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Assessing the Impact of Image Preprocessing on Convnext Performance for Waste Classification

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Abstract: *Waste has become an increasingly urgent environmental issue in everyday life. The waste is constantly increasing due to population growth, urbanization, and consumption. The increasing amount of waste needs more intelligent systems to help with the management of waste, especially with the sorting of waste. Unfortunately, the absence of the public's awareness of the importance of waste management has led to the ineffective collection of waste. Thus, there is a need of classifying the waste into technological systems based on various waste types. This research's has computing waste types using ConvNetX. The research methodology is based on the collection and preprocessing of data that includes different image enhancement techniques such as CLAHE and bilateral filtering. This study employed the 'Garbage Classification Dataset' found on Kaggle. The dataset is split into 80% of it as training data, 10% of it as testing data and the last 10% of it as validation data.*
The ConvNeXt model was trained using one of the training sets after the data was split and was subsequently measured using the validation and test sets for the training of the model. This research analyzed the effects of image preprocessing by using a baseline, which was no preprocessing (Scenario 1), and then using preprocessing (Scenario 2). The results from the experiments showed Scenario 2 had a higher accuracy of 94% compared to the baseline of 90%. The use of CLAHE and Bilateral Filtering positively impacted the F1 Score by increasing it to Glass (96%) and Plastic (92%) and having a full recall (100%) for Metal. Scenario 2 resulted in a total training time of 20.86 minutes and Scenario 1 was 11.83 minutes, which means that Scenario 2 had a lower computational efficiency. Nevertheless, the additional time was well spent for the considerable consistency improvement in the classification of all categories. This makes it evident that substantial image preprocessing is necessary for the model to be able to generalize and classify images with complex visual details.

Keywords: ***ConvNeXt, Waste Classification, Image Preprocessing***

1. Introduction

The problem of waste management continues to be of great concern due to rapid urbanization and high consumption levels from the public [1]. The waste generated includes plastics, organics, papers and metals [2]. The National Waste Management Information System (SIPSN) reported that in the year of 2024, 329 regencies or cities in Indonesia generated a total of 34,969,723.79 tons of waste [3]. However, the management of waste is, in fact, very unbalanced, as 66.91% (23,398,261.33 tons) of the waste was reported to be unaccounted for. This is further aggravated by the lack of public concern in waste sorting, necessitating technological interventions to address the issue [4].

The recent improvements of Computer Vision and Deep Learning technologies in sorting automation, mainly Convolution Neural Networks (CNN), are noteworthy. CNN learns visual features picture by picture using multiple filters in their convolutional layers [5], [6], learn features in each layer and from each layer to the next [7], and can learn to recognize hierarchically from simple to complex structures [8]. Mao et al. [9] were the first to report classification of waste with 96 % accuracy using DenseNet121 architecture while 77.62 % validation accuracy was reported by Chan and Chong [10] using VGG16. ConvNeXt is a modern evolution of the above convolutional neural networks, blending the CNNs with contemporary architectural principles [11]. This model incorporates modern design advancements including large-kernel depthwise convolutions and inverted bottlenecks [11, 12], with an emphasis on scalability to ensure practical applicability [13]. ConvNeXt was superior in waste classification to several models including the Swin Transformer, YOLOv3, and ResNet-50 achieving 79.88% accuracy as reported by Qi et al [14]. High accuracy has also been noted in medical imaging with the combination of ConvNeXt and CLAHE 88.31% by Devanshi et al [15].

ConvNeXt was chosen for this study because of the shortcomings of ResNet, MobileNet, and DenseNet relative to texture and illumination challenges. He et al. [16] specified ResNet's small kernels and corresponding narrow receptive field that can miss out on wider contextual visual spans. Sandler et al. [17] mentioned that MobileNetV2's representation are shallower and hence not the most optimal for extracting rich texture. Huang et al. [18] acknowledged that DenseNet achieves better feature propagation, but struggles at modeling global features under severe illumination. In contrast, Liu et al. [11] showed that the 7x7 depthwise convolution in ConvNeXt greatly enhances the model's sensitivity to finer gradient patterns and retention of spatial information. ConvNeXt's global information retention and robustness to information perturbations are further enhanced to increase model efficacy by ImageNet-based transfer learning techniques that are documented to boost ConvNeXt's performance [11]. The approach is able to afford rapid and data-efficient training due to utilization of pre-optimized weights [19].

