Advanced CNN Architectures for Improved Garbage Image Classification: An In-depth Evaluation

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***Abstract*—Convolutional Neural Networks (CNNs) have become instrumental in advancing image classification, particularly in the context of garbage image classification, a critical component for efficient waste management. This paper introduces a tailored CNN architecture that demonstrates enhanced accuracy in garbage classification tasks, even with constrained datasets. Our architecture incorporates multiple convolutional, max-pooling, and fully connected layers, with dropout regularization strategically applied to curb overfitting and improve model generalization across a varied waste image dataset. Comparative evaluations reveal that our model achieves a significant improvement in accuracy over existing CNN models. The results not only validate the robustness of our approach but also contribute valuable insights toward developing more precise and efficient systems for garbage image classification.**

***Index Terms*—Garbage Image Classification, Deep Learning, Image Processing, Convolutional Neural Networks, Computer Vision, Dropout Regularization**

I. Introduction

Waste management is a critical global issue, characterized by challenges such as environmental pollution, health risks, and resource depletion due to improper disposal practices [6]. In response to these challenges, there is a pressing demand for sustainable waste management practices, notably effective waste sorting and recycling technologies [36]. Among the various emerging technologies, garbage image classification using deep learning has emerged as a promising solution, offering the potential to significantly improve recycling rates and reduce landfill use, thereby mitigating the environmental impact of waste [4].

Deep learning, a powerful subset of machine learning, utilizes layered artificial neural networks to autonomously extract and learn complex features from large datasets. This technology has not only revolutionized fields such as medical diagnostics and weather forecasting but has also proven instrumental in enhancing predictive modeling across diverse industries, enabling businesses to foresee market trends and optimize operations with unprecedented accuracy [5], [8], [9], [11], [20], [22], [25], [26], [27], [30], [32].

In the specific realm of garbage image classification, deep learning techniques, particularly Convolutional Neural Networks (CNNs), have been adept at identifying and categorizing various types of waste materials. These networks effectively handle the inherent variability in waste material appearances, a notable challenge in this field [10], [18], [19], [24]. Despite their success, the development of these systems is often hindered by the scarcity of extensive and diverse datasets, which are crucial for training robust models [7], [29].

This paper presents a CNN-based model tailored for high-precision garbage image classification. Our model is evaluated against an extensive and diverse waste image dataset and compared with other CNN architectures and transfer learning approaches to highlight its superior performance and efficiency [29]. The primary goal of this investigation is to conduct a comprehensive assessment of our CNN-based model, examining its ability to accurately identify diverse waste materials [13], [28]. The findings are intended to contribute to the existing research in garbage image classification and provide insights into optimal deep learning techniques for waste management applications. This study's results are poised to guide the development of more precise and efficient garbage image classification systems, thereby enhancing waste sorting accuracy and improving overall waste management practices.

Despite the impressive strides made, deep learning continues to face challenges related to interpretability, ethical considerations in AI applications, and the environmental impact of training large models.

II. Related Work

Various algorithms have been devised for image classification, including Recurrent Neural Networks (RNNs), Support Vector Machines (SVMs), and Artificial Neural Networks (ANNs). Among these, Convolutional Neural Networks (CNNs) have consistently demonstrated superior performance

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[12]. The significance of CNNs in image classification was prominently highlighted with their success in the 2012 ImageNet Large-Scale Visual Recognition Challenge (ILSVRC) [14]. Since then, numerous CNN architectures have been developed, each tailored to address specific challenges within the field of image classification [31], [37].

In the late 1990s, a system for metal scrap recycling that utilized a mechanical shape identifier was developed at the Lulea University of Technology [38]. This early system was expanded upon with the integration of features from the Scale-Invariant Feature Transform (SIFT) and outline shapes within a Bayesian computational framework, utilizing the Flickr material database to advance image-based material classification [17]. Concurrently, the emergence of smartphone technology facilitated the development of an application that allowed for the rough identification of garbage types in images, achieving an average accuracy of 85% with a pre-trained AlexNet model [21].

