Enhancing waste management through municipal solid waste classification: a convolutional neural network approach

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Article Info

Article history:

Received Apr 1, 2024
Revised Sep 30, 2025
Accepted Oct 16, 2025

Keywords:

Convolutional neural network
DarkNet53
Deep learning
Municipal solid waste
Waste classification

ABSTRACT

The escalation of population, economic expansion, and industrialization has resulted in an increase in waste production. This has made waste management more challenging and has resulted in environmental deterioration, negatively impacting the quality of life. Recycling, reducing, and reusing are viable methods to eradicate the escalating waste issue, requiring the appropriate classification of municipal solid waste. This study focuses on comparing six advanced waste classification systems that employ a pre-trained convolutional neural network (CNN) designed to recognize twelve distinct categories of municipal waste. It has been determined that DarkNet53 is the most effective classifier among these six models. To assess the effectiveness of each waste classifier, the confusion matrix, precision, recall, F1 score, the area under the receiver operating characteristic curve, and the loss function are examined. It has been found that DarkNet53 has an F1 score of 98.7% and validation accuracy of 99%, respectively. The suggested approach will be useful in promoting garbage recovery and reuse in the direction of a circular and sustainable economy.

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1. INTRODUCTION

The management of municipal solid waste (MSW) has emerged as a significant concern in developing nations, particularly in Bangladesh, due to the ongoing acceleration of economic growth and urbanization [1]. According to the World Bank in 2020, urbanization in Bangladesh is one of the quickest in any South Asian economy. Fast urbanization has led to a notable rise in garbage volume and its administration's intricacy, particularly in densely populated areas such as Dhaka. This has adversely affected urban life, the environment, and public health.

Sustainable development goal (SDG) 11, which focuses on sustainable cities and communities, aims to achieve a specific objective of diminishing the detrimental environmental effects per individual in urban areas. These objectives emphasize addressing air quality concerns and enhancing municipal and other waste management practices, aiming to accomplish these goals by 2030. However, achieving SDG targets is impeded by inadequate management practices and the development of a substantial quantity of solid waste.

It is found that the quantity of waste produced in Bangladesh increased by 1,34,300 metric tons annually, from 1,07,78,497 metric tons in 1970 to 1,47,78,497 metric tons in 2012 [2], [3]. In 2014, the annual production of urban areas amounted to 5,200,919 tons, or 0.35 kilograms per capita per [3]. Based on the latest available data, it has been observed that the average per capita MSW generation varies across several municipal districts, between 0.2 to 0.56 kg/cap/day [4]. According to a study conducted in 2016–2017, Dhaka, the capital of Bangladesh, produced a daily average of 6448.373 metric tons of MSW. This amounts to around 0.57 tons per capita each day [5]. Roughly 50% of the garbage produced in Dhaka city is effectively collected by the city corporation, while 40–60% of the garbage stays abandoned and is not disposed of safely. It is worth noting that this uncollected waste has approximately 80% organic material [4].

The accumulation of uncollected waste, namely plastic and polyethylene materials, ultimately finds its way into drainage systems and water sources, obstructing water movement inside the drains. Furthermore, the detrimental impact of waste disposal on sources of water, agricultural regions, and other crucial locations harms biodiversity and overall well-being [6]. The anticipated time for plastic degradation in the soil is around 400 years [7], and the typical timeframe for the degradation of a glass bottle when discarded in the ground as garbage is around one million years. In this scenario, the environmental impact resulting from the disposal of recycling materials, such as plastic, glass, and metal, as waste is substantial and should not be underestimated.

To a large extent, recycling infrastructure allows for the recapture of materials that would otherwise be discarded. A potentially possible approach for enhancing the handling of waste levels and transforming MSW into valuable materials or products is the implementation of source separation, as opposed to the conventional practices of incineration or landfilling. The concept of source separation involves the segregation of MSW into distinct categories based on the unique properties of each item before any further treatment processes [8]. The classification of MSW has significance since each waste category necessitates a distinct approach to its management. The methods of classified accumulation, classified shipping, and classified burial are implemented based on the distinctive characteristics of all sorts of waste. The implementation of garbage separation is a fundamental and crucial approach in MSW management, aiming to attain waste reduction, resource utilization, and environmental safety [9].

Hence, the proficient administration of MSW can substantially contribute to the development of an ecologically sustainable ecosystem. Effectively addressing waste accumulation through the adoption and application of recycling and reuse methodologies may result in this. The optimum performance of recycling systems may be achieved through the integration of technical advancements. However, it should be noted that in these systems, the breakdown of waste continues to rely on human involvement [6], [10].

Nevertheless, the advancement of artificial intelligence technologies and the implementation of deep learning frameworks have the potential to enhance system productivity in the foreseeable future, surpassing the contributions of human involvement. More specifically, the control mechanisms used by the human brain may be successfully and rapidly transformed into AI-enabled machines. In the context of this particular advancement, it becomes apparent that the use of recycling systems that rely on deep learning frameworks for waste categorization is an inevitable result [11].