The features available on the Garbage Classification Dataset have case of class imbalance and high variability in the visual features such as light, shadow, and background noise and thus calls for such efficiency strategies. The varying heterogeneity of the dataset precludes the features extraction process, requiring the use of illumination preprocessing. Liu et al. [11] referring the ConvNeXt architecture, highlighted the importance of input features in maintaining stable visual representation. For fix the issues of contrast, Contrast Limited Adaptive Histogram Equalization (CLAHE), as a modification to the Adaptive Histogram Equalization (AHE) method, is valuable because of the ease and efficiency it provides to the processing of images [20]. Jin [21] has explained that the clip-limit mechanism in CLAHE is meant to increase local contrast while minimizing noise amplification. Regarding the smoothing process, Yamaguchi et al. [22] noted the weakness in the the smoothing process and the Gaussian filters which led to edge blurring, thus Lin et al. [23] recommended the usage of bilateral filtering that was designed to preserve the edges that are degraded by the Gaussian smoothing. Notwithstanding the undeniable reliability of individual components, the quality of the input features that result from the combined preprocessing remains unexplored in relation to the ConvNeXt architecture applied to intricate waste datasets. While ConvNeXt has been demonstrated as state-of-the-art [14, 15] and bilateral filtering is recognized as a viable method for noise reduction [24], their combination is yet to be thoroughly examined. Unlike the investigated works that concentrate on the assessment of ConvNeXt in a more immediate sense, the current work focuses on the quality of input features that is presumed to be enhanced by the application of CLAHE in combination with bilateral filtering on the ConvNeXt's stability regarding the waste dataset visual representations. This study contributes to the literature by providing a combination of CLAHE and bilateral filtering that is expected to improve the signal-to-noise ratio and ensure the maximum utilization of ConvNeXt in waste images feature extraction.

2. Methods

For this study, an organized methodological framework is being utilized to reduce potential errors during research. Themethodological framework is unwrapped in a set of interrelated tasks/activities that reflect research in waste classification. The activities include Data Collection, Data Preprocessing, Dataset Splitting, Model Design, and Model Evaluation, which will be described in the subsequent sections.

A. Data Collection

This phase starts with the acquisition of the dataset 'Garbage Classification' created by CCHANGCS which is available in Kaggle [25]. The original dataset contains six classes which are Cardboard, Glass, Metal, Paper, Plastic, and Trash, however, this study will only be concerned with five classes which are the main target classes, Cardboard, Glass, Metal, Paper, and Plastic. Due to considerable data imbalance, the Trash class was specifically left out of the experimental analysis. The Trash class includes 127 photos, which is radically fewer than the other classes, which collectively have 2,467 images. Keeping such a minor class would pose the risk of generating considerable imbalance during training, which could influence the model's generalization capacity. The removal of the Trash class facilitates a more even distribution of data, allowing for the ConvNeXt model to concentrate on the more representative data categories. The images that best exemplify the five categories that were chosen are presented in Figure 1.

(1) **(2)** **(3)** **(4)**

(5)

Figure 1. Sample image of : Plastic **(1)**, Paper **(2)**, Metal **(3)**, Glass **(4)**, and Cardboard **(5)**

B. Data Preprocessing

Previously gathered data from Kaggle undergoes the first step of preprocessing by resizing the images to the required model size of 224x224 pixels. Then data augmentation techniques are performed which include rotation, shift, shear, zoom, and horizontal flip. These methods have been shown to improve the data quality and subsequent model accuracy [26]. As stated by [27], augmentation acts as a sort of regularization by forcing the model to learn and not simply memorize the training images. The model, therefore, learns generalizable information. In geometric augmentation, techniques such as the ones mentioned help to model robust to shifts in pose, orientation and object location, which in the case of waste images are extremely prevalent as the images often contain clutter and the objects are not centered or not from a consistent viewpoint. For final resizing and augmentation, the other preprocessing methods utilized are CLAHE and Bilateral Filtering, where the former amplifies the image's contrast and the latter preserves edges and reduces noise in a blurry image.

