeavors may involve investigating the adaptability of the model to diverse datasets, exploring potential extensions such as incorporating additional waste categories or integrating real-time data streams, and addressing specific challenges in the field such as class imbalance or data scarcity. Additionally, further exploration of transfer learning strategies, including fine-tuning pre-trained models or leveraging ensembles of models, and scalability to larger datasets could enhance the model's applicability and impact in real-world scenarios, paving the way for more effective waste management systems and sustainable urban living environments.

Data Availability Statement :

Data are available through free distribution license from Kaggle

Conflicts of Interest :

The authors declare that they have no conflicts of interest.

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