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Implementation of ResNet-50 for Solid Waste Image Classification

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Abstract *– Operational efficiency of municipal solid waste management is critically hampered by manual sorting, a process that is slow, labor-intensive, and poses occupational health risks. This study investigates the application of deep learning to automate this task, specifically by developing and accessing a classification model using Residual Network (ResNet-50) architecture. Utilizing a public dataset of 24,705 images of organic and recyclable waste, we implemented a transfer learning protocol. The pre-trained ResNet-50 model, with weights initialized from ImageNet, was fine-tuned for this binary classification problem. To ensure model robustness and prevent overfitting on the specialized dataset, a comprehensive data augmentation strategy was applied, expanding the training set to 207,522 images. Upon evaluation with a dedicated test set of 6,177 that was previously unseen, the model demonstrated high evaluation metrics, achieving an all-around classification accuracy of 95%. Another key evaluation metrics, like precision, recall (sensitivity), specificity, and F1-score, corroborated the result with a weighted average of 0.95. These findings establish that a transfer-learned ResNet-50 model provides a highly effective and reliable solution for automated solid waste classification, offering a technologically robust foundation for next-generation recycling and waste management systems.*

Keywords**:** *Deep Learning; Image Classification; Residual Network; Solid Waste; Transfer Learning*.

1. INTRODUCTION

Solid waste is a global problem that continues to grow over time. According to data from the World Bank, in 2020 global waste production is calculated to reach 2.01 billion tons per year and is having the trajectory to increase up to 3.4 billion tons by the year of 2050, in line with population growth and urbanization [1]. Manual waste sorting is still the primary practice in many countries, especially in developing countries. However, this approach has several significant drawbacks, such as manual sorting being highly dependent on human labor, which not only reduces efficiency but also poses health risks such as musculoskeletal disorders due to poor working posture [2][3]. Improperly managed solid waste can lead to environmental pollution, including soil, air, and water contamination, and have adverse effects on the surrounding environment [4]. Therefore, the usage of tools in this case a deep learning model to enhance the automation of waste management is necessary to improve efficiency in the sorting and recycling of solid waste [5].

As of late, advancements in artificial intelligence technology, particularly in the subfield of deep learning have provided powerful new tools for image-based pattern recognition [6]. Convolutional Neural Networks (CNNs) as a type of deep neural networks Have achieved outstanding results in processing and classifying large-scale image data with high levels of accuracy making them ideally suited for automating visual inspection tasks [7]. Among the many available CNN architectures, the Residual Network (ResNet) family, introduced by He et al., stands out for its ability to train very deep models effectively, achieving state-of-the-art results on numerous computer vision benchmarks [8].

Previous research in automated waste sorting has validated the potential of CNN-based approaches. For instance, Nnamoko et al. [5] employed a custom 5-layer CNN to identify waste images into two different classes, organic and recyclable categories, establishing a performance baseline of 80.88% accuracy. Further studies conducted by Feng et al. [9] on a GECM-EfficientNet model, have explored lightweight architectures to improve efficiency. While these studies confirm the feasibility of automated classification, a significant

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performance gap remains before these systems can be deployed with high confidence in real-world scenarios. The limitations of shallower or custom-built architectures suggest that more powerful, pre-trained models may be required to handle the high visual variance of waste materials.

This study seeks to address this performance gap, we hypothesize that a deeper more sophisticated architecture, like ResNet-50 can yield a substantial improvement in classification accuracy. By employing a transfer learning method, we leverage the rich feature representation learned by the ResNet-50 model on the vas ImageNet dataset. This approach is coupled with a rigorous data augmentation designed to improve the model's ability to generalize from the training dataset. The purpose of this research is to develop an accessing a ResNet-50 based classifier for organic and recyclable waste aiming to establish a new performance benchmark and provide a robust and scalable solution for enabling automated waste management system.

2. RESEARCH METHODOLOGY

The research was conducted through a systematic workflow comprising five key stages: (1) dataset sourcing and preparation, (2) image pre-processing and augmentation, (3) model architecture design using ResNet-50 with transfer learning, (4) model compilation and training, and (5) performance evaluation. This structured approach was made to make sure that the development of a robust and also reproducible classification system. The overall research workflow is shown in Figure 1.