C. Dataset Splitting

After preprocessing is complete, the dataset is split as follows: 80% is training, while 10% is set aside for both testing and validation, respectively. This is generally referred to as an 80:10:10 split.

D. Model Design

In this part, the necessary system architecture is created to maximize the performance of the waste classification system. The beginning of this stage is resizing the input images to the required resolution of 224 × 224 pixels. The system then employs a data augmentation and data preprocessing pipeline. For this architecture, a ConvNeXt-Tiny model along with the pretraining from ImageNet-22k dataset is used. As a feature extractor, this model has its first few weights frozen so that the model can retain a considerable depth of visual knowledge from the previous training on a large dataset. Also, the model has a Transfer Learning component whereby the classification head of the base is replaced to accommodate five classes for the target outputs: Cardboard, Glass, Metal, Paper and Plastic.

Data augmentation and normalization on training data are performed in an extensive manner to add robustness using random resized cropping, horizontal flipping, random rotations, random erasing and final normalization to standard ImageNet. All training and testing data are preprocessed with CLAHE contrast enhancement and Bilateral Filtering to reduce noise while preserving edges. For the testing phase only, Gaussian noise is added to the images to assess robustness. A crucial step to assess the model's reliability and performance to hold high classification performance despite sensor noise and degradation of image quality.

The model has been trained for 50 epochs with a batch size of 16 with the AdamW optimizer and a starting learning rate of 0.0005. In the training stage, the loss function is categorical cross entropy with the metric of focus being accuracy; however, class weights are added to mitigate data imbalance and ensure proper representation of the minority and majority class for fair discrimination. The experiments took place in a hardware setup that contains an Intel Core i7 13th Gen CPU, a NVIDIA RTX 4060 GPU, together with 16 GB of RAM and Windows OS in which the most up to date versions of PyTorch and timm libraries were installed. After the training phase, the model is tested against the test dataset in which the results are validated with a Confusion Matrix that summarizes the model’s precision, recall, F1-Score, and overall classification accuracy. The detailed architecture design is shown in Figure 2.

