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Research Article

Smart Waste Sorting Using Deep Learning and Image Augmentation

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Abstract:
The global challenge of waste management has caused significant environmental and health concerns. As the volume of waste continues to increase, manual sorting methods are proving inadequate and potentially hazardous. This research aims to develop an automated waste categorization system using deep learning algorithms to provide an innovative solution for waste classification and recycling. We have used images from trashnet dataset to train and test our model as trashnet dataset contains images from six different waste category that are close to real world. We implemented image augmentation techniques on the dataset to enhance the model's learning capacity. The classification task was conducted using the ResNeXt-50 convolutional neural network, pre-trained on the ImageNet dataset. The model underwent training and validation across 50 epochs to ensure its accuracy and generalization capabilities. The methodology employed demonstrated robust performance, achieving a maximum validation accuracy of 99.17%. T The model exhibited better generalization performance than some of the recent works reported in the literature, which proves its applicability for the waste classification task. The innovation of this research resides in the integration of image augmentation with the ResNeXt-50 architecture for waste classification, coupled with the achievement of substantially higher accuracy compared to previously reported models. This research demonstrates the potential for developing scalable, automated waste sorting systems utilizing deep learning techniques.

Keywords: Waste Classification, Deep Learning, Trashnet, Image Augmentation

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1. Introduction:

As populations grow and production increases, efficient waste management has become a critical concern. The daily rise in global waste generation poses significant environmental, social, and economic risks. Inadequate waste disposal can result in contamination of air, water, and soil. To mitigate the negative impact of human activities on the environment, it is crucial to accurately classify waste materials based on their type, characteristics, and composition, in order to enhance recycling efforts. Conventional waste classification methods were dependent on methods such as manual sorting through visual inspection. This is not practical nowadays due to the vast quantities of waste produced daily and the potential health hazards for workers involved in such processes. The evolution of technology has revolutionized waste sorting methods through the integration of automation, robotics, and artificial intelligence (AI). These advancements have led to more efficient, accurate, and cost-effective classification techniques. Recently, machine learning [1] [2], deep learning [3] [4] [5], and artificial intelligence based approaches have emerged as game-changers in waste classification research. The introduction of benchmark datasets, such as TACO [6], Trashnet [7], Waste Classification Data [8], Garbage in Image [9], and TrashICRA19 [10], has further enhanced these methodologies, providing valuable resources for improving waste categorization systems. In the domain of image recognition, advanced deep learning techniques like convolutional neural networks (CNNs) have proven highly effective in facilitating automated classification of waste materials based on visual cues and patterns. Despite technological advancements in waste management, significant challenges persist. Traditional manual sorting methods, which depend on visual inspection, struggle to cope up with the increasing waste production, facing obstacles in scalability, precision, and employee safety. Automated systems appear to be a feasible solution; however, they frequently struggle with accuracy when categorizing intricate waste types, especially when utilizing restricted or inadequately labelled datasets. Most of the current waste classification deep learning models are trained on the general datasets which are limited in the representation of the real world therefore they are ineffective in diverse environments. Moreover, current methods often lack robust image augmentation techniques to address limited data and improve model resilience. These concerns indicate that more complex waste categorization systems should be developed to ensure better performance and flexibility. The aim of the present study is to address these issues by means of employing advanced deep learning as well as advanced image augmentation techniques for better waste classification and enhancement of performance in different environments.

Over the past few years, researchers have employed a variety of machine learning techniques to effectively detect and classify different types of waste. One such effort was made by Ahmed et al. [11], who designed and implemented a system using Convolutional Neural Networks (CNN) along with existing pre-trained models like DenseNet169, MobileNetV2 and ResNet50V2 for automatic sorting of trash. Further in a more recent study conducted in the year 2023, Volkan Kaya [12] deployed a number of deep leaning frameworks such as Xception, InceptionResNetV2, MobileNet, DenseNet121, and EfficientNetV2S. Moreover, Kaya proposed two additional methods that were XceptionCutLayer and InceptionResNetV2CutLayer. These new methods were very effective achieving an accuracy of 89.72% and 85.77% respectively. A method for improving CNN-based object detectors to identify waste in real-time was developed by Melinte, Travediu, and Dumitriu [13], utilizing the TrashNet database and achieving high accuracy and efficiency. The study focused on enhancing pre-trained CNN object detectors for waste recognition, resulting in improved accuracy, generalization capabilities, and faster detection rates.