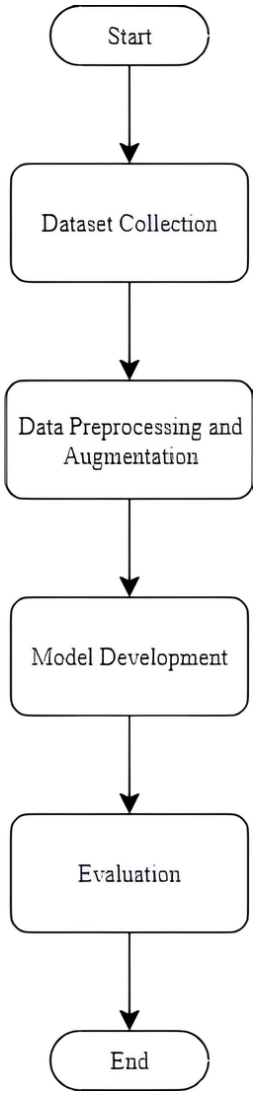


Figure 1. Research workflow.

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2.1. Dataset Collection

The image dataset for this study was sourced from a public Kaggle repository, originally curated by Sekar [10] and utilized by Nnamoko et al [5]. The dataset includes a total of 24,705 RGB images, divided into two separate classes: organic (13,880 images) and recyclable (10,825 images). The images exhibit variability in resolution, with dimensions ranging from 191x191 to 264x264 pixels. Figure 2 shows the image example from each class.



Figure 2. Image example.

2.2. Data Preprocessing and Augmentation

First, all of images in the dataset were resized to the same dimension of 224×224 px. This step was necessary to conform to the standard input tensor size required by the ResNet-50 architecture. Following resizing, pixel values were normalized. This was handled by the preprocess_input function within the Keras library, which scales pixel values to the appropriate range expected by the pre-trained model.

To prepare the data for the modeling process, it was split into three dataset subsets: a training set, a validation set, and lastly a test set. A 60:15:25 split ratio was used, allocating the majority of the data for training while reserving substantial portions for validation and final testing. This partitioning is a critical step to enable an objective evaluation of the model's generalization [11]. The model is built using the training set, tuned and checked for overfitting with the validation set, and then its final objective performance is measured on the completely separate test data [12].

Second, to enhance model robustness and reduce the probability of overfitting, a suite of online data augmentation techniques was used exclusively to the training set. Augmentation artificially inflates the diversity of the training data by applying random transformations to the images, which compels the model to learn more generalizable features rather than memorizing specific examples [13][14]. The ImageDataGenerator class in Keras was used to apply a series of random geometric and photometric transformations during training. This process expanded the effective size of the training data to 207,522 images. The specific configuration of these transformations is detailed in Table 1, and the example of an image after augmentation is shown in Figure 3.

Table 1. Augmentation parameter.

Parameters	
horizontalFlip	verticalFlip
rotation	widthShift
heightShift	shearRange
zoom	blur
brightness	contrast
gamma	

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Figure 3. Example of augmented image.

2.3. Model Architecture

The core of the classification system is the ResNet-50 architecture, a 50-layer deep CNN renowned for its performance in large-scale image recognition challenges [8]. Instead of training this complex model from scratch, which would be computationally prohibitive and data-intensive, a transfer learning approach was adopted. This technique leverages the knowledge encapsulated in a model that was trained on a large, public, general-purpose dataset, like the ImageNet, which have 1000 classes with over 14 million images. The underlying premise is that the lower-level features learned from ImageNet (e.g., edges, textures, shapes) are universal and can serve as a powerful feature extractor for other computer vision tasks [15].