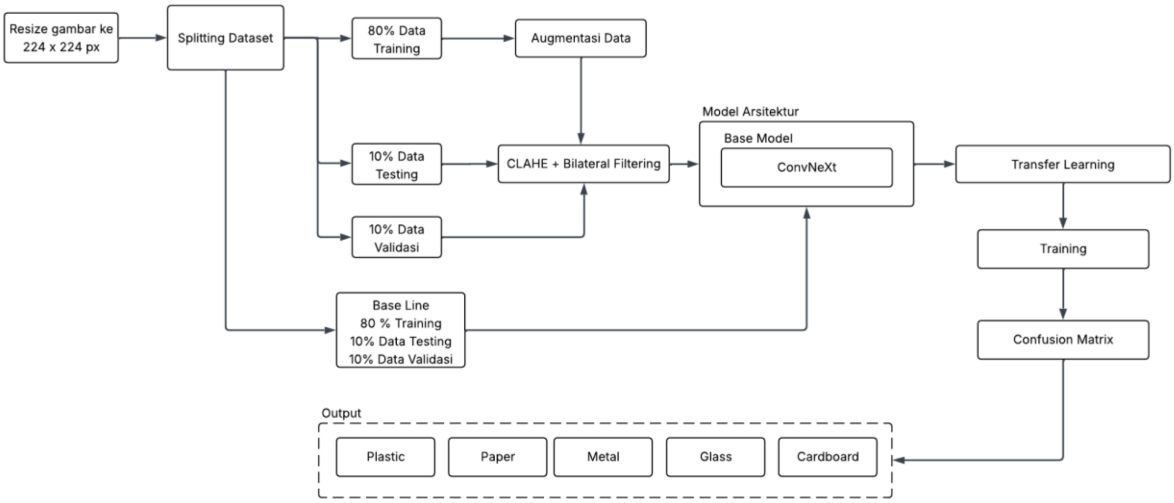


Figure 2. Stage of Model Design

E. Model Evaluation

This study uses several experimental scenarios to evaluate several of the preprocessing methods illustrated in Table 1

Table 1. Experimental Scenarios

	Scenarios	Configuration
1	Scenario 1	Base Model
2	Scenario 2	CLAHE + Bilateral Filtering

When the testing is complete, the calculation of the model's run time will commence. The performance metrics will also be computed, and a Confusion Matrix will be utilized for the calculation of the precision, recall, accuracy, and F1-Score for the measurement of the method's performance.

3. Results and Discussion

The efficiency evaluation of the waste classification model for this study was considered using two test cases to compute the models operational efficiency and overall effectiveness. The efficiency of the computational work was evaluated in controlled conditions for uniformity. The training procedure was performed using a batch of 16 and a warm-up period of 5 epochs to steady the hardware functioning and the learning rate before the final timing metrics were recorded. The timing was done using the sequential epoch-level timing method to guarantee the accurate determination of the mean value of the time spent on each of the iterations. The training was completed on both test cases, and the temporal information is presented in Table 2.

Table 2. Computational Training Time Comparison

	Metric	Scenario 1	Scenario 2
1	Batch Size	16	16
2	Warm-up Epochs	5	5
3	Total Training Time	11.83 Minute	20.86 Minute
4	Average Time per Epoch	29.52 Second	54.35 Second

According to the information presented in Table 1, Scenario 1 achieved a baseline in total training time at 11.83 minutes, with an average of 29.52 seconds per epoch. Incidentally, Scenario 2 experienced an increase in total training time to 20.86 minutes, with an average epoch time of 54.35 seconds. 76% of the increase in training time over baseline is due to the addition of CLAHE and Bilateral Filtering, which incorporate an overhead to each training image in the data pipeline. Though Scenario 1 is more time efficient, the additional cost required in Scenario 2 to increase the training time is a necessary tradeoff to build a model with a greater ability to extract high-quality features.

After analyzing the time consumed, a model consistency evaluation of Scenarios 1 and 2 for the recognition of the five object classes of Cardboard, Glass, Metal, Paper, and Plastic was undertaken. Table 3 summarizes the results for the comparison of the two Scenarios.