The design and implementation of a solid trash sorting system using deep learning and embedded Linux operated system components was undertaken by Fu et al. [14]. The central processor in this system was a Raspberry Pi 4B bundled with a touch screen, different sensors, a two-degree of freedom servo device, and a camera. Use of experiments conducted on the Huawei Garbage Classification Challenge Cup dataset confirmed that the system recognized objects achieving 92.62% classification accuracy and processed each item in 0.63 seconds. In their study, He et al. [15] examined the supervision of waste collection and transportation by utilizing an enhanced YOLOv3 model to improve waste classification accuracy. The researchers modified the YOLOv3 model by incorporating depth-wise separable convolution to boost detection speed and implementing triplet attention to tackle issues related to location precision and multi-target performance.

In a study carried out by Tian et al. [16], the researchers presented a concise model meant for garbage classification based on a tailored garbage dataset and a pre-trained MobileNetV3 architecture within PyTorch framework. The model yielded accuracy of 96.55% on dataset created by them, as well as lower memory footprint and faster recognition time. These characteristics make the model well-suited for implementation in embedded devices designed for garbage classification. A Deep Learning model utilizing EfficientNet Architecture for trash type classification was developed by Abhishek et al. [17]. Their model demonstrated a 98% accuracy rate when tested on the TrashNet dataset. A Waste Classification Method utilizing a Multilayer Hybrid Convolution Neural Network was developed by Shi et al. [18]. Their research also examined how different optimizers, including Adam, SGD, and SGDM Nesterov, affected the classification of waste images. Among these, SGDM Nesterov demonstrated notable effectiveness in terms of classification accuracy. Jianfei Wang. [19] undertook a study whose focus was the incorporation of machine learning in conducting automated home waste disposal. In the course of the study, deep learning, ensemble learning, and optimization techniques were integrated in order to enhance the results for waste classification. Based on the trashnet dataset such method reported great success level of 98.81%. A two-step approach for waste detection was made by Majchrowska et al. [20], which was based on EfficientDet-D2 object localization and EfficientNet-B2 classification. This method reached an average precision of around 70% in waste detection and around 75% in classification after being assessed on the dataset. The authors also presented benchmark datasets called detect-waste and classify-waste which were composed from multiple open-source libraries to provide a reproducible foundational level for litter recognition. The datasets were constructed so that they would act as a benchmark for the subsequent studies focusing on waste detection.

2. Materials and Methods:

2.1 Dataset Used:

For our study, we have used trashnet dataset that contains total of 2527 images of total six different class of garbage i.e. cardboard, glass, metal, paper, plastic and trash. Number of images for each class are displayed in Table-1. These classes of garbage are versatile and include trash typically found in the current experience. Figure-1 shows some sample images of different classes from the Trashnet dataset.

Table-1. Number of images available for each garbage class in Trashnet dataset

Class	Number of images
cardboard	403
glass	501
metal	410
paper	594
plastic	482
trash	137

2.2 Image Augmentation:

We have used image augmentation techniques during preprocessing stage in order to introduce diversity in training dataset, improve the robustness of the model to variation in input data and to enhance the robustness and generalization capabilities of the deep learning model.

Random Resized Crop: A random area of 224 pixels x 224 pixels id cut out from the input image and resized afterward in order to normalize the image sizes.

Figure-1. Sample images from trashnet dataset (a), (b) cardboard (c), (d) glass (e), (f), metal (g), (h) paper (i), (j) plastic (k), (l) trash

Random Horizontal Flip: The images collected are subjected to horizontal flipping with 0.5 probability to create mirror copies of the images in the dataset in order to further enhancing the dataset.

Color Jitter: Random adjustments to brightness, contrast, and saturation are applied to introduce variations in color and lighting conditions.

Random Rotation: Images are rotated by a maximum angle of 20 degrees to simulate different orientations and perspectives.

Our model architecture is described here in Figure-2.