As one of the more sophisticated image processing techniques, deep learning outperforms the human eye in terms of performance and yields accurate findings [12]. In the study of waste categorization, Mao *et al.* [13] utilized TrashNet dataset in a genetic algorithm to optimize fully-connected-layer of DenseNet121 and classified only six categories of waste, while Zhang *et al.* [14] applied DenseNet169 on NWNU-TRASH dataset, achieving an accuracy of 82%. Wang *et al.* [15] classified only nine waste categories with MobileNetV3 and cloud computing at 94.26% accuracy. Altikat *et al.* [16] found that five-layered convolutional neural networks (CNN) where four-layer models outperformed particularly for organic waste.

An EfficientNet-B0 model was presented by Malik *et al.* [17] to categorize specific litter categories. Nnamoko *et al.* [18] demonstrated that image resolution can have a considerable impact on performance in the classification of recyclable and organic waste, while Yudhana and Fahmi [19] categorized images into organic and inorganic garbage using CNN. Pitakaso *et al.* [20], [21] proposed a variety of CNN models of a dual ensemble deep learning framework where geometrically enhanced pictures were selected for post-disaster waste classification.

However, Hamzah *et al.* [22] used Faster R-CNN to categorize five trash categories in an integrated mobile app, Jose and Sasipraba [23] presented a hybrid model that combined Faster R-CNN with a complex-valued encoding multi-chain seeker optimization algorithm (CMSOA) method. The effectiveness of enhanced CNN models was shown in [24], who achieved an accuracy of 94.40%. With 93.28% accuracy, Chhabra *et al.* [25] presented an improved deep convolutional neural network (DCNN). For garbage classification, Prasanth and Raut [26] favored EfficientNetB0 above alternative models, with a 94.15% accuracy rate, and Qiu *et al.* [27] achieved 95.4% accuracy by enhancing CE-EfficientNetV2 with data augmentation and attention methods.

CNN models such as DenseNet169, MobileNetV2, and ResNet50V2 were compared for garbage classification [28]. Abood and Al-Talib [29] assessed VGG16, InceptionV3, MobileNetV2, and EfficientNetB0, with accuracies ranging from 92% to 97%. On the other hand, Jayaraman and Lakshminarayanan [30] created MSW-Net, a hierarchical model employing CNN and Bayesian-optimized MobileNet models, whereas a CNN and Graph-LSTM model with a 97.5% accuracy for six waste classes was provided by Li and Chen [31]. Using ResNext-101 with federated learning, Khan *et al*. [32] obtained an accuracy of 89.62%. Tasic *et al*. [33] used CNNs with AdaBoost and XGBoost to classify organic and recyclable garbage in a binary manner with an accuracy of over 89.61%. Islam *et al.* [34] proposed a tailored DenseNet201 architecture with an integrated attention mechanism, setting a new benchmark for adaptable waste classification.

Previous research has integrated image classification technologies and machine learning approaches to enhance waste classification. However, these studies are subject to certain constraints. The limitations of the study encompass several aspects. Firstly, the waste classification system under investigation exhibits a limited number of waste items. Secondly, the existing waste classification model's accuracy falls short of the desired level. The proposed model addresses both of these problems. The proposed waste classifier is distinctive in that, unlike the previous classifier, which can categorize a maximum of six classes, the proposed model can classify twelve classes. In this study, six CNN architectures, specifically Resnet50, Resnet101, Resnet152, DarkNet53, GoogleNet, and InceptionV3, are employed to classify 12 distinct kinds of municipal waste through the extraction of high-quality features from the image of waste.

2. METHOD

2.1. Sample collection

To construct a predictive model, it is imperative to undergo a training process [35]. The utilization of intelligent systems in lieu of human labor within waste management facilities is an essential prerequisite for achieving both economic efficiency and ensuring a safe recycling process. Hence, the objective of this study is to identify and acknowledge several prevalent recyclable materials, including paper, cardboard, organic waste, metal, and plastic.

The train data set has been sourced from Kaggle. Kaggle is an online platform and community that facilitates data science competitions and serves as a gathering place for data scientists and machine learning practitioners. The dataset comprises a total of 15,150 images, each belonging to one of twelve distinct categories representing various types of municipal waste. These categories include paper, cardboard, organic content, metal, plastic, green-glass, brown glass, white-glass, clothes, shoes, batteries, and trash.

2.2. Data preprocessing

Data pre-processing is the crucial step in machine learning that involves cleaning, transforming, and preparing the data to make it suitable for the model prediction [36]. In this project, three types of data transformation, namely rescaling, random crop, and random flip, are used to process the data set. The rescaling layer scales the pixel values of the input images by dividing them by 255. This step ensures that the pixel values are in the range of [0, 1]. The RandomCrop layer randomly crops the input images to a specified size of 224×224 pixels. This step helps in data augmentation and introduces variations in the input data. The RandomFlip layer randomly flips the images horizontally. This augmentation technique further enhances the diversity of the training data. The rescaling layer does not change the image size but only scales the pixel values. The RandomCrop (training data) and resizing (test data) layers modify the image size by cropping or resizing, respectively. After all this, we got pixel size 224×224 for every image.

