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Garbage Classification based on Dense Network (GCDN) using Transfer Learning and Modified Hyper Parameter

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Abstract: Garbage classification plays a vital role in waste management and sustainability of the environment. Traditional methods of waste classification often depend on manual sorting, which is very time-consuming and prone to human errors which can lead to policy inadequacy by the government. In this paper, we proposed a deep learning-based DENSNET201 approach Garbage Classification based on Dense Network (GCDN) for garbage classification to automate and improve the accuracy of this process. Our method utilizes an additional layer of convolutional neural networks (CNNs) to classify garbage into 12 categories such as shoes, green-glass, paper, cardboard, battery, biological, plastic, metal, brown-glass, white-glass and trash. We have executed the different state of the art models of deep learning on a publicly available dataset comprising images of various types of garbage collected from diverse environments. We then employed image augmentation methods followed by transfer learning techniques to fine-tune pre-trained CNN models on this dataset. During the analysis of the results, we have achieved the high classification accuracy of training and validation phase 98.64% and 93.23% respectively. Experimental results demonstrate the effectiveness of our approach in accurately classifying garbage, even in challenging scenarios with diverse backgrounds and lighting conditions. Furthermore, we discuss the potential applications of our system in real-world waste management scenarios, including smart waste bins and recycling facilities, to streamline garbage sorting processes and promote environmental sustainability.

Keywords: *Garbage Classification, Waste Classification, Machine Learning, Deep Learning, Transfer Learning, Image Augmentation*

1. Introduction

Sorting waste, also called garbage classification, which involves categorizing waste into different groups based on their properties. The main purpose of the study is to simplify disposal, so we can improve recycling and finally reducing environmental impact and supporting sustainability. Waste usually classified into different categories like: 1. Organic waste, which consists of food scraps, garden waste, and paper products. 2. Recyclable materials includes paper, cardboard, glass, certain plastics, aluminium, and metals. 3. Hazardous waste includes batteries, electronic waste, certain chemicals, paints, solvents, and pesticides.4. Non-recyclable or residual waste, such as plastic bags, certain types of packaging, diapers, sanitary products, and other mixed waste. 5. Specialized waste streams, like medical waste, construction and demolition waste, and specific industrial waste [1].

Proper waste sorting usually requires educating people and communities about the segregation of waste, setting up distinct labelling and collection systems, and establishing facilities for appropriate disposal and recycling. Governments, local authorities, companies, and individuals have vital roles to play in advocating for sustainable waste management practices and lessening the environmental impact of waste.

1.1. Garbage Classification using machine learning algorithm

Garbage classification using machine learning involves training algorithms to automatically classify waste into different categories based on input data such as images or sensor readings. Machine learning process [2][3] involves data collection to get a dataset of images of different types of waste and to clean and preprocess the data using tasks such as resizing images, normalizing pixel values, and handling missing or noisy data and to apply selected machine learning model for garbage classification. As research study shows, Convolutional Neural Networks (CNNs) are commonly used for image classification tasks. Selected model is trained using a training dataset and the remaining dataset will be used as validation and test sets. Train the selected model on the training data and fine-tune hyperparameters using the validation set to optimize performance.

Techniques like data augmentation [4][5] (for image data) can be used to improve model generalization. Evaluate the trained model on the test set to assess its performance in classifying garbage accurately. Common evaluation

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metrics include accuracy, precision, recall, F1-score, and confusion matrices. Iterate on the model by retraining it with additional data or fine-tuning parameters as needed to maintain or enhance classification accuracy.

To build an effective garbage classification system using machine learning evolves several challenges and issues [6][7], some of these issues include high-quality and diverse datasets, as garbage comes in various shapes, sizes, and conditions, and capturing this variability in training data is essential for building robust classification models. Manually labeling and annotating garbage images can be time-consuming and labor-intensive. So it requires a set of benchmarks for the garbage classification dataset [8][9][10][11].