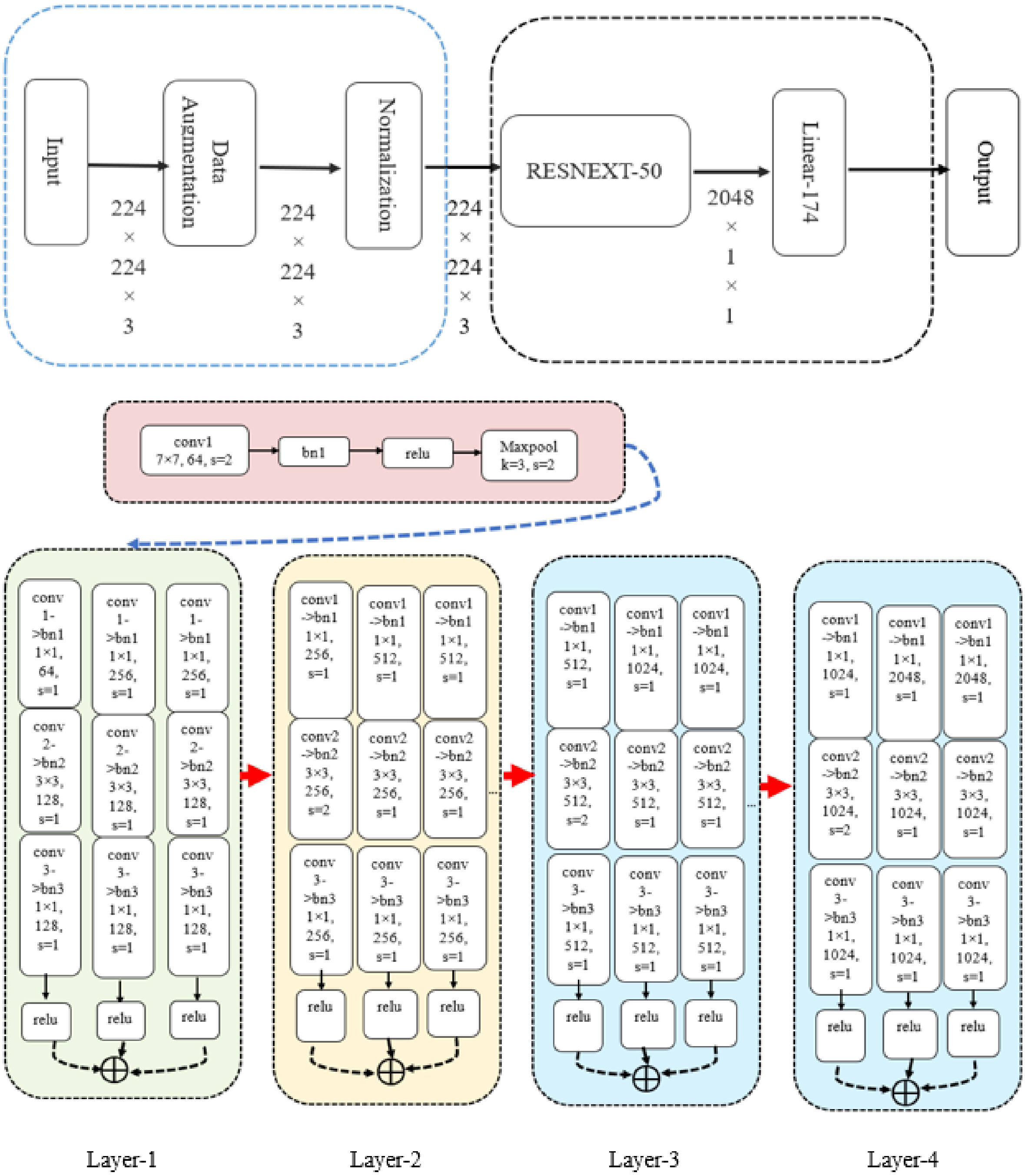

Figure-2. Proposed model architecture

3. Result Analysis:

We have obtained promising experimental results after training and evaluation of our model which are explained in this section. After 50 epoch of training, we have achieved validation accuracy of 99.17%. The high validation accuracy achieved by the model indicates its capability to generalize well to unseen data, demonstrating robust learning of discriminative features for waste classification. Figure-3 shows graph that displays evolution of train and validation accuracy over time with every epoch. The validation accuracy curve reflects the model's generalization performance on unseen validation data throughout the training process. A stable increment in both train and test accuracy indicates successful learning as well as model convergence showing that the model is able to extract relevant patterns and features from the input data that have been provided for training purposes. Figure-4 shows progression of both train and validation loss metrics over training epochs. The train loss curve depicts the magnitude of errors made by the model when predicting labels for samples from the training dataset during successive epochs. At the beginning, train loss typically starts at a relatively high value as the model's parameters are initialized randomly which will result into high error rates. Later the model gradually adjusts its parameters through optimization techniques over every epoch which will result into decrease in train loss.