Table 3. Comparison Performance Between Two Scenarios

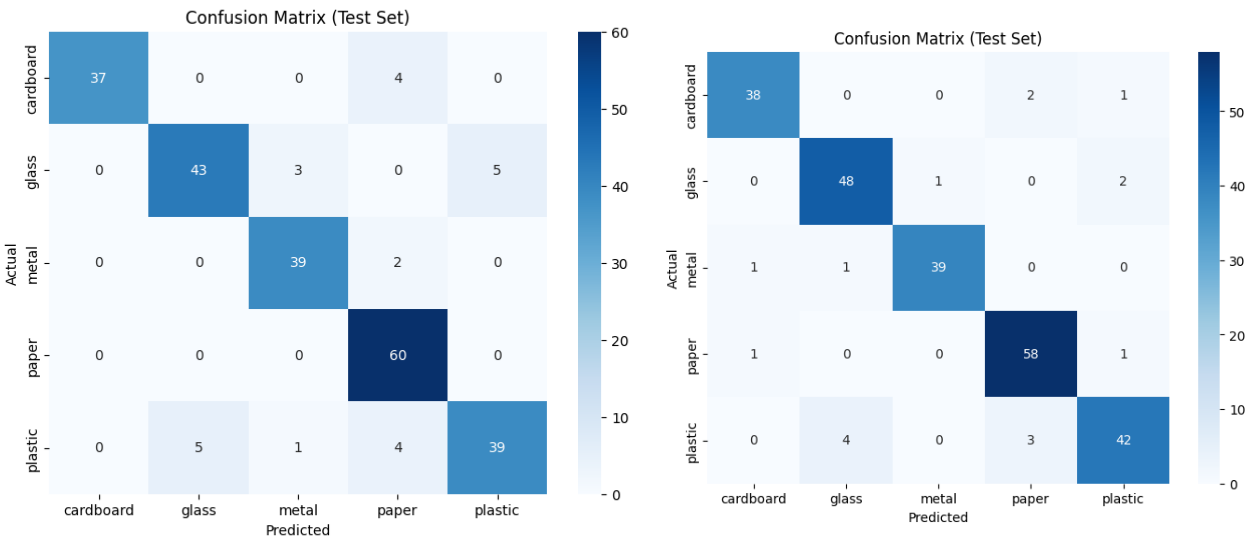
	Scenarios	Class	Precision	Recall	F1-Score	Accuracy
1	Scenario 1	Cardboard	100%	90%	95%	
		Glass	90%	84%	87%	
		Metal	91%	95%	93%	90%
		Paper	86%	100%	92%	
		Plastic	89%	80%	84%	
2	Scenario 2	Cardboard	97%	88%	92%	
		Glass	96%	96%	96%	
		Metal	93%	100%	96%	94%
		Paper	88%	97%	92%	
		Plastic	98%	88%	92%	

Based on Table 2 pertaining to the result of the first scenario (baseline), it can be seen for that scenario that the overall accuracy recorded is 90%. This scenario reports that the model has the following traits such that for the Cardboard class it has a perfect precision of 100% but has a recall of 90%. This indicates that the model never misclassified any of the other classes as cardboard, but there is also a portion of the cardboard that the model did not detect. There is also an imbalance particularly in the Paper class, where recall was recorded as perfectly every time at 100%, however, precision in that same class was simply at 86%. This suggests that the model in the raw data is more on the positive side of classifying data as paper, and as a result, more False Positives were triggered. In contrast, in the baseline model, the Plastic and Glass classes were the most difficult where the lowest recall were recorded to be 80% and 84% and also the F1-Score was also not good at 84% and 87% which indicates that the model is having a difficult time to extract features of transparent objects without the help of some pre-processing.

In Scenario 2, the use of feature preprocessing led to an increase in performance with an overall accuracy of 94%. The greatest performance improvement was in the Glass class, which exceeded all metrics (Precision, Recall, and F1-Score) and plateaued at 96%. Such metrics were a significant improvement compared to the previous scenario. The improvement of feature quality was also seen in the Metal class, which had a perfect recall of 100% and an F1-Score of 96% in this scenario. It was the class with the most complete detection. Another notable improvement was the increase in precision in the Plastic class which was recorded at 98%. This improvement also showed that preprocessing had successfully removed noise that had been previously causing difficulties regarding the detection of plastics. Although there was also a minor drop in recall for the Cardboard class to 88%, the F1-Score for all classes in Scenario 2 are now at 92% and above which means that the model has reached a much better equilibrium.

In general, the differences between the two scenarios showed that Scenario 2 was better at handling the complexities of the visual features than Scenario 1. Scenario 1 experienced a large bias toward the Paper class and also suffered large misses in the identification of the Glass and Plastic classes. Scenario 2 showed that the model had gained in robustness and fairness due to the new preprocessing by showing a reduction of false positives for transparent objects (improved Glass and Plastic precisions) and a larger swing in the predictions associated with the presence of a metal object. Ultimately, the even greater consistency of Scenario 2 in maintaining F1-Scores of more than 90% across all classes demonstrates the reliability of the method and its usefulness in automated waste classification systems.

To further assess the distribution of the prediction errors, the confusion matrices from each scenario have been plotted and illustrated in Figure 3.