Further advancements in the application of deep learning were marked by the development of a smart sweeping robot that used YOLOv2 as a core network module. This robot was capable of classifying garbage into 25 distinct subcategories based on shape and volume [23]. Meanwhile, an alternative approach that implemented the background difference algorithm using OpenCV for the extraction and classification of objects from images was introduced, proving effective in identifying various medical equipment items [3].

The utilization of automatic recognition and detection of waste from images has significantly increased, gradually replacing manual sorting methods [15], [35]. Over time, a variety of machine learning algorithms have been explored to enhance the precision of automatic waste classification. In recent years, deep neural networks, especially CNNs, have become the preferred method, showing remarkable effectiveness in image classification tasks [33]. By processing images of solid waste, CNNs enable the automated categorization of waste into relevant classes, thereby proving their utility in this application [16].

Efforts to enhance waste classification accuracy have included evaluations using undisclosed CNN architectures, with f-scores for various waste categories such as paper, plastic, organic, and glass ranging from 59% to 75% [2]. The exploration of both customized and unspecified CNN models has been a significant focus within the field, with some investigations achieving accuracy rates as high as 95%, thereby marking significant strides towards more precise garbage image classification [16].

III. Methodology Foundations

This section delves into the fundamental methodologies that underpin our approach to garbage image classification using Convolutional Neural Networks (CNNs). As the core of our model, CNNs are extensively discussed, highlighting their pivotal role in feature detection and image analysis. Additionally, this section explores other crucial technologies and frameworks that support our model, including TensorFlow, Keras, and various layers essential for building effective CNNs. Each subsection provides a detailed overview of the components, their functions, and their relevance to enhancing the performance and accuracy of our deep learning model. By understanding these foundational elements, we can appreciate how they collectively contribute to sophisticated image classification tasks and ensure the robustness and efficiency of our proposed solutions.

A. Convolutional Neural Networks

CNNs (Convolutional Neural Networks) leverage pixel arrangements in images to recognize patterns. During training, these networks autonomously learn complex patterns from various segments of images, thus enhancing their capability for tasks such as medical image analysis. CNNs are particularly adept at identifying features automatically through convolutional and pooling layers, complemented by fully connected layers to facilitate precise data classification. The introduction of additional fully connected layers can increase accuracy by simplifying the complexity of image data.

Much like multilayer perceptrons, CNNs consist of input, hidden, and output layers. The convolutional layer is integral, focusing on accentuating image features, while downsampling performed in pooling layers improves computational efficiency. This structured layering enables CNNs to extract and process complex visual information with minimal preprocessing, making them highly effective for tasks in computer-assisted medical diagnosis and monitoring.

B. Tensorflow

Developed by Google, TensorFlow is an open-source framework designed for executing complex mathematical computations, which is essential in building deep learning models. It manages dataflow graphs that represent how data progresses through various computational steps. Nodes in these graphs denote mathematical operations on multidimensional data arrays (tensors), and edges define the movement of these tensors between operations.

TensorFlow's efficiency spans across multiple devices, from mobile phones to extensive systems equipped with CPUs and GPUs. This versatility is crucial for optimizing computational resources, particularly in training large, complex deep learning models like those used in image recognition tasks.

C. Keras

Keras is a high-level, Python-based interface designed to simplify the creation and training of deep learning models, particularly through TensorFlow integration. It abstracts the complexities involved in direct tensor manipulations, allowing developers to focus more on building neural network architectures. Keras facilitates model construction via its Sequential API, where layers are stacked sequentially. This modularity is ideal for standard deep learning models, as it ensures that each layer receives a single input tensor and produces an output tensor, streamlining the model-building process and enhancing developmental efficiency.