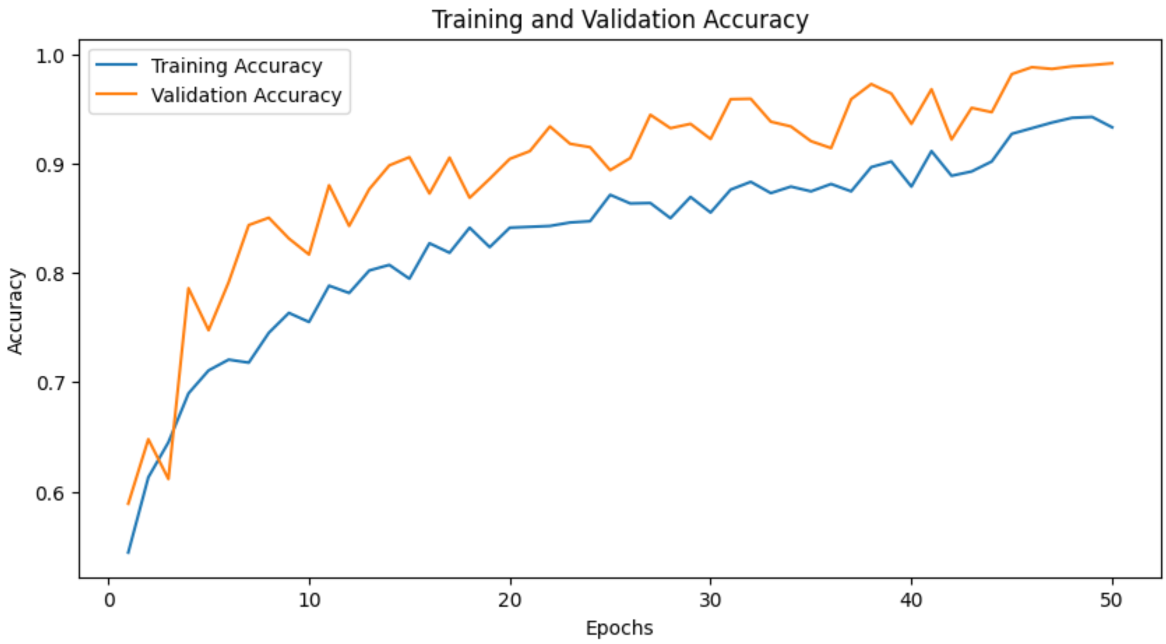

Figure-3. Training and validation accuracy over time

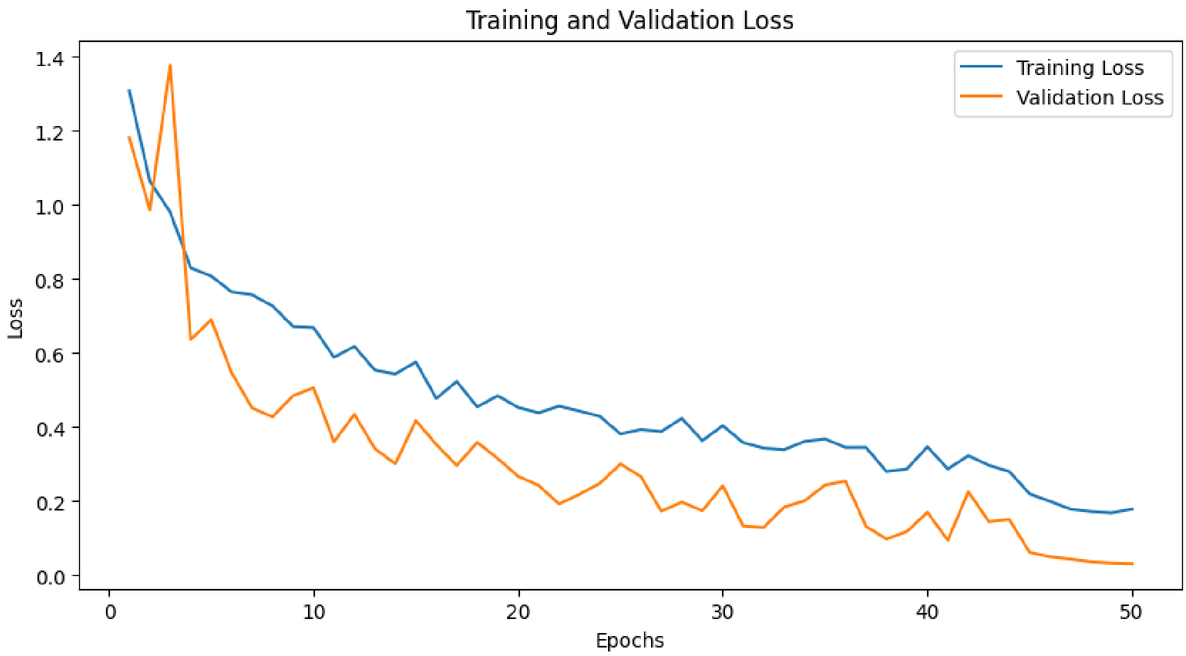

Figure-4. Training and validation loss over time

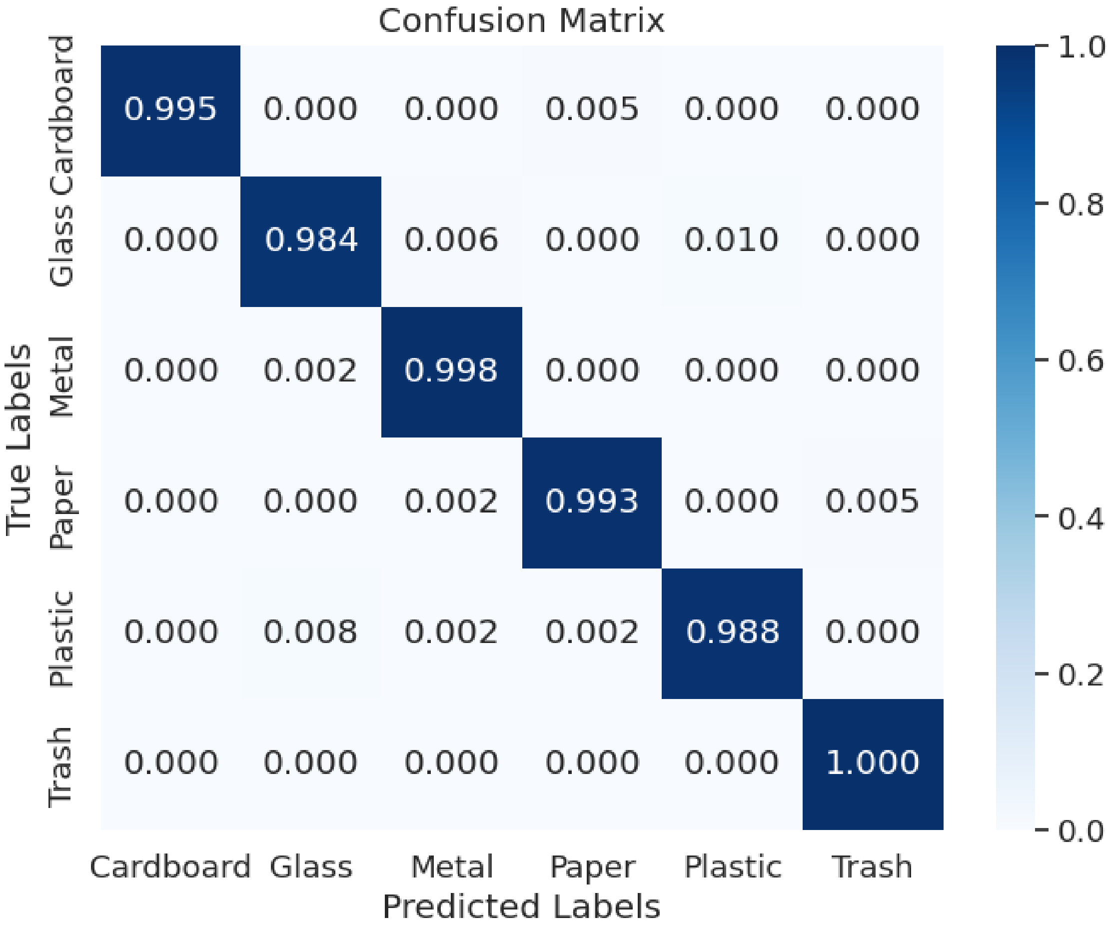

Figure-5. Confusion matrix for proposed approach

$$Precision = \frac{True\ Positives\ (TP)}{True\ Positives\ (TP)+False\ Positives\ (FP)} \quad (1)$$

$$Recall = \frac{True\ Positives\ (TP)}{True\ Positives\ (TP)+False\ Negatives\ (FN)} \quad (2)$$

$$Accuracy = \frac{True\ Positives\ (TP)+True\ Negatives\ (TN)}{Total\ Number\ of\ Samples\ (TP+FP+TN+FN)} \quad (3)$$

$$F1-score = 2 * \frac{Precision*Recall}{Precision+Recall} \quad (4)$$

$$Misclassification\ Rate = \frac{Total\ Incorrect\ Predictions}{Total\ Predictions} \quad (5)$$

Table-2 Values of Precision, Recall and F1-Score for six classes of Trashnet dataset

Class	Precision	Recall	F1-score
Cardboard	1.0000	0.9950	0.9975
Glass	0.9900	0.9840	0.9870
Metal	0.9879	0.9976	0.9927
Paper	0.9949	0.9933	0.9941
Plastic	0.9896	0.9876	0.9886
Trash	0.9786	1.0000	0.9892

Table-3. Comparative analysis of our approach with some existing approaches

Study Name	Accuracy (%)
Zheng et al. [21]	92.00
Zheng et al. [22]	93.50
