DeepMSWC: Municipal Solid Waste Classification (MSWC) using a lightweight Deep Learning Model

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Abstract

The impact of properly classifying municipal solid waste on waste management is a critical aspect of zero waste landfill (ZWL). Effective waste classification allows for more targeted recycling, composting, and disposal efforts, which in turn can reduce the strain on natural resources and minimize environmental impact. Additionally, proper waste classification promotes the implementation of sustainable practices and policies, contributing to overall ZWL and social well-being. In the context of urban development, image-based garbage classification has emerged as a critical focal point within the computer vision community. Convolutional Neural Networks (CNNs) have proven to be highly adept at feature learning, making them the prevailing approach in image classification. However, CNNs often entail a substantial number of parameters and rely on extensive training data. This article addresses the challenge of developing a lightweight neural network for municipal solid waste classification, with a focus on learning classifiers with minimal model parameters. The study leveraged the TrashNet benchmark dataset and extended it to include a new class, ‘compost’, in addition to the original classes such as ‘cardboard’, ‘glass’, ‘metal’, ‘plastic’, ‘paper’, and ‘trash’. Notably, the research employed two powerful architectures, RegNet and EfficientNet, to create a more resilient and efficient model. The proposed hybrid model utilizes feature extraction from both RegNet and EfficientNet, integrating their respective features for classification. This lightweight deep learning (DL) model, DeepMSWC, achieved an impressive validation accuracy of 92.73 %.

Keywords: Classification, convolutional neural network, deep learning, Efficient Net, municipal solid waste, RegNet, zero waste landfill.

1. Introduction

Solid waste includes different types of waste such as domestic waste, sanitary waste, commercial waste, and others. Waste generators, including individuals, residential, and non-residential establishments, are responsible for managing the waste they produce, according to the Solid Waste Management Rules of 2016 [33]. These rules require waste generators to segregate and store the waste they produce in three separate streams: biodegradable, non-biodegradable, and domestic hazardous wastes. They should then hand over segregated waste to authorized waste pickers or collectors. Additionally, they must ensure that solid waste is not thrown, burnt, or buried in open public spaces or water bodies. If these rules are violated, the consequences can include imprisonment for up to five years and/or a fine of up to Rs. one lakh, with an additional fine for each day the offense continues.

Sorting waste is essential for improving recycling efficiency, reducing landfill waste, conserving resources, creating economic benefits, and minimizing pollution. Accurate sorting leads to better recyclables and efficient waste handling, while also reducing emissions and extending landfill life. Moreover, recycling conserves resources and reduces environmental impact, as well as creates jobs and generates revenue from recycled materials. Effective waste sorting and recycling also help minimize pollution and manage hazardous waste. Waste management practices often lack efficiency and require substantial human intervention, the need for automatic waste segregation becomes increasingly apparent. The significance of deep learning based classification models is increasingly gaining attraction among researchers. This has further motivated future researchers to harness their innovative thinking abilities to expand the domain of artificial intelligence (AI) based solutions.

In this work, a deep learning-based solution has been proposed for municipal solid waste classification, specifically the recyclable waste materials. Furthermore, designing any deep learning model may require an additional burden of higher computation cost due to the huge model parameter constraints. On the other hand, decreased model parameters may result in poor validation accuracy which is not desirable to any automated system. Hence, the design of a lightweight model requiring fewer model parameters that also provides higher performance measure is highly acceptable specifically in embedded system-based application domain.

Contribution of the proposed model:

- The work has considered two recently proposed deep learning models RegNet and EfficientNet to design our hybrid model architecture.
- The dataset that has been utilized into our framework is a popular benchmark dataset TrashNet. Additionally, some changes have also been incorporated by adding one additional class called ‘compost’ to make the model robust against challenging situations.

- The proposed model has scored higher performance measure in terms of validation accuracy by considering fewer model parameters. Hence this type of model can be applied to embedded systems as well as mobile based applications.
- The paper also shows a comparative study among different state-of-the-art classification models and shows that the proposed hybrid model achieves highest performance measures, hence is more preferable specifically for the application domain such as MSW classification.

2. Related Works

In this paper, a number of papers ranging from the year 2019 to 2023 have been considered to prepare the review study. In these five years of window, a number of neural network based models implemented for the task of image classification, object detection, and object segmentation. In this section, some recent works specifically neural network based frameworks have been considered that are designed for waste classification and detection tasks. The papers that have been considered in this review study can be categorized into three sub-categories: machine learning (ML) based, deep learning based, embedded system based.