1.2. Garbage Classification using Deep Learning Algorithm

Using deep learning algorithms, particularly Convolutional Neural Networks (CNNs), for garbage classification can help to address some of the challenges associated with traditional machine learning approaches [12]. Below mentioned points define how deep learning can ease these issues: Feature Learning [13] - Deep learning algorithms can automatically learn hierarchical representations of features directly from raw data. This eliminates the need for handcrafted feature engineering done in various machine learning models. By leveraging convolutional layers, CNNs can extract informative features from garbage images, improving the model's ability to discriminate between different waste types. Size of Dataset-Transfer learning [14] allows pre-trained CNN models (e.g., trained on ImageNet [15]) to be fine-tuned on smaller garbage classification datasets, which is reducing the need for large amounts of labeled data. Generalization and Adaptation - pre-trained models on large and diverse datasets can generalize well to new environments and unseen data. Moreover, techniques such as data augmentation and domain adaptation can further increase model generalization and adaptation to new levels. There exist several deep learning models for garbage image classification, each with its strengths and applicability based on factors like model complexity, computational resources, and classification accuracy.

Below discussed some of the commonly used deep learning models for garbage image classification:

ResNet (Residual Neural Network): ResNet [16] known for its ability to train very deep networks effectively. Using skip connections, it can diminish the vanishing gradient problem, allowing for the training of extremely deep networks. ResNet variants, such as ResNet-50, ResNet-101, and ResNet-152, have been pre-trained on ImageNet and can be fine-tuned for garbage image classification tasks.

VGGNet (Visual Geometry Group Network): VGGNet [17] consists of multiple convolutional layers followed by max-pooling layers, with small (3x3) convolutional filters. Despite its simplicity, it has shown competitive performance on various image classification tasks.

Inception (Google Net and MobileNet) [18]: The Inception Architecture Developed by Google researcher introduces the concept of inception modules. It consists of parallel convolutional layers with different filter sizes and pooling operations. It is specially known for their efficiency and ability to capture multi-scale features. MobileNet is designed for resource-constrained environments like mobile and embedded devices. It reduces computational complexity and maintains high accuracy. MobileNet variants, such as MobileNetV2 and MobileNetV3, offer different trade-offs between model size, speed, and accuracy.

EfficientNet: EfficientNet [19] uses a compound scaling method to balance model depth, width, and resolution, leading to highly efficient and effective models across a range of tasks. It achieves very good performance with efficiency in terms of parameters and computational cost.

DenseNet (Densely Connected Convolutional Networks): DenseNet [20][21][22] is a deep convolutional neural network architecture that introduces dense connectivity patterns between layers. It facilitates feature reuse and promotes feature propagation throughout the network. DenseNet models have shown strong performance on image classification tasks and can be applicable to garbage image classification as well.

The choice of model depends on many factors like computational resources, desired accuracy, and deployment constraints. Experimentation and evaluation are essential to determine the most suitable model for a garbage image classification task.

2. Review of Existing work

The survey paper [23] contains details of a few comprehensive surveys done on waste detection and classification. The initial part of this paper shows the various domains of waste. The physical state, technical elements, reusable potentials, biodegradable potential, manufacturing source, the degree of environmental effects and material nature (liquid, solid and gaseous) are some of the specific features considered in the classification of garbage. This survey paper contribute by reviewing some of the existing deep learning models includes AlexNet, VGG16, ResNet, MobileNet, Inception-ResNet, DenseNet, YOLO, CenterNet, EfficientNet, ExtremeNet and Mask-RCNN [23] for detecting and classifying waste. It also highlights the various datasets of waste and the future challenges.

In the paper [24] the authors focused on improving the performance of the MobileNetV3-Large model based system. Where software application part Wechat is used and Hardware module Raspberry Pi is used. The dataset developed using crawling technology which combined with Baidu open datasets. The dataset images are classified into four major categories and further categorized it into sub-categories using deep separable convolution, inverse residual structure, lightweight attention structure and the hard_ swish activation function. The MobileNetV3-Large model based system performance evaluated with the number of iterations of the model. The result shows at 10th iteration it accuracy reached more than 80% and the loss value decreased to the middle of the interval of 0.5–0.6. As the number of iterations increased, the accuracy of the model gradually tended to grow flat and finally stabilized at 81%.

The paper [25] describes research study on trash classification, where author proposed a Deep Learning model based on EfficientNet Architecture, where model achieve 98% of training accuracy. The used dataset combined TrashNet (2527 images) and other standardized datasets (8135 images) named ScrapNet into one dataset. The proposed model uses EfficientNet B0 as a base model and then applies compound scaling to develop large networks. The test performed on different variant (B0-B7) of the EfficientNet. ResNet50 achieved an accuracy of 83.11%. ResNet101 and ResNet152 shows fall of 1.9% and 2.1% respectively. The performance evaluation shows that the accuracy increased from EfficientNet B0 to B2 (92.87%) and peaked at B2 before declining substantially from B3 (89.21%) to B7.