D. Convolutional Layers

Convolutional layers are fundamental in CNNs for identifying spatial features in images, such as edges, textures, and shapes. These layers function by sliding a filter or kernel over the input image, calculating the dot product of the filter values with the underlying pixel values at each position. The convolution operation is defined mathematically as follows:

$$S(i,j) = (I*K)(i,j) = \sum_{m}\sum_{n} I(i+m, j+n) \cdot K(m,n) \quad (1)$$

where $S(i,j)$ is the output feature map, I is the input image, K is the kernel, and (i,j) represent the coordinates on the feature map. The filter, typically smaller than the input image, contains weights learned during training and slides over the image to detect specific features, contributing significantly to the effectiveness of feature extraction.

E. Pooling Layers

Pooling layers play a critical role in reducing the spatial dimensions of the feature maps within CNNs, crucial for decreasing computational demands and enhancing model generalization. By summarizing the features in patches of the feature map, pooling layers help in reducing the likelihood of overfitting and maintaining essential information, thus improving the adaptability of the network. Max pooling, a common technique, selects the maximum value from each window of the feature map to pass to the next layer, effectively capturing the most prominent features required for tasks like image recognition.

F. Batch Normalization

Batch Normalization (BN) is a technique used to enhance the stability and speed of neural network training by normalizing the inputs to each layer, ensuring they have a consistent mean and variance. This normalization addresses the problem of internal covariate shift, where the distributions of inputs change during training, which can slow convergence and cause instability. The operation of BN is mathematically expressed as:

$$\hat{x}_i = \frac{x_i - \mu_B}{\sqrt{\sigma_B^2 + \epsilon}} \quad (2)$$

where x_i is the input to a layer, μ_B and σ_B^2 are the mean and variance calculated over the batch, and ϵ is a small constant for numerical stability. This process allows higher learning rates and more efficient training phases, ultimately leading to improved model performance.

G. Dropout

Dropout is employed to prevent overfitting in neural networks, particularly in deep learning environments with complex architectures. It randomly disables a subset of neurons during training, thereby reducing dependencies among them and forcing the network to learn more robust features. Mathematically, if a neuron's output is x, dropout modifies it using:

$$x' = d \cdot x \quad (3)$$

where d is a random variable from a Bernoulli distribution, being 1 with probability p (retention probability) and 0 with probability $1 - p$. This variability ensures that each training iteration uses a slightly different network architecture, enhancing the generalization capabilities of the model.

IV. Proposed Architecture

This section presents the proposed CNN architectures developed to enhance the precision of garbage image classification. The primary objective of this study is to evaluate these models extensively, assessing their capability to categorize diverse waste materials accurately. The outcomes of this research are expected to contribute significantly to the field of garbage image classification using deep learning, providing insights into optimal methodologies for waste management applications. Additionally, the results have the potential to inform future refinements and innovations, leading to more precise and efficient classification systems that could improve waste sorting processes and advance overall waste management practices.