Papers [1, 5], show an integrated ML based approach that has utilized the ResNet-50 for the task of feature extraction. After the process of feature extraction, the extracted features are fed to the multi-class SVM model to do the classification. In some works [2, 22], the deep learning frameworks utilized the EfficientNet as the base model and proposed some efficient model architectures such as EfficientDet-D2 to localize litter, EfficientNet-B2 or EfficientNet-B0 for classifying litter. The paper [6] has made a comparative study among three ML models such as SVM, random forest, and decision tree; along with one DL based solution. The paper clearly shows that the DL based solution framework outperforms the others. Some recent works [7, 8, 21] have utilized the concept of residual neural networks such as ResNet18, ResNet50, and Inception-ResNet for the task of waste classification. Some other models [9, 14, 15] have also been incorporated to reduce the computational burden by considering the transformer based model architectures that have utilized the concept of parallel computing, hence reducing the training time. There are some simple deep learning models [11, 12, 18] that have used very simple model architecture such as VGG16, VGG19, and AlexNet as the base model to implement their model architectures. Some recent works [16, 17] implemented their waste classification model by utilizing some advanced DL frameworks such as MobileNetV2 and ConvNeXt. Similar to classification models, the review also shows some waste detection models [10, 19, 20] that have utilized the one-stage object detection framework such as YOLO to perform the waste detection task. Furthermore, some embedded frameworks [3, 4, 23] are also designed by utilizing some microcontroller based IoT methodology to acquire the data and then uses machine learning or deep learning-based methodology to do the waste classification.

3. Proposed Methodology

3.1 Dataset Description

The proposed methodology has utilized the benchmark dataset TrashNet [34] which contains 2527 images of six different classes: cardboard (403) images, glass (501) images, metal (410) images, plastic (482) images, paper (594) images, and trash (137) images (as shown in Figure. 1). Whereas, our work has upgraded the original dataset to the new customized TrashNet dataset which contains 2751 images after adding several compost (177) images and some images (47) to the 'trash' class data. Hence the final dataset contains 7 different waste categories for both recyclable and bio-degradable wastes such as 'cardboard', 'glass', 'metal', 'paper', 'plastic', 'trash', and 'compost' (as shown in Figure. 2). The training dataset contains 2187 images, and test dataset contains 564 images.

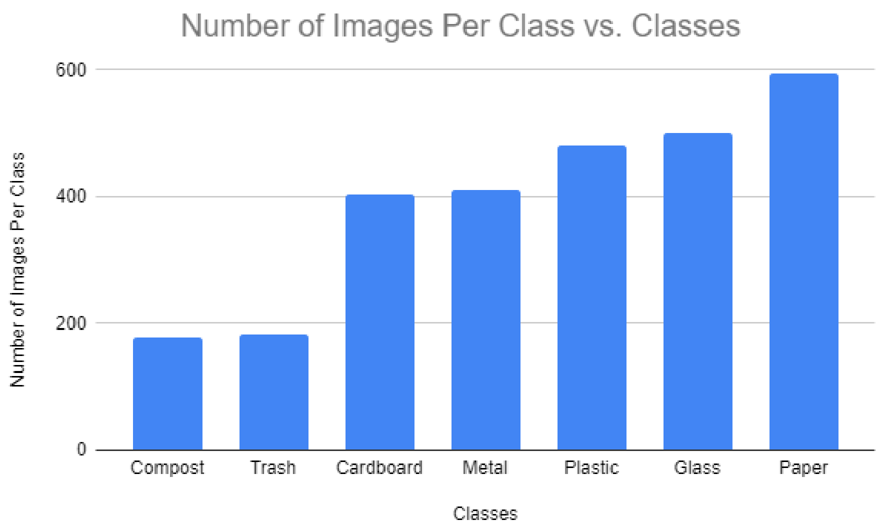
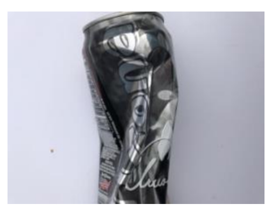


Figure. 1: Distribution of images per class.


(a) Cardboard


(b) Glass


(c) Metal


(d) Paper


(e) Plastic


(f) Trash


(g) Compost

Figure. 2: Sample dataset images for each seven categories.

3.2 Details of Some Deep Learning Models

The work also considered some state-of-the-art classification models such as: AlexNet, VGG16, ResNet50, InceptionV3, Xception, MobileNet, EfficientNet, NASNetMobile, and RegNetX002. The following table (Table 1) shows the description for each of the model architectures.

Table 1: Details of all the model architectures that are utilized in our MSW classification task.