2.3. Data partitioning

Total observation is divided into three parts: training data, validation set, and test data. Train data is used to train the predictive model, validation data is used to validate the model, and the test data set is used to evaluate the performance of the final model [37]. A total of 60% of the data is used to train the model, 20% of the data is used to validate the model, and the remaining data is used to test the final predictive model.

2.4. Model training and testing

The proposed model employs pre-trained weights from ImageNet to initialize the ResNet50, ResNet101, and ResNet152 models. Subsequent to the freezing of the layers within the models, additional layers are incorporated to facilitate the process of classification. Before compiling an overview of the model's architecture, the model is assembled by incorporating an optimizer, loss function, and metrics. The process that is used for each ResNet architecture entails utilizing input images with dimensions of (224, 224, 3) pixels, where the height is 224 pixels, the width is 224 pixels, and there are three color channels corresponding to the RGB color model. The ResNet model accepts input images with dimensions (224, 224, 3) and proceeds to process them through its numerous layers. The ResNet101 model maintains the original dimensions of the input images.

Following the implementation of the ResNet model, a GlobalAveragePooling2D layer is incorporated. The following layer does global average pooling across the spatial dimensions of the feature maps produced by the preceding layers, resulting in a reduction of the spatial dimensions to a predetermined size. Consequently, a feature vector with dimensions of (1, 1, 2048) is obtained. Afterwards, a dense layer comprising 12 units is incorporated after the global average pooling layer. The fully connected layer is responsible for acquiring and discerning distinct patterns and features that facilitate classifying images into 12 distinct classes. The feature vector obtained from the preceding phase is flattened and fed into the dense layer. Following that, a softmax activation function is incorporated into the activation layer after the dense layer. The aforementioned layer generates the probability of each class within the set of 12 classes.

The ResNet model maintains a consistent image size throughout its architecture without altering the dimensions of the images. The alterations in size solely transpire during the preprocessing stages preceding the model. The model is trained for 20 epochs, after which its performance is determined. After the model training, the test data is applied to the model, and the performance of the model is evaluated.

3. RESULTS AND DISCUSSION

This study employs six distinct CNN architectures to categorize twelve municipal solid debris classifications accurately. The model is trained using the stochastic gradient descent momentum method for optimization, with an initial learning rate of 0.001. The initial learning rate was set at a small number since a high value might lead the rate to diverge or produce worse-than-ideal results. Nevertheless, the stochastic gradient descent process tends to fluctuate while following the trajectory of the steepest drop towards the optimal solution. One method to decrease this oscillation is by including momentum parts in the parameter update [38]. The momentum parameter in this study is assigned a constant value of 0.9.

In this study, data normalization is performed prior to the use of training data to prevent overfitting. Normalization is a crucial and effective technique for reducing generalization errors and dealing with overfitting in deep learning models caused by various parameters. In this study, the L2 regularization is adjusted at 10e-4 to limit the gradient value and provide a threshold for the gradient. The evaluation of each waste classifier involves analyzing the confusion matrix, area under the receiver operating characteristic curve, precision, recall, F1 score, and loss function to determine their efficacy.

3.1. Confusion matrices

Figure 1 illustrates the confusion matrix, with DarkNet53 in Figure 1(a), GoogleNet in Figure 1(b), InceptionV3 in Figure 1(c), ResNet50 in Figure 1(d), ResNet101 in Figure 1(e), and ResNet152 in Figure 1(f) [39], [40], all of which were utilized in the performance evaluation of the classification models. The confusion matrix is also evaluated for the rest of the models. The rows of the matrices contain the predicted values for the following categories: cardboard, glass, metal, paper, plastic, and debris. The columns of the matrices contain the actual values corresponding to the same categories.

In Figure 1(a), the diagonal line reflects the accurate classification of trash photos, while the values elsewhere indicate the number of waste images that are not correctly classified. In Figure 1(a), 365 battery trash photos are appropriately labeled as batteries, but four paper samples, four metal samples, and one shoe category sample are wrongly labeled as batteries. It is found that the confusion matrix for DarkNet53, InceptionV3, GoogleNet, ResNet50, ResNet101, and ResNet152 can correctly sort up to 6144, 6121, 5954, 2980, 2993, and 2993 pictures, respectively.

The precision of predicting each class may be determined using the confusion matrix. Figure 2 illustrates a comparative comparison of several categorization methods based on their precision values. A higher precision score indicates that the model can accurately categorize the most positive classifications within a certain category. The graph demonstrates that the DarkNet53 model accurately identifies most categories. DarkNet53 demonstrates effective classification in eight out of the twelve categories. In the four remaining categories, InceptionV3 outperforms DarkNet53 is performing well. Nevertheless, the accuracy of DarkNet53 for these four categories is marginally inferior to that of InceptionV3.