In this implementation, the convolutional base of the ResNet-50 model was instantiated with its pre-trained ImageNet weights, and its layers were "frozen" (i.e., made non-trainable by setting layer.trainable = False). This preserves the learned features and transforms the base into a fixed feature extractor. A new, custom classification head was then stacked on top of the frozen base. This head was designed specifically for the binary waste classification task and consists of the following layers in sequence:

a. A GlobalAveragePooling2D layer, which reduces the spatial dimensions of the feature maps from the base into a single feature vector. This drastically reduces the number of parameters, a key strategy for controlling overfitting [16].
b. A Dense (fully connected) layer with 192 neurons, using the Rectified Linear Unit (ReLU) activation function. This layer learns non-linear combinations of the features extracted by the ResNet base [17].
c. A Dropout layer in this research is using a value of 0.3 (30%). During training, this layer randomly sets 30% of the neuron activations from the preceding layer to zero. This regularization technique prevents neurons from co-adapting and significantly improves the model's performance for it be able to generalize unseen or real life test data [18][19][20].
d. A final Dense output layer with 2 neurons, corresponding to the 'Organic' and 'Recyclable' classes, SoftMax function is used for the activation. The SoftMax function converts the model's raw output value in shape of a vector (logits) into a probability classes distribution, representing the model's confidence for each class.

The complete model was compiled with the Adam optimizer as it is widely used and effective optimization algorithm. The learning rate was fine-tuned to a value of 0.0035 to ensure stable convergence. The loss function chosen for this multi-class (though binary in this case) classification problem was categorical cross entropy, which is standard for measuring the dissimilarity between predicted class label and the true class label. The model is trained with 10 epochs and a batch size value of 32. The key hyperparameters used for training are displayed in Table 2 for clarity and also reproducibility.

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Table 2. Training parameter.

Parameter	Value
Size	224×224×3
Batch Size	32
Optimizer	Adam
Learning Rate	003517
Epoch	10
Dropout Rate	0.3

2.4. Evaluation Metrics

To conduct an analysis and assessment of the trained model's classification performance, a standard set of evaluation metrics was employed. These metrics are stems from the possible outcomes of a binary prediction, which are typically: True Positives (TP), True Negatives (TN), False Positives (FP or Type I Error), and False Negatives (FN or Type II Error). Accuracy is used to evaluate the proportion of correct predictions (both true positives (TP) and true negatives (TN)) out of all predictions made. While accuracy is a useful general indicator, it can be misleading on imbalanced datasets [21][22].

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \times 100\% \quad (1)$$

Precision measures the ratio of the positive predictions that are correct as the label intended. High precision is important if the consequence of a false positive (Type I Error) is high [23]. Recall (or sensitivity) Measures the proportion of actual positives that were correctly identified by the model. High recall is essential when the cost of missing a positive case (a false negative) is high [24]. Specificity is used to evaluate the ratio of actual negatives that were identified with high fidelity. As the counterpart to recall, specificity is important when correctly identifying negatives is a priority [25].

$$Precision = \frac{TP}{TP + FP} \times 100\% \quad (2)$$

$$Recall = \frac{TP}{TP + FN} \times 100\% \quad (3)$$

$$Specificity = \frac{TN}{TN + FP} \times 100\% \quad (4)$$

F1-Score is a metric to summarize a model's performance with a single number that balances precision and recall. It's calculated as their harmonic mean, which means it punishes models that are extremely good at one metric but terrible at the other. It's the go-to score when you can't afford to ignore either false positives or false negatives [26].

$$F1\text{-}Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \times 100\% \quad (5)$$

Together with confusion matrix, aforementioned metrics provide multiple point of view of the model's performance, allowing for a deeper analysis beyond a single accuracy value [27].

3. RESULTS AND DISCUSSION

This section details the empirical findings of the study. Result analysis begins with an examination of the model's learning behavior during training, followed by a quantitative assessment of its final classification performance on the test set, and concludes with a qualitative analysis of prediction errors.

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3.1. Analysis of Training Dynamics and Generalization

An examination of the model's learning curves over 10 epochs offers valuable information about its training behavior and generalization capacity. Figures 4 and Figure 5 illustrate the progression of training accuracy and training loss for both the training and validation datasets.