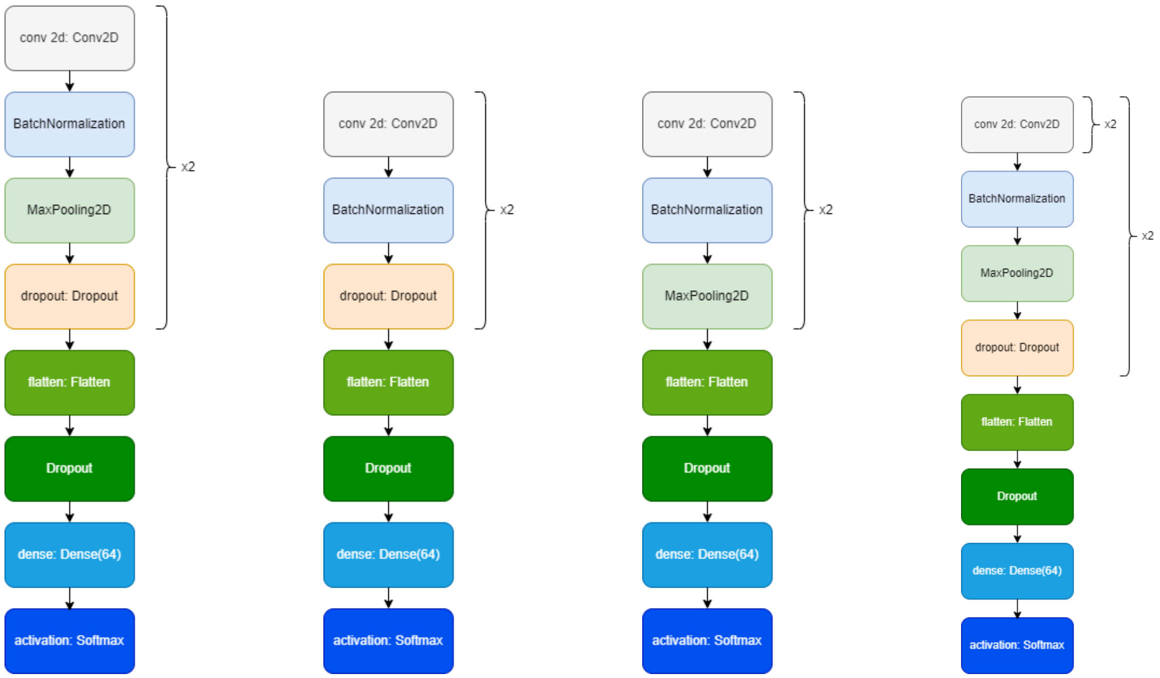
The proposed CNN architecture begins with an input layer that processes image data. Following the input, multiple convolutional layers equipped with filters are used to effectively detect spatial features. Each convolution operation is accompanied by batch normalization, which standardizes the inputs to each layer to stabilize the learning process. Pooling layers succeed the convolutional layers to reduce the size of feature maps, simplifying computations and focusing on essential features.

After the feature extraction and reduction phases, the data is flattened and processed by dense neural network layers. These layers perform a deep analysis of the features, culminating in the final classification output. To explore the effects of different configurations on model performance, four distinct architectural designs are proposed and visualized.

Figure 1 illustrates the detailed layer setups and operations of each model, providing a quick visual reference that aids in understanding the structural differences and functionalities of the architectures.

Complementing the visual diagrams, Table I offers a concise summary of the distinctive features and layer sequences of each architectural configuration, facilitating a deeper comparative analysis.

The models are initially assessed using various performance metrics to determine optimal configurations. Their efficacy is subsequently compared within a unified framework to establish which design best meets the requirements of efficient and accurate waste material classification. Integral to all four architectures are layers including Conv2D for feature extraction, Batch Normalization for stabilization, MaxPooling2D for dimensionality reduction, Dropout to prevent overfitting, and Dense and Softmax layers for classification. These components are crucial for improving accuracy in image classification



(a) First Proposed CNN Architecture

(b) Second Proposed CNN Architecture

(c) Third Proposed CNN Architecture

(d) Fourth Proposed CNN Architecture

Fig. 1. Detailed diagrams of the four proposed CNN architectures, each showcasing layer configurations and operational flows to optimize garbage classification.

TABLE I
LAYER SEQUENCES AND OPERATIONS OF EACH PROPOSED CNN ARCHITECTURE

Architecture	**Layer Sequence and Operations**
1st	(Conv2D → BatchNorm → MaxPooling2D → Dropout) ×2 → (Flatten → Dropout → Dense) → Softmax
2nd	(Conv2D → BatchNorm → Dropout) ×2 → (Flatten → Dropout → Dense) → Softmax
3rd	(Conv2D → BatchNorm → MaxPooling2D) ×2 → (Flatten → Dropout → Dense) → Softmax
4th	(Conv2D ×2 → BatchNorm → MaxPooling2D → Dropout) ×2 → (Flatten → Dropout → Dense) → Softmax

tasks, and their systematic arrangement in each model is designed to maximize performance.