3.2. Receiver operator characteristic and area under the curve

The receiver operator characteristic (ROC) curve is a tool that researchers have utilized to assess the predictive power of a model [41]. The confusion matrix may be used to obtain the ROC curve. The area under the curve (AUC) is beneath the coordinate axis and the ROC curve [42].

The typical range for AUC is 0.5 to 1. The accuracy rate of a classifier is higher if its AUC is larger. Concerns about binary classification are particularly amenable to the application of the AUC-ROC curve. However, by utilizing one-to-many techniques, it is possible to extend its scope to encompass other classification issues that involve many classes [43]. This study examines twelve distinct classifications of garbage, and Figure 3 illustrates the ROC curves, with DarkNet53 in Figure 3(a), GoogleNet in Figure 3(b), InceptionV3 in Figure 3(c), ResNet50 in Figure 3(d), ResNet101 in Figure 3(e), and ResNet152 in Figure 3(f). One common use of ROC analysis is evaluating classification algorithm performance by demonstrating the correlation between true positive and false positive [44]. There is a way to evaluate the effectiveness of the categorization using the AUC. A higher AUC indicates more precise categorization. By analyzing the ROC curve of several classifiers, it is evident that the AUC is greater for the DarNet53 classifier than for other classification models. Hence, DarkNet53 has superior predictive capabilities compared to the other models. Additionally, it is noted that when comparing DarkNet53 to other models, the true positive rate is greater across all category types. Concerning the entire number of positive samples, the classifier properly identifies the most positive samples. As a result, the model's sensitivity is high.

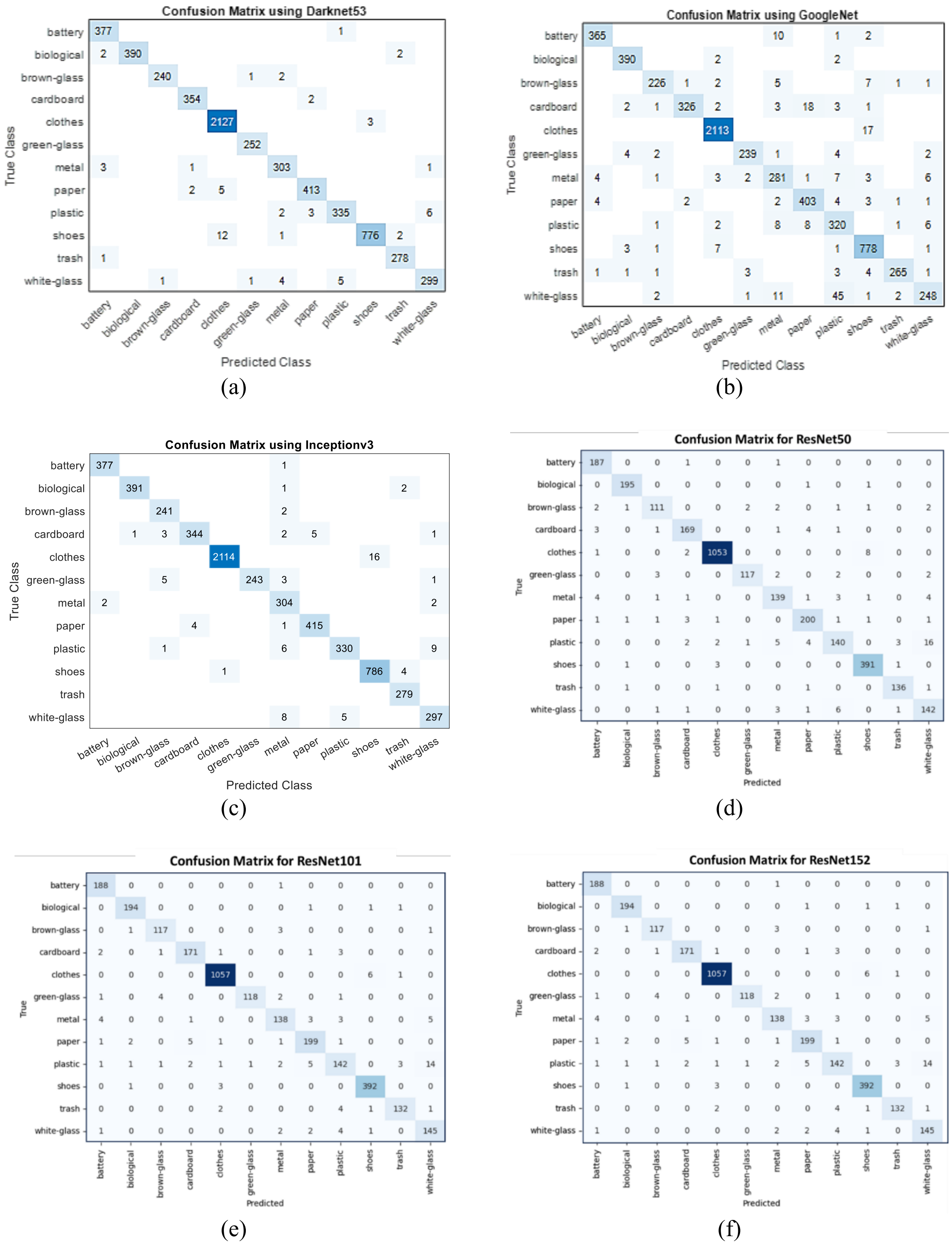


Figure 1. Confusion matrix for (a) DarkNet53, (b) GoogleNet, (c) InceptionV3, (d) ResNet50, (e) ResNet101, and (f) ResNet152