Model	Number of CNN Layers	Number of Fully Connected Layers
AlexNet [24]	5	3
VGG16 [25]	13	3
ResNet50 [26]	49	1
InceptionV3 [27]	83	1
Xception [28]	36	1
EfficientNetB0 [29]	33	1
MobileNet [30]	27	1
NASNetMobile [31]	73-78	1
RegNetX200 [32]	27	1
Proposed Model (DeepMSWC)	43	2

3.3 Proposed Model Architecture

In this paper, a deep learning (DL) based model has developed to achieve higher performance measures by utilizing fewer model weight parameters. While designing any deep learning based model, it has observed that decreasing the number of model parameters may decrease the performance measure. Whereas, the proposed model has achieved higher performance measures instead of decreasing the model weight parameters.

Step1: Selection of the Base Models used in the Proposed Hybrid Model

Before the implementation of our model, some recently introduced classification models have also been utilized for the task of waste classification. Our work has analyzed the working principle of various models to identify the most suitable candidates for the proposed model architecture. Our evaluation focused on the balancing of both the model performance and the number of model weight parameters, leading us to select **RegNet** and **EfficientNet** as our base models. These models were chosen due to their relatively low number of parameters, making them ideal for applications where efficiency and resource constraints are critical.

Step 2: Determine the Learning Mechanism to Design the Hybrid Model

The work has employed the concept of ensemble learning to perform model hybridization. In creating a hybrid model, ensemble learning allows us to combine multiple models, leveraging their individual strengths while mitigating their weaknesses. This approach aims to develop a more reliable and accurate predictive model by integrating different learning algorithms or methodologies, ultimately enhancing overall model performance.

Step 3: Selection of Fusion Methodology used by the Proposed Model

There are various types of fusion methodologies that can be incorporated to design any hybrid model such as: Fusion of model architecture and fusion of extracted features. Moreover, combining different types of model architectures creates a more powerful and versatile machine learning system. This approach leverages the strengths of various architectures and can improve performance by integrating diverse learning strategies. On the other hand, fusion of features means after completing the training process, it is possible to gather and combine features from various models in order to construct a more extensive and thorough feature representation. This approach can lead to a more robust and insightful understanding of the underlying data. After implementing the feature fusion by using a concatenation operation the concatenated feature vector get forwarded to the fully connected (FC) layer to do the classification.

Both fusion methodologies were implemented and the feature fusion [13] approach demonstrated provides superior performance measures compared to the other method. The following figure (Figure 3) presents the block diagram of the feature fusion-based model hybridization technique, which is a key component of the proposed model architecture.

Table 2: List of model hyperparameters that remain fixed for all the models into consideration.

Model Hyperparameters	
Activation Function	‘relu’
Loss Function	‘categorical_crossentropy’
Optimizer	‘Adam’
Learning Rate	1e-5
Epochs	50
Image Size	224 × 224
Batch Size	32