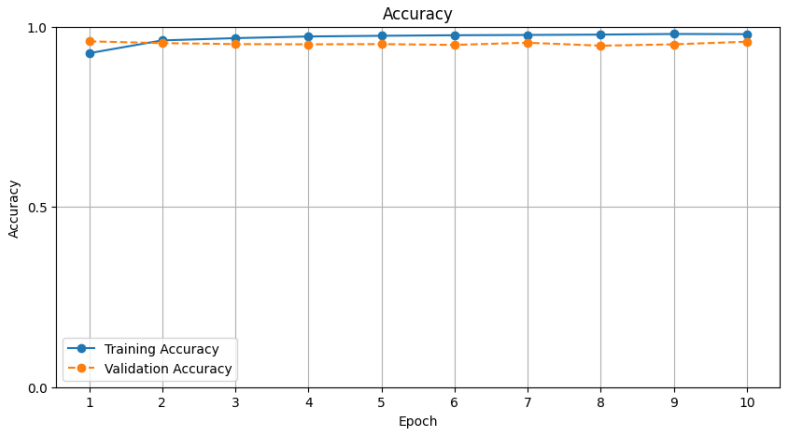


Figure 4. Accuracy in training phase.

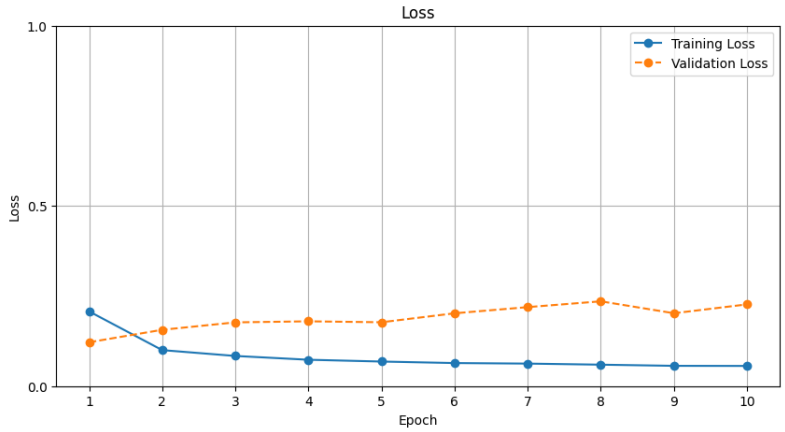


Figure 5. Loss in training phase.

The training accuracy curve (Figure 4) shows a consistent increase, starting at 92.65% and reaching 97.93% by the end of training phase, shows that the model demonstrated a strong ability to learn from the training sets. The validation accuracy, however, shows more of a fluctuation, peaking at 95.94% in the first epoch and finishing at 95.83%. While the final accuracy is high, a more telling story emerges from the loss curves (Figure 5). The training loss steadily decreases from 0.2073 to 0.0560, as expected. In contrast, the validation loss, after an initial drop, begins to diverge and increase after the second epoch, rising from a low of 0.1217 to 0.2268 by the end of epoch 10.

This divergence between the training and validation loss is a classic indicator of the onset of overfitting. This indicates that even as the model became more accurate on the training set, its capability to generalize to the validation data began to deteriorate slightly after the initial epochs. The model began to overfit in the training process. Its performance on the validation set started to decline, which shows it was beginning to memorize noise from the training data rather than learning the transferable patterns. The fact that the model still achieved a high final accuracy of 95% is a testament to the power of the ResNet-50 base architecture and the regularizing effect of the extensive data augmentation and dropout layer, which successfully mitigated the worst effects of this overfitting, this observation also implies that the model's generalization could be further enhanced.

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3.2. Classification Performance

The primary evaluation of the model was conducted on the test set that has 6,177 images that the model had not previously encountered. The results demonstrate a strong result, as model achieve an overall accuracy of 95%. Table 3 summarizes the comprehensive review of the evaluation for each class.

Table 3. Classification report.

Class	Precision	Recall	Specificity	F1-Score	Support	
Organic	0.97	0.95	0.96	0.96	3470	
Recyclable	0.93	0.96	0.95	0.95	2707	
Macro Average	0.95	0.95	0.95	0.95	6177	
Weighted Average	0.95	0.95	0.95	0.95	6177	
Accuracy					6177	0.95

The model exhibited excellent performance for the 'Organic' class, with a precision of 0.97 and a sensitivity of 0.95. This shows that when the model makes a prediction of an image as organic, it has 97% confidence, and it properly classifies 95% of all the real organic images. For the 'Recyclable' class, it has a precision of 0.93 and a sensitivity of 0.96. The slightly lower precision for the recyclable class suggests a marginally higher rate of misclassifying organic items as recyclable. The consistently high values for the F1-score and specificity across both classes, along with a weighted average of 0.95 for all key metrics, underscore the model's balanced and robust classification capability.