V. Experimental Evaluation

A. Dataset

The dataset used in this study comprises a diverse collection of 15,150 images spanning 12 distinct categories of household waste [1]. These categories include newspapers, cardboard, organic waste, steel, plastic, green glass, brown glass, white glass, clothing, footwear, batteries, and general waste. The expanded range of categories, extending beyond the typical 2 to 6 classes found in most datasets, aims to enhance the granularity of waste sorting and, consequently, the efficiency of recycling processes.

Balancing the dataset was crucial to avoid biases in the machine learning model. The equal representation of each category ensures that the model learns to recognize and classify each type of waste effectively. Table II provides a detailed breakdown of the number of images per category:

TABLE II
DETAILED DISTRIBUTION OF IMAGES ACROSS VARIOUS WASTE CATEGORIES IN THE DATASET

Battery	945	**Biological**	985	**Brown Glass**	607
Cardboard	891	**Clothes**	5,325	**Green Glass**	629
Metal	769	**Paper**	1,050	**Plastic**	865
Shoes	1,977	**Trash**	697	**White Glass**	775

This balanced distribution is essential for training the models to recognize and classify waste accurately, which is critical for automated systems employed in modern recycling facilities.

B. Results

In the comprehensive evaluation below, the performance metrics of the four proposed CNN architectures are detailed across various epochs and batch sizes. Table III showcases the loss, accuracy, and training time for each architecture at batch sizes of 64, 128, and 256, providing a granular view of how each configuration scales over time with increasing data processing loads. The data captured at specific epochs—1, 5, 10, 15, and 20—helps illustrate the progression and efficacy of the learning process, offering insights into the optimal conditions for model training in waste classification tasks.

TABLE III
PERFORMANCE METRICS FOR FOUR ARCHITECTURES

Epochs	Loss	Accuracy	Time	Loss	Accuracy	Time	Loss	Accuracy	Time
(Conv2D $\rightarrow$ BatchNorm $\rightarrow$ MaxPooling2D $\rightarrow$ Dropout) $\times 2$ $\rightarrow$ (Flatten $\rightarrow$ Dropout $\rightarrow$ Dense) $\rightarrow$ Softmax									
	Batch Size = 64			**Batch Size = 128**			**Batch Size = 256**		
1	2.780	0.2563	204	2.628	0.2595	203	3.041	0.1340	214
5	1.948	0.4246	197	1.949	0.4052	198	2.226	0.3204	181
10	1.634	0.6971	180	1.716	0.5608	197	1.948	0.5955	198
15	1.533	0.7042	195	1.940	0.6000	195	1.895	0.6071	199
20	1.441	0.7346	197	1.579	0.6984	178	1.746	0.7570	198
(Conv2D $\rightarrow$ BatchNorm $\rightarrow$ Dropout) $\times 2$ $\rightarrow$ (Flatten $\rightarrow$ Dropout $\rightarrow$ Dense) $\rightarrow$ Softmax									
	Batch Size = 64			**Batch Size = 128**			**Batch Size = 256**		
1	2.887	0.2460	387	3.023	0.2421	327	3.364	0.2265	328
5	1.991	0.3825	322	2.199	0.3560	319	2.310	0.3133	315
10	1.730	0.6550	321	1.842	0.6155	380	2.007	0.5871	319
15	1.589	0.6841	321	1.664	0.6589	320	1.923	0.6149	313
20	1.449	0.7294	322	1.565	0.6893	319	1.786	0.6460	302
(Conv2D $\rightarrow$ BatchNorm $\rightarrow$ MaxPooling2D) $\times 2$ $\rightarrow$ (Flatten $\rightarrow$ Dropout $\rightarrow$ Dense) $\rightarrow$ Softmax									
	Batch Size = 64			**Batch Size = 128**			**Batch Size = 256**		
1	2.558	0.2751	479	3.024	0.2201	194	3.008	0.2803	448
5	1.740	0.4731	188	1.975	0.3916	188	2.111	0.3722	187
10	1.531	0.5074	172	1.740	0.5654	188	1.822	0.4259	189
15	1.405	0.6184	190	1.563	0.7042	187	1.723	0.5628	188
20	1.320	0.7463	187	1.435	0.7340	184	1.625	0.6913	187
(Conv2D $\times 2$ $\rightarrow$ BatchNorm $\rightarrow$ MaxPooling2D $\rightarrow$ Dropout) $\times 2$ $\rightarrow$ (Flatten $\rightarrow$ Dropout $\rightarrow$ Dense) $\rightarrow$ Softmax									
	Batch Size = 64			**Batch Size = 128**			**Batch Size = 256**		
1	2.858	0.2045	505	3.100	0.2117	295	3.089	0.2395	299
5	1.885	0.4045	276	2.078	0.3683	348	2.201	0.3534	378
10	1.630	0.4744	272	1.663	0.4835	278	1.946	0.4104	283
15	1.665	0.5660	273	1.577	0.5977	341	1.887	0.5149	272
20	1.509	0.7113	265	1.446	0.7294	356	1.698	0.7770	279