(1) **(2)**

Figure 3. Confusion matrix of : Scenario 1 **(1)**, and Scenario 2 **(2)**

The first part of Scenario 1 along with the Confusion Matrix shows why the model had lower precision for the Paper class. It shows a high amount of misclassifications (False Positives) for Paper, with several samples of Cardboard, Metal, and Plastic being misclassified to Paper. This shows that the model was unable to differentiate texture features between flat paper and other flat materials. Additionally, the Scenario 1 matrix also shows significant overlap between the Glass and Plastic classes. Significant cross-error patterns for Glass being Plastic and Plastic being Glass were recorded. The overlap of features for these two materials was the most important factor leading to the low recal and accuracy scores for these two classes and the baseline values.

The matrix presented in Fig. 4 (b) for Scenario 2 shows that a gradual change in structure concerning the predictions are distributed. The matrix shows that the main diagonal is darker indicating that there is a consistent increase in the True Positive predictions across all classes. The highest increase was noted concerning the False Negatives in the Paper column. There was a notable increase in the number of samples from other classes that were misclassified as Paper, thus increasing Paper's precision value in the results table. Also, the disparity between the Glass and Plastic classes is of a greater magnitude. There was a significant decrease in the errors of cross-classifications. This suggests that the preprocessing phase improved the edges and the reflective noise that previously fooled the model was removed. The Scenario 2 matrix indicates that the prediction errors are also for the Cardboard class, so there are still small prediction errors in that class, but Scenario 2 is a definite improvement in prediction errors. The model appears to have a stronger and more refined decision boundary than Scenario 1.

The analysis presented above proves that the techniques used to improve the training dataset also offer more than just an improvement in the accuracy metrics. The model also advances in its ability to predict with lower bias. Though the method in Scenario 2 takes more training time (20.86 mins) than the baseline (11.83 mins), the 4% uplift in overall accuracy, coupled with the stabilization of accuracy within individua; classes, reasonably offsets the extra time toward more reliable automated waste classification system.

4. Conclusions

This research involved analyzing the influence captured during the absence of any image preprocessing and during the presence of image preprocessing on the performance of a CNN based waste classification system. Emphasizing the difference of baseline (Scenario 1) and preprocessed (Scenario 2) approaches during the research, this work proves the necessity of improving quality of input data for identification of material in more precise manner.

The experimental results show that Scenario 2 outperformed the baseline and achieved 94% accuracy (compared to 90% accuracy in Scenario 1). However, Scenario 1 baseline models faced difficulties with transparent and reflective materials, and thus, had low Glass (84%) and Plastic (80%) recall and high Paper false-positive rates. In Scenario 2, the advances in preprocessing led to increases to the F1-Scores for Glass (96%), and Plastic (92%), as well as gaining full recall (100%) for Metal. In terms of the computational efficiency of the study, a processing lag was noticed compared to the effort put into the model. Scenario 2 accumulated a total training time of 20.86 minutes (average 54.35 seconds per epoch) which was about 76 % more than Scenario 1 which recorded a time of 11.83 minutes (average 29.52 seconds per epoch). Even so for such an increase in overall accuracy, it was well worth the total time for maintaining the classification performance across all the different classes of the model.

There was a slight compromise in the recall of the Cardboard class, however, the overall Scenario 2 consistency where each class F1-Score was above 92% demonstrates that the proposed method is likely to refine generalized capabilities. Thus, the study suggests there is value in computationally expensive preprocessing in strengthening the automated waste classification systems to diversify difficult target objects.

While there was a marginal decline in the recall on the Cardboard category, Scenario 2 was the only one in which all classes had F1-Scores over 92%. This demonstrates the overall homogeneity of the scenario and ecology of the methodology, which can be concluded most optimally generalized. Therefore, the key point going forth is the need for a significant amount of preprocessing, and while the cost is elevated, it is essential for the creation of a viable, fully automated waste sorting system capable of processing a wide variety of waste streams.

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