The paper [26] focus is on classifying non-biodegradable waste by employing various YOLOv5 architectures, specifically those denoted as p5 models (nano, small, medium, large and extra large). All these models vary by their parameters size. Models were trained with image resolution of 640 pixels, batch size of 20 and at epoch size of 150. The ratio of 63% for training and 37% was used for testing with small dataset with subclasses like paper, Plastic and metal. The parameters like batch size and epochs were changed for model training. The result shows YOLOv5 model has 33% chances of mistaking metal for paper due to small sample size. Where paper and plastic predicted correctly. The YOLOv5 large at 150 epochs, the precision was achieved 73.6% and recall was 98.21%. The multiclass accuracy shows 93.33%. The YOLOv5 large was trained with various epochs, at 347 epochs model shows the most overfitting and at the 25 epochs is under-fitting. The author concluded number of the most optimal epochs will depend on the size of the dataset.

The paper [27] proposed a low-cost, accurate and easy-to-use solution for handling the garbage effectively using dataset (2000 images) of solid waste. After the Image augmentation 6000 new images were generated, the proposed “Garbage Detection System Using an Unmanned Aerial Vehicle” using two CNN model was trained using 80% of images. The both CNN model has three and five convolution layers respectively and max pool layers with one dropout layer and flattening layer. The proposed model performance was evaluated for different learning rates and the number of epochs at two different optimizers: RMSprop and Adam [28]. Performance evaluated using four learning rates (0.1, 0.001, 0.0001, and 0.00001), batch size 32 at three different epochs (10, 30, and 50) using precision, recall, F1-score, and accuracy matrices. The CNN1 model shows 94% of accuracy in garbage detection.

The paper [29] study depicts use of fine-tuned convolutional neural networks (GoogleNet, ResNet, DenseNet, ResNext, EfficientNet) with two optimization algorithms (SGD momentum, Adam) to segregate public dataset in different category (12 classes). Proposed model achieve high accuracy of 95%, where a pre-trained model was selected and its parameters were changed to achieve desired result.

The paper [30] aims to develop an automatic plastic waste segregation method into defined categories to emphasize preventing waste and maximizing raw material utilization for reuse of materials, reducing processing costs and environmental impact. The proposed model uses resembling the mammalian visual cortex for objects detection in images. The training conducted for different data splits, learning rates and no. of epochs. The performance was evaluated with different parameters and concluded that 15-layer network outperformed the 23-layer network in terms of accuracy and required time for learning. The proposed model achieved training accuracy of 97.43% and validation 74%.

The paper [31] focuses on the achieving accuracy to sort garbage waste. The author proposed garbage image classification using a modified ResNext model. To get most variety of features in the given input image, the model uses the concept of parallel branches with different filter sizes. The evaluated performance shows the model identifies the garbage within a short time with the 98.9% accuracy.

The author proposed deep learning algorithm DenseNet-201[32] for garbage classification using the approach of transfer learning, optimization and loss function. The model performance evaluated and compared with ResNet a deep learning model. The result shows it requires more training time but it is more parameter efficient with 90% Train accuracy and 84% test accuracy.

3. Garbage Classification based on Dense Network (GCDN)

Proposed GCDN's architecture has utilized the fusion of transfer learning method and image augmentation with some modified hyper parameters as shown in Figure-1. Below is a method proposed for sorting garbage using DenseNet-201 architecture:

● Transfer learning approach using DenseNet-201with imagenet dataset.

● Image augmentation methods like () has been applied to enhance the accuracy of the model.

● To ensure balanced datasets split the dataset into an 80% training set and a 20% validation set. We will train the modified DenseNet-201 model using transfer learning on the training dataset. Fine-tuning of the pre-trained model parameters will be done on the garbage classification dataset. Data augmentation techniques will be applied to improve the model's generalization

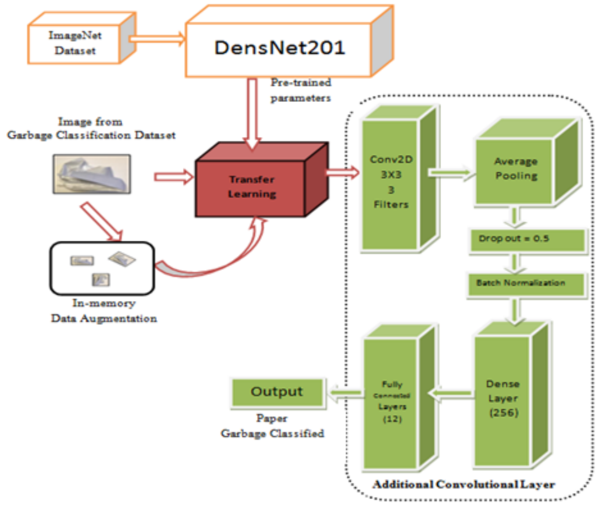


Figure 1. Proposed GCDN Architecture

● Hyperparameter Tuning: In the proposed system, hyper parameters like learning rate has been set to 0.005, batch size to 64, and Adam optimizer has been used to optimize the model's performance.