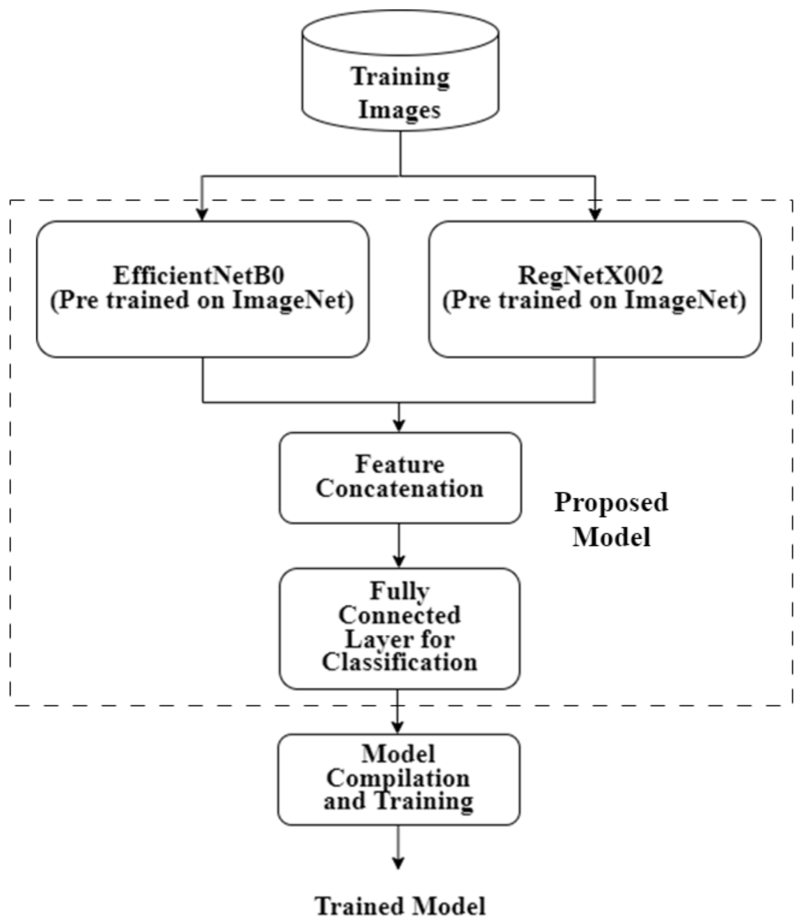


Figure. 3: Block diagram of our proposed hybrid model architecture.

4. Experimental Results

4.1 System Specification

The work has used the Google Colab Pro+ environment, which allows us to write and execute Python code designed for a specific machine learning based application through the browser. Furthermore, no initial setup is required because it has a built-in Jupyter notebook service that requires no setup while providing resources, including Graphics Processing Units (GPUs). The experimental environment consisted of a Windows 10 operating system, Intel® Xeon® 2.30 GHz Processors, 26 GB running memory (RAM), NVIDIA Tesla P100-PCIE-16 GB GPU, and 129 GB disk space.

4.2 Performance Evaluation

While evaluating the performance of the various models that are considered in this paper, the various performance measures that have been utilized are ‘loss’ and ‘accuracy’. The loss values of the models have been calculated by considering ‘categorical_crossentropy’, as the work has developing a multiclass classification model. On the other hand, model’s classification accuracy has been computed by observing the ration among the number of correct predictions and the number of total predictions. Equations for both the loss and accuracy have been given below (as shown in Eq. 1 and Eq. 2).

The categorical cross entropy loss has computed by using the following formula:

$$\text{Loss} = -\frac{1}{n}\sum_{i=1}^{n}\sum_{c=1}^{C} y_{i,c}\log(\hat{y}_{i,c}) \quad \ldots\ldots\ldots\ldots\ldots \text{Eq, (1)}$$

Where,

n = Number of samples,

C = Number of classes,

$y_{i,c}$ = Binary indicator (0 or 1) if class label c is the correct classification for sample i,

$\hat{y}_{i,c}$ = Predicted probability of class c for sample i.

The classification accuracy of a model is a measure of how often the model’s predictions match the actual labels. The formula for calculating classification accuracy is:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad \ldots\ldots\ldots\ldots\ldots \text{Eq, (2)}$$

Where,

TP (True Positives)**:** The number of positive samples correctly classified as positive,

TN (True Negatives)**:** The number of negative samples correctly classified as negative,

FP (False Positives): The number of negative samples incorrectly classified as positive,

FN (False Negatives)**:** The number of positive samples incorrectly classified as negative.

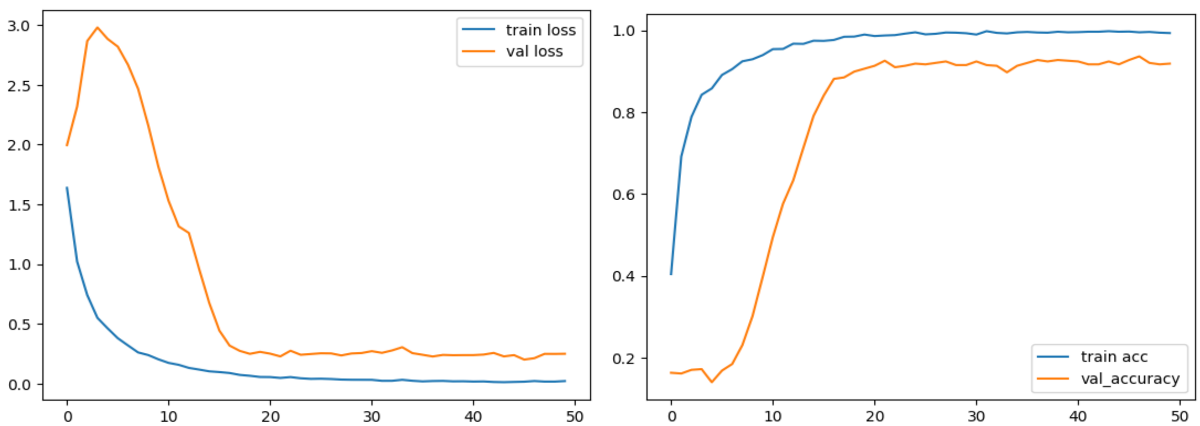
4.3 Comparative Study among Various Models

In this work, various state-of-the-art classification models have implemented, followed by a comparative study among them. During the comparison (as shown in Table 3), certain hyperparameters, listed in Table 2, were kept constant across all models under consideration.