Singh et al. [23]	98.02
Yuan et al. [24]	98.50
Our Approach	99.17

The drop in the training loss curve suggests that the model is learning and improving with respect to the training data. The validation loss sheds light on how well the model will do on the validation data that has not been seen yet. It shows model's ability to generalize to new samples. Here, we can see continuous decrease for both train loss and validation loss over the epoch which indicates that model is successfully minimizing the error and improves performance over time. A confusion matrix illustrating the effectiveness of the mode for each of the six classes is represented in Figure-5. The important performance parameters such as precision, recall, and f1-score in reference to the confusion matrix are presented in Table-2. The necessary equations for these calculations are given here as equation (1), (2), (3), (4), (5). The accuracy of the model turns out to be 99.17% while the misclassification rate is 0.83%. We have compared results obtained by our approach with some similar garbage classification studies that have been carried out on Trashnet dataset. This comparison has been summarized in Table-3.

4. Conclusion and Discussion:

This study introduces a method for categorizing waste using deep learning and image enhancement algorithms. Image augmentation techniques were employed in the Trashnet dataset images and the ImageNet pre-trained ResNeXt-50 architecture was used for training and testing purpose. The Trashnet dataset was subjected to intensive experimentation and analysis to ascertain the method's efficacy, revealing an accuracy of as high as 99.17%. Our model also shows impressive values for precision, F1-score and recall for all six garbage classes contained in the Trashnet dataset. Moreover, a detailed comparison with other similar studies that were tested on trashnet dataset exhibits the strength and accuracy that our approach has when it comes to classifying garbage into appropriate categories. In future, the study can be expanded to include more waste categories that will enable the system to be more flexible and robust. The proposed study also find its applications in incorporating this model in intelligent garbage collection systems like smart bins or recycling plants to improve how they operate.

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