● Additional Layer: Additional layer of convolution, average pooling and dense layer has been added with batch normalization and dropout ration of 0.5. This additional layer has improved the accuracy then the traditional state-of-the art algorithms.

3.1. Transfer Learning (Image net)

One of the effective machines learning technique is transfer learning, specifically using a model trained on ImageNet. ImageNet is a popular dataset for image classification tasks, containing millions of labeled images in thousands of categories. In our GCDN system, we have used pre-trained model of ImageNet with the DenseNet201. It has been utilized as a feature extractor that helped us to reduce the training time of model.

3.2. Data Augmentation

In image augmentation, we have used different techniques to improve and change images like rotation, scaling, translation, shearing and flipping. When image augmentation applied, the image data undergo random transformations before given as a input into the model. Using this technique we can train the model with large set of images, which can prevent overfitting.

3.3. DenseNet for Image Classification

As shown in below Figure 2, dense blocks are made up of several sequential convolutional layers (with batch normalization and activation function). Each layer within the same dense block gets input from all previous layers.

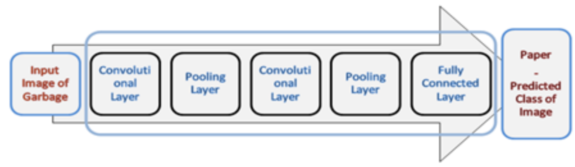


Figure 2. DenseNet-201 Architecture

To reduce spatial dimension of feature maps transition layers are kept between dense blocks using pooling techniques (like average pooling) as shown in Figure 3.

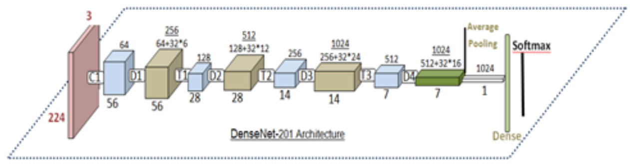


Figure 3. DenseNet-201 layer: Convolutional – Dense Block – Transition

In-detailed working of DenseNet algorithm in our proposed system has been given below:

The output of one layer is connected to the next layer after applying a combination of operations, which includes convolution, pooling, batch normalization, and an activation function. The same is represented by the following equation-1:

$$y = f\left(BN\left(g\left(conv(pool(x))\right)\right)\right) \quad (1)$$

Where:

• x is the input to the layer (e.g., input image or feature map).

• conv denotes the convolution operation.

• pool denotes the pooling operation (e.g., max pooling or average pooling).

• g represents the optional activation function applied after pooling.

• BN represents batch normalization operation.

• f represents the activation function applied after batch normalization.

Each operation modifies the given input data thus final output consist the combined result of all sequenced operations and then it combines the output feature maps of each layer with incoming feature maps. The same can be explained, let x(0) is the input to the DenseNet block and x(1) described as the feature map at layer l. Likewise the output of all the layers can be represented by using below mentioned equation(2):

$$x^{(l)} = H^l\left(\left[x^{(0)}, x^{(1)}, x^{(2)}, x^{(3)} \ldots \ldots \ldots x^{(l-2)}, x^{(l-1)}\right]\right) \quad (2)$$

Where: Hl is the transformation applied to the concatenated feature maps.

$[x^{(0)}, x^{(1)}, \ldots, x^{(l-1)}]$ represents the concatenation of feature maps up to the current layer.

DenseNet maintain feature concatenation across layers, this allows each layer to access the feature maps of all preceding layers. This helps in reusing features and promote feature propagation within the network, this can aid in continuous learning from data. Transition Layers are used to down sample between DenseBlocks, it uses batch normalization, a 1x1 convolution, and a 2x2 pooling layer. The described flow extracts the features and maintains the computing power and parameter control in the defined network.