Table 3: Performance measures provided by each of the models along with their number of model weight parameters.

Model	Number of Model Parameters	Accuracy

AlexNet	222.44 MB	65.07%
VGG16	156.15 MB	88.65%
ResNet50	484 MB	91.84%
InceptionV3	91.20 MB	91.13%
Xception	177.59 MB	90.43%
MobileNet	61.32 MB	89.54%
NASNetMobile	66.83 MB	85.82%
RegNetX002	26.53 MB	86.52%
Proposed Model (DeepMSWC)	108.69 MB	**92.73%**



(a) (b)

Figure. 4: (a) Loss graph for the proposed model; (b) Accuracy graph for the proposed model.

4.4 Results and Discussions

In this section, the reader will get the key insights and findings that are derived from the results that are given in Table. 3. The result analysis part has considered two different measures: ‘Model Parameters’ and ‘Accuracy’, to compare various classification models that have been employed for the task of municipal solid waste classification. Some additional observations based on the loss and accuracy measures also been highlighted in Figure. 4.

The summary of our experimental result analysis has described below.

- As discussed earlier, one of the primary objectives of this study is to develop a deep learning model to utilize fewer model weight parameters, hence reducing the computational burden to achieve higher performance measures. The above table has shown that the number of model weight parameters of our proposed model has reduced by 51.14%, 30.39%, 77.54%, and 38.80% with respect to AlexNet, VGG16, ResNet50, and Xception models, respectively.

- The proposed model also shows improved performance measures in terms of model accuracy. By analysis the accuracy measures of various models, it has been concluded that the proposed model has achieved improved classification accuracy score which is increased by 29.83%, 4.40%, 0.96%, 1.72%, 2.48%, 3.44%, 7.45%, and 6.70% with respect to AlexNet, VGG16, ResNet50, InceptionV3, Xception, MobileNet, NASNetMobile, and RegNetX002, respectively.
- The result analysis section also helps the reader to get a clear pictorial overview of the behaviour of the model. Furthermore, Figure. 4a shows how the loss of the model decreases both for the training and validation data depicted by two different curves. On the other hand, Figure. 4b shows how the accuracy of the model increases at the optimum level for the training as well as validation data. Both the loss and accuracy curves have been calculated using Eq. 1 and 2, respectively, to generate the graph responses.

5. Conclusion

In this study, a deep learning based model (DeepMSWC) has been implemented for the task of municipal solid waste classification. The key insights and findings that are observed in this study are listed below:

- The proposed deep learning based model utilized fewer number of model weight parameters, hence produces responses much faster by reducing the overall computational burden. Furthermore, the lightweight model that has been developed by reducing the model weight parameters can also be utilized by some other models requiring real-time based applications.
- While developing the hybrid model architecture, a feature-level fusion methodology has been incorporated after generating the features from the two other classification models, to achieve improved performance measures.
- The dataset has considered fewer numbers of training samples due to the limited computational resources. Hence, to make the training process much more efficient our design framework has utilized the concept of transfer learning.
- The proposed model has created a customized 'TrashNet' dataset to train and validate the model. The original 'TrashNet' dataset contains only six classes, which is further populated by introducing one additional category of waste 'Compost' to make the model robust against images that are bio-degradable.
- The paper has also conducted a comparative study among various state-of-the-art deep learning based classification models employed for the task of municipal solid waste classification. The study clearly shows that the proposed model outperforms the others in terms of classification accuracy by utilizing minimal number of model weight parameters.

6. Future Scope

This section has described about some of the open problems that are going to be addressed by some other findings utilizing some different domain of applications.

- The proposed model has achieved higher performance measure by considering fewer model weight parameters, hence able to be integrated with some embedded systems that require generating real time responses.
- The proposed model has only been employed in object classification based applications; hence in future the model can also be utilized for detection and segmentation tasks.
- The dataset that have utilized considered recyclable and bio-degradable waste materials, hence future researches can also accommodate large category of waste materials such as industrial waste, bio-medical waste, e-waste, battery waste, radio-active waste, and many more.
- The current study considered single modal data such as images while designing the model architectures. In future, the researcher may include multi-modal data such as images and the tabular data containing the chemical property of the material, or acoustic data to make a more robust model.

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