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Leveraging Transfer Learning with a Modified ResNet-50 Model for Enhanced Solid Waste Classification

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Convolutional Neural Network, Deep Learning, ResNet-50, Transfer Learning, TrashNet, Waste Classification, Waste Management

ABSTRACT
In developing countries like Nigeria, addressing the significant challenges associated with solid waste management is daunting. Therefore, this research paper proposed a modified ResNet50 model for the classification of solid waste, employing the transfer learning approach. The MATLAB platform was employed to modify and train the model on the TrashNet dataset, which comprises six solid waste categories. The TrashNet dataset was randomly divided into a training set (75%) and a validation set (25%) to facilitate the proposed model's training and evaluation. The proposed model underwent training for three different durations: 7, 15, and 30 epochs, respectively. The performance of the model was assessed using evaluation metrics, including accuracy, confusion matrix, precision, and recall. The results of this study revealed that the modified ResNet50 model achieved commendable accuracy levels of 93.65%, 98.09%, and 94.60% for the 7, 15, and 30 epochs, respectively. Notably, at the 15-epoch mark, the proposed model maintained the highest accuracy when compared to other pretrained models, like AlexNet, GoogleNet, MobileNetV2, and ResNet-50. Additionally, for each waste category, the model, particularly after 15 epochs, demonstrated remarkable accuracy values ranging from 0.957 to 0.99984, coupled with precision values spanning from 0.9531 to 1.0000. Furthermore, the