If Hl in a DenseNet produces k feature maps each time, we can generalize the l^{th} layer as follows:

For a DenseBlocks: $x^{(l)} = H^l([x^{(0)}, x^{(1)}, \ldots, x^{(l-1)}])$

For a Transition Layer: $x^{(l)} = T^l(x^{(l-1)})$

Where: H^l in a DenseBlocks is the transformation that generates k feature maps at each step. T^l in a Transition Layer, which applies down-sampling, it is a combination of batch normalization, a 1x1 convolution, and a 2x2 pooling layer.

During the transition layer, the size of the feature map usually decreases because of pooling. It is important to cut down the computing time, resources and managing the number of parameters.

Dense Layers: Based on proposed GCDN architecture, we can see that each layer contributes 32 new feature maps to the existing features volume thus it increases to 64, 256 after going through 6 layers. The Transition Block plays a key role in this process using 1x1 convolutions with 128 filters and 2x2 pooling with a stride of 2. This mechanism reduces the size of the volume and the number of feature maps by half. Using his pattern, we can deduce that the volume in a Dense Block stays the same, while both the volume and feature maps are cut in half following each Transition Block.

3.4. Additional Convolutional Layer

We have observed that while applying output of transfer learning to the output layer directly, model is not giving the higher validation accuracy. Sometime the loss is being increased drastically over the quarter of epochs. So, to minimize the accuracy deviation, we have attached the additional layer as given in the figure-4.

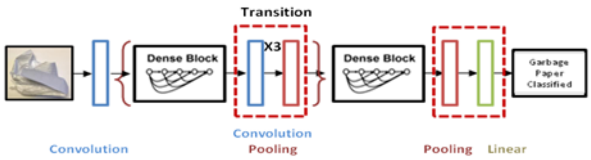


Figure4. Convolutional Neural Networks (CNNs)

CNNs have hyperparameters that are predetermined before training a machine learning model and are not acquired from the data. These parameters play a key role in the model's performance and are usually in tune through experimentation. The selection of hyperparameters is subjective by different factors, the dataset being used and the architecture in question. It often involves trial and error to find the best settings for optimal performance.

4. Experimental Setup and Result Analysis

This selection describes the training and validation accuracy, loss progress of RESNET50, DENSNET121, VGG16, and GCDN models over 50 epochs. We have used the standard garbage collection datasets publicly available at Kaggle site consisting of 12 classes of different garbage. During result analysis, we have executed all the existing models over the same datasets along with image augmentation and additional layers and compared with our model which is the GCDN. In this result analysis, we have also evaluated the class-wise training accuracy of all the models. Table 1 below describes the comparative analysis of the GCDN model with other deep learning models for 50 epochs.

Table 1: Comparative analysis of different models over 50 epochs

Model	Training Accuracy	Validation Accuracy	Final Loss
VGG16	0.9615	0.9123	0.1207
RESNET50	0.6772	0.7538	1.0070
DENSNET121	0.9776	0.9214	0.0668
GCDN	0.9864	0.9323	0.0411

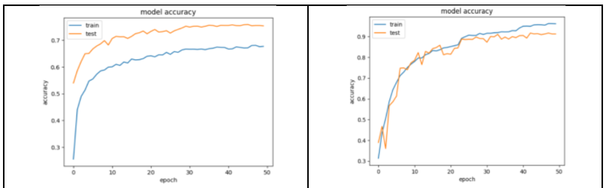
As shown in Table 1. Proposed DenseNet201 with proposed additional layer and image augmentation outperformed all other models during training as well as validation phase. We have also evaluated the class-wise accuracy of the models as shown in Table 2. The evaluation result shows GCDN's accuracy is more compared to DenseNet121, ResNet50v2 and VGG16 in major defined classes.

As shown in Table 2. The proposed GCDN model is able to correctly classify class labels green-glass, cardboard, biological waste, brown-glass and trash with more than 99% accuracy. While in other class labels the accuracy achieved more than 98%.

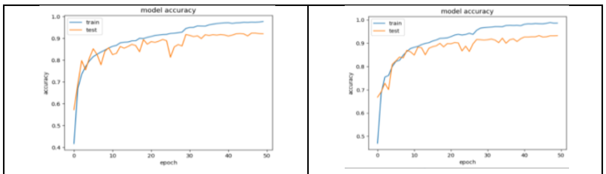
Table 2: Class wise analysis of Accuracy for different models over 50 epochs compared with GCDN.