This 95% accuracy represents a substantial improvement over previous benchmark. It surpasses the 80.88% accuracy achieved by the simpler 5-layer CNN model proposed by Nnamoko et al. (2022) by over 14 percentage points. This significant gain highlights the profound impact of using a deeper, more sophisticated architecture like ResNet-50 combined with transfer learning. Furthermore, the performance is highly competitive with the 94.54% accuracy reported by Feng et al. (2022) using a GECM-EfficientNet model, confirming that the ResNet-50 approach is a state-of-the-art solution for this classification problem. The strong performance validates the methodological choices, including the extensive data augmentation and the transfer learning strategy, as being highly effective for this domain.

3.3. Error Analysis

To achieve an in-depth understanding of the model's predictive behavior, a confusion matrix was used for evaluation on the test set, as shown in Figure 6.

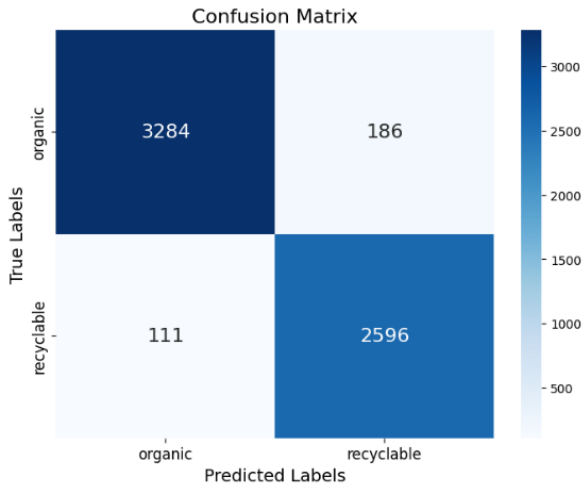


Figure 6. Confusion matrix.

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The matrix reveals the following distribution of predictions:

a. True Positives (Organic): 3,284 organic items were correctly classified as 'Organic'.
b. True Negatives (Recyclable): 2,596 recyclable items were correctly classified as 'Recyclable'.
c. False Positives (Type I Error): 111 recyclable items were incorrectly classified as 'Organic'.
d. False Negatives (Type II Error): 186 organic items were incorrectly classified as 'Recyclable'.

Of all the correct predictions (3,284 + 2,596 = 5,880) out of 6,177 test images confirms the overall accuracy of 95%. More importantly, the matrix exposes an asymmetry in the model's errors. The model is more prone to misclassifying an organic item as recyclable (186 instances) than it is to misclassifying a recyclable item as organic (111 instances). This suggests that certain visual features present in some organic waste may share similarities with materials in the recyclable category. This points to an opportunity for further improvement, either through the refinement of the dataset to include more examples of these ambiguous cases or by exploring more advanced feature extraction techniques.

4. CONCLUSIONS

This research has successfully demonstrated the high efficacy of a Deep Residual Network (ResNet-50) model for the automated classification of solid waste images. By leveraging transfer learning method and extensive augmentation on the original dataset, the developed model yielded an overall accuracy of 95% with an unseen test set. The performance metrics, including a precision of 97% for the 'Organic' class and a sensitivity of 96% for the 'Recyclable' class, confirm the model's robustness and balanced predictive power. The architectural strengths of ResNet-50, particularly its ability to overcome the vanishing gradient problem via skip connections, proved crucial for extracting complex, hierarchical features from the waste imagery.

The performance achieved represents a significant advancement over existing benchmarks that rely on simpler or custom-built CNNs, validating our initial hypothesis. The architectural advantages of ResNet-50, particularly its capacity to learn complex, hierarchical features via its deep residual connections, proved to be instrumental in distinguishing between the visually diverse categories of waste. This study confirms that the ResNet-50 transfer learning approach is a powerful and reliable methodology for this critical environmental technology application, establishing it as a competitive state-of-the-art solution.

LITERATURE

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