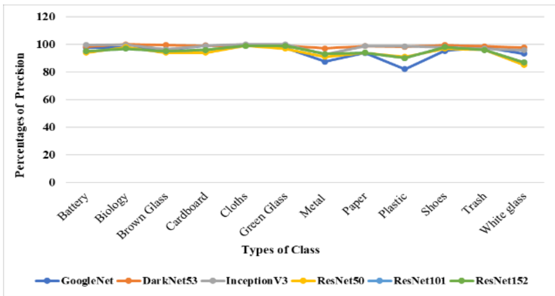
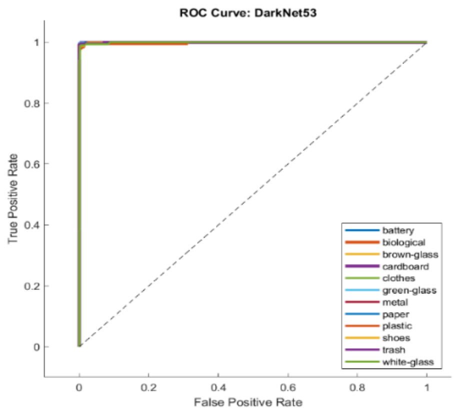


Figure 2. The precision of different models for different classes



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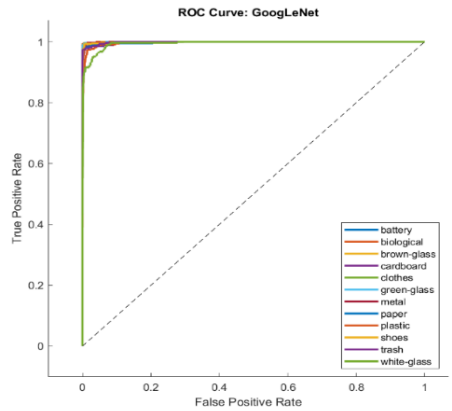

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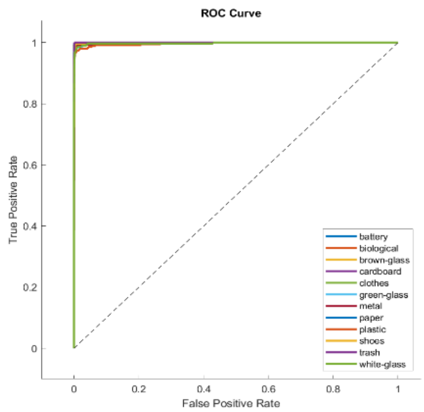

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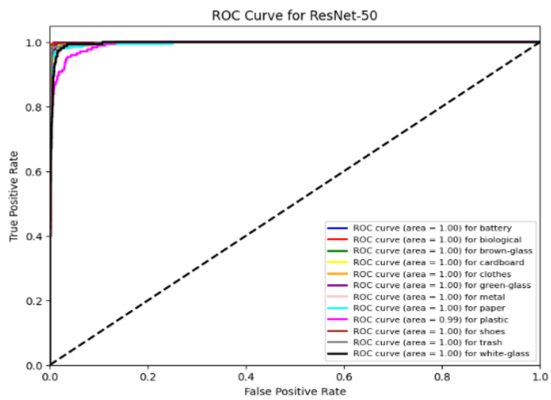

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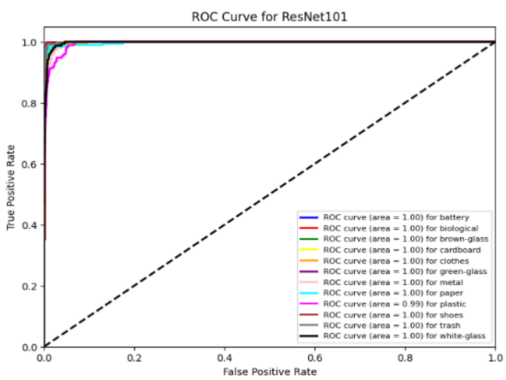

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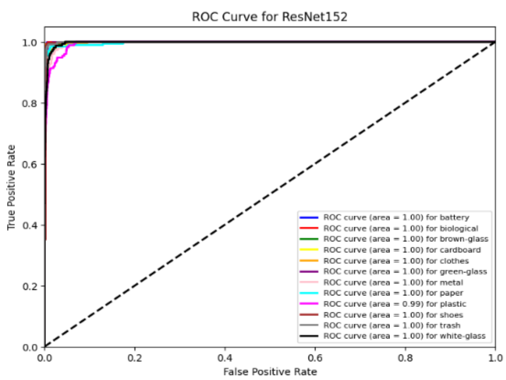