Model Name Class Label	*DenseNet121*	*ResNet50v2*	*VGG16*	*GCDN*
clothes	97.93	90.23	97.15	98.31
shoes	98.13	92.18	96.99	98.41
green-glass	99.52	98.09	99.21	99.45
paper	98.4	96.01	97.15	98.71
cardboard	99.35	97.26	98.94	99.62
battery	98.84	98.8	97.75	98.78
biological	98.87	98.8	98.73	99.01
plastic	97.5	97.63	96.1	98.18
metal	97.97	98.51	95.71	98.31
brown-glass	99.55	98.97	99.15	99.35
white-glass	98.33	98.68	96.84	98.48
trash	99.01	98.21	98.06	99.15

Below mentioned Figure 5. and Figure 6. shown below is the accuracy and loss progress of models over 50 epochs.

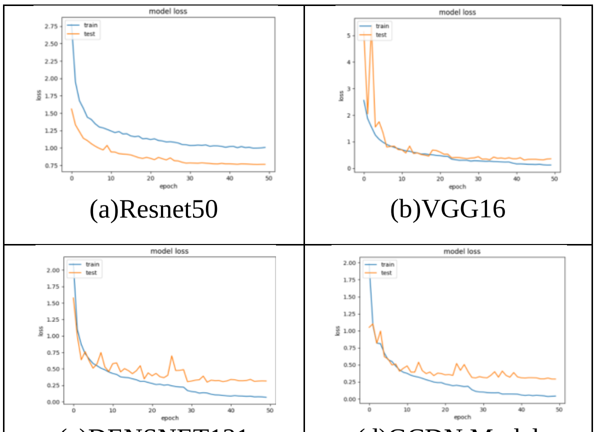


(a)Resnet50 (b)VGG16



(c)DENSNET121 (d)GCDN Model

Figure 5. Training and Testing accuracy of different models over 50 epochs



(a)Resnet50 (b)VGG16

(c)DENSNET121 (d)GCDN Model

Figure 6. Training and Testing Loss of different models over 50 epochs

During training time accuracy improvement of the RESENT50 and VGG16 will get stagnant at 67% and 88% accuracy at 25th epochs. However, the same accuracy has been achieved by the proposed model during the 10th epochs only. Oscillations decrease the loss during the validation phase in almost every model. We will work in future to achieve linearity in the validation loss function.

5. Potential real world application of the deep learning based garbage classification

This can be useful for the Governments, local authorities, Municipalities and many companies, who are specifically related with implementation of waste classification in city area. The robotic systems can be developed to identify and classify the waste and place the waste into correct bins. Such system equipped with cameras, sensors and use of this machine learning models to identify and segregate different types of waste.

The Agency which requires kind of plants to automatically sort and classify different types of waste for further use. Where collected waste from street, city were bifurcated which can helps them to identify the recycled waste or hazardous waste. In such way environment pollution can be prevented.

The classify garbage into distinct class can solve many problems related to human health, clean environment which lead to development of healthy society and nation. This can be used as educational tools to increase the awareness about recycling, reuse and well defined garbage disposal practices.

6. Conclusion

In this paper, we have proposed the Garbage Classification based on DenseNet (GCDN) model for classification of garbage into 12 different classes. In the proposed model, we applied in-memory image augmentation techniques like flipping, cropping, zooming, etc. to increase the training data. Image augmentation helped to address the overfitting issue as well as stability in the training of the model.

A transfer learning based model of DenseNet201 with additional convolution layer has improved the accuracy of the garbage collection classification as compared to other model. We have also showcased the potential application of the proposed model in the real word scenario for the production.

During the training and validation of the model, we have identified that all the state-of-the art models experienced the wide variations during initial learning process. In future, we will further modify the GCDN to achieve the stable performance in the both training and validation phase which justify the reliability of model for the actual production.

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Author contributions

Kirit Rathod: Conceptualization of proposed method, selection and articulation of dataset, Drafting of proposed system, Preparation of Analysis tables and Drafting of potential applications **Chinmay Vyas:** Execution of all existing models and generation of comparative results and graphs, drafting of section 4 (Experimental result) **Kamlesh Makvana:** Development of proposed model, Drafting of Abstract, Introduction and Conclusion **Karshan Kandoriya:** Review of existing system and drafting of section 2(Literature review). **Ashish Nimavat:** Formulation of methodology, study of Deep learning models, Drafting of proposed system.

Conflicts of interest

The authors declare no conflicts of interest.

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