The results indicate that smaller batch sizes generally result in faster learning and more significant reduction in loss over epochs but can be more susceptible to overfitting. Conversely, larger batch sizes tend to stabilize the learning process, showing slower improvements but achieving consistently higher accuracy towards the latter epochs. For instance, while the architecture with batch size 64 shows rapid improvement in accuracy, it levels off quicker than the configurations with larger batch sizes.

Training time across different architectures varied, with more complex configurations requiring longer durations per epoch. For example, the fourth architecture, which involves multiple convolution and pooling layers, exhibited the highest training times but also showed significant gains in accuracy, particularly at larger batch sizes.

Among the configurations, the fourth architecture with a batch size of 256 demonstrated the highest overall accuracy by the 20th epoch, underscoring the effectiveness of deep layered networks combined with adequate batch processing in handling complex classification tasks. However, this configuration also required the most extended training time, suggesting a trade-off between performance and computational efficiency.

Stability in learning was observed as a function of both architecture and batch size. Architectures that incorporated frequent batch normalization and dropout layers tended to exhibit more stable accuracy improvements across epochs, mitigating sharp fluctuations in loss and accuracy.

These detailed insights into the performance of different model configurations under various conditions highlight the critical balance between model complexity, batch size, and training duration in achieving optimal classification performance. Such findings are instrumental in refining the design of CNNs for practical applications in waste classification, where both accuracy and operational efficiency are paramount.

VI. CONCLUSIONS AND FUTURE WORK

This study presented a detailed exploration of four CNN architectures tailored for the classification of household waste into twelve distinct categories. The primary goal was to enhance the precision of garbage image classification and, consequently, the efficiency of recycling processes. Our experimental results demonstrated that varying the batch size and the architectural configurations significantly impacts the accuracy, loss, and training duration of the models.

The findings suggest that architectures with deeper layers and more frequent utilization of techniques like batch normalization and dropout tend to perform better in terms of accuracy and stability, although at the cost of increased computational resources and training time. The optimal balance between batch size and epoch number also emerged as crucial for maximizing performance. Smaller batch sizes typically accelerated learning but required careful management to avoid overfitting, while larger batch sizes provided more stable but slower learning trajectories.

Looking ahead, the research into CNN architectures for waste classification presents numerous opportunities for further exploration. One promising direction involves the deployment of these models in real-time waste sorting systems that could provide valuable insights into their operational effectiveness and practical challenges. Expanding the dataset to include a wider variety of waste items and environmental conditions, such as different lighting, would also be beneficial in testing the robustness of the proposed models further. Another area of potential development is the combination of CNN architectures with other machine learning approaches, such as reinforcement learning or unsupervised learning, which might yield further improvements in accuracy and efficiency [34].

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