(f)

Figure 3. ROC for (a) DarkNet53, (b) GoogleNet, (c) InceptionV3, (d) ResNet50, (e) ResNet101, and (f) ResNet152

3.3. Accuracy and loss curve

In addition, the accuracy plot and the training loss curve were utilized to assess the performance of the various classification models. When learning models are introduced to a new task, learning curves are thought to be useful tools for tracking their success. Learning curves are a mathematical description of the learning process that happens as a result of task repetition [45]. Throughout the training process of a machine learning model, it is possible to assess the model's present state at each iteration of the training algorithm. The model's performance may be assessed by evaluating it on the training dataset, providing insights into its learning capabilities. Additionally, it may be assessed using a separate validation dataset that is not included in the training dataset. The model's generalizing abilities are shown by analyzing the validation dataset. Based on the accuracy curve, it is evident that all models exhibit strong performance on the training data. Their validation and training accuracy are progressively improving, suggesting that the learning model effectively fits the training data. The accuracy curve of DarkNet53 is represented in Figure 4. The accuracy curve for InceptionV3, ResNet50, ResNet101, ResNet152, and GoogleNet can be found in Figures 5(a) to 5(e). It is found that the validation accuracies of GoogleNet, DarkNet53, InceptionV3, ResNet50, ResNet101, and ResNet152 are determined to be 95.92%, 99%, 98.61%, 94.29%, 94.21%, and 95.10% correspondingly.

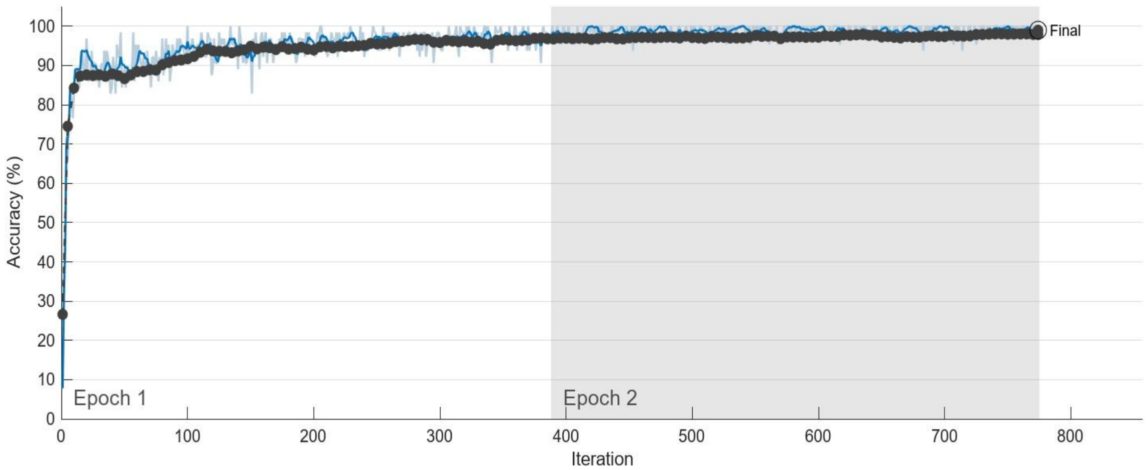


Figure 4. The accuracy curve for DarkNet53

The loss curve is another metric for evaluating the deep learning model's efficacy. The loss curve for DarkNet53, InceptionV3, GoogleNet, ResNet50, ResNet101, and ResNet152 can be found in Figures 6(a) to 6(f). The loss curve of all models demonstrates a consistent decrease in training and validation loss as the number of iterations rises. The loss curve for the GoogleNet, DarkNet53, and InceptionV3 models exhibits reduced training and validation losses compared to the other models. Additionally, it is evident that the training error is smaller than the validation error, and the discrepancy between the validation and training errors is minimal. These indicators suggest that the models are not suffering from overfitting. Table 1 presents a comparative comparison of six distinct MSW classifiers. Table 1 demonstrates that DarkNet53 exhibits greater recall and precision values. The recall value of 98.7% indicates that the model can accurately categorize 98.7% of trash items into a certain category. Roughly 1.3% of certain trash is misclassified into other categories. The harmonic mean of accuracy and recall is represented by the F1 score [46]. Elevated values of the F-measure, which range from zero to one, indicate superior classification performance. The F1 score of DarkNet53 is significantly high, as shown in Table 1. As a result, DArkNet53 exhibits superior classification performance compared to the other models.

Table 1. Comparative analysis between different predictive models

Criteria	DarkNet53 (%)	InceptionV3 (%)	GoogleNet (%)	ResNet50 (%)	ResNet101 (%)	ResNet152 (%)
Accuracy	99	98.61	95.92	94.29	94.21	95.10
Precision	98.8	97.94	94.75	94.16	94.91	94.91
Recall	98.71	98.20	93.94	94	95	95
F1 Score	98.8	98.1	94.34	94	95	95

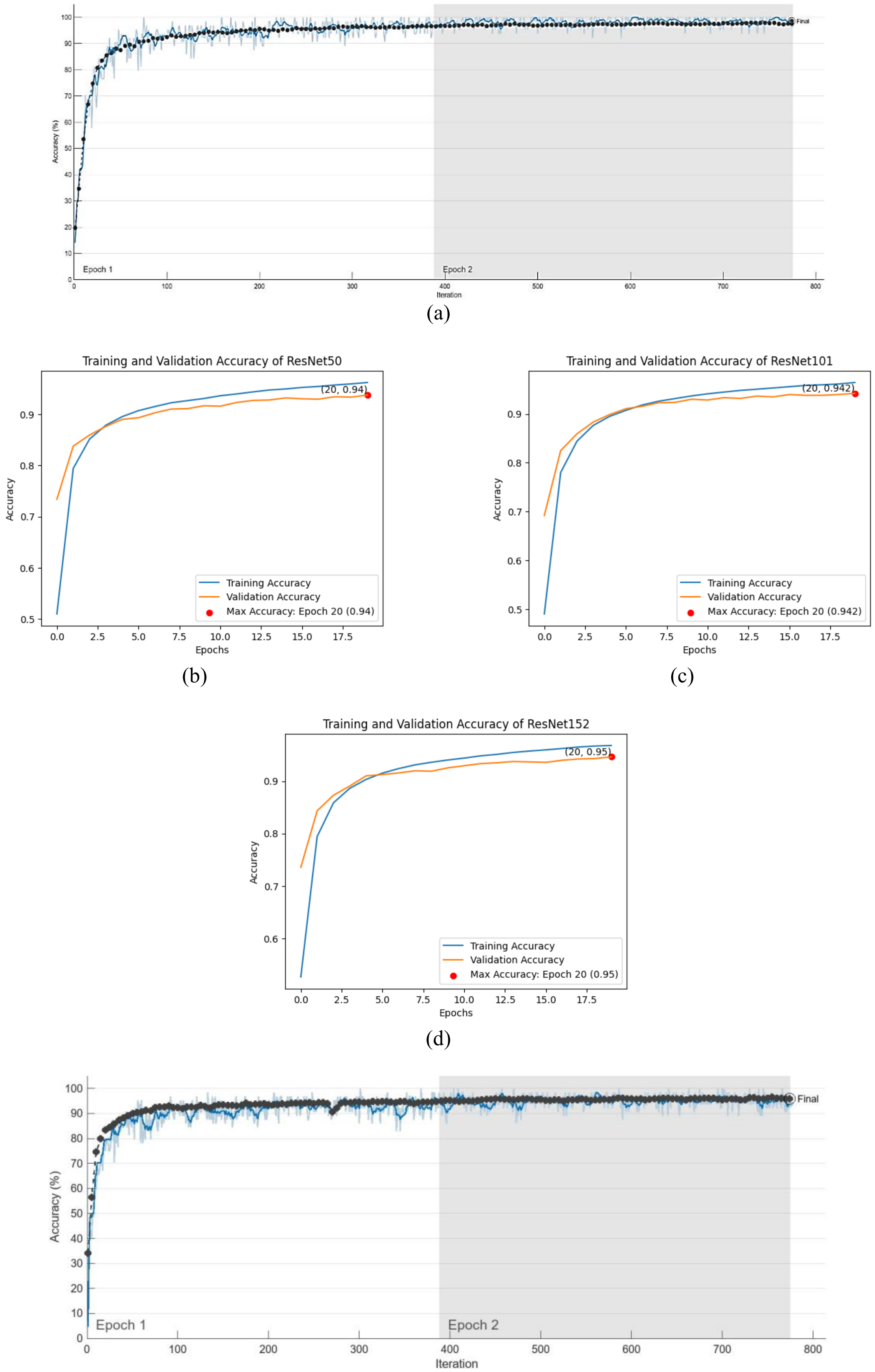
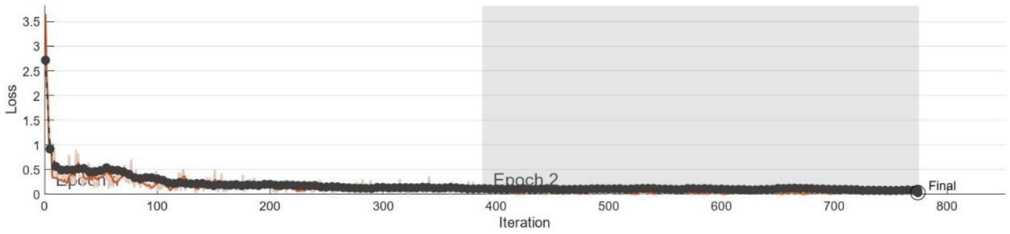
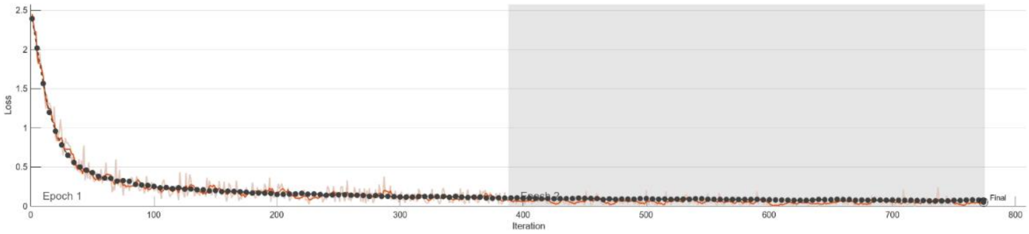


Figure 5. Accuracy curve for (a) InceptionV3, (b) ResNet50, (c) ResNet101 (d) ResNet152, and (e) GoogleNet



(a)



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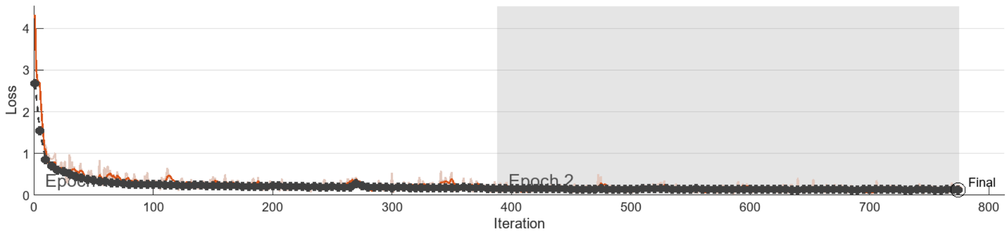

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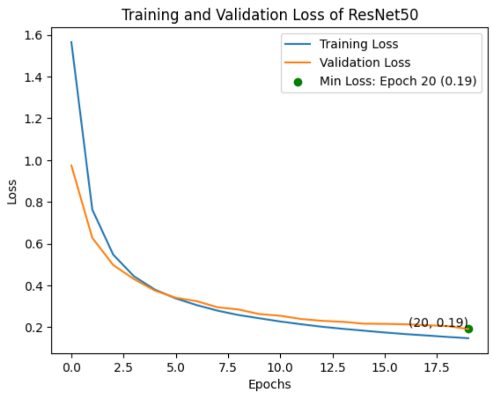

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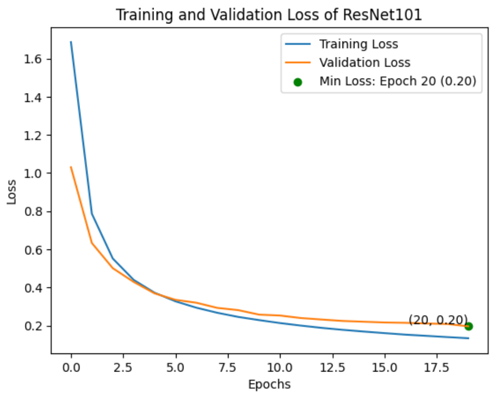

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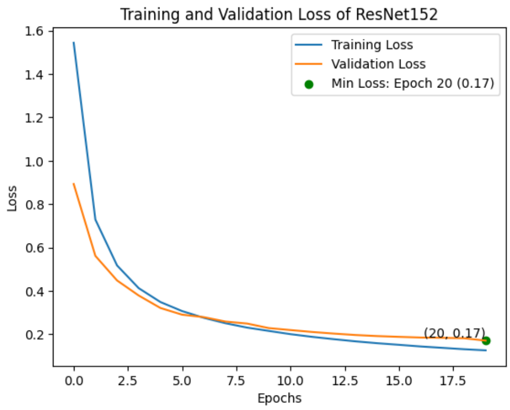

(f)

Figure 6. Loss curve for (a) DarkNet53, (b) InceptionV3, (c) GoogleNet, (d) ResNet50, (e) ResNet101, and (f) ResNet152

4. CONCLUSION

This research study presented an effective waste classification model categorizing twelve distinct forms of MSW. Six distinct models for classifying garbage are presented, and a thorough study is conducted to compare them. The performance of these six classifiers is assessed based on the confusion matrix, ROC, accuracy curve, loss curve, precision-recall, and F1 score. It has been determined that DarkNet53, which has a validation accuracy of 99%, is the most effective classifier among these six models. However, garbage exhibits many shapes, encompassing various sorts, colors, and textures. Additionally, the methods of rubbish collection differ significantly from those used for regular commodities. Due to this factor, the suggested model will exhibit subpar performance when applied to actual photos that overlap with each other. Simultaneously, while categorization is undeniably a crucial stage, the actuator's effectiveness must also be considered for achieving actual automated sorting. Subsequent research will involve evaluating the suggested model on more datasets and developing an effective actuator to enhance the overall accuracy and efficiency of categorization.

FUNDING INFORMATION

Authors state no funding involved.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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Zakir Hossain					✓	✓	✓			✓	✓			
Md. Sabbir Reza			✓	✓	✓	✓	✓			✓				
Shajjadul Haque					✓	✓	✓			✓				

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

Data utilized to support the outcome of this study addressed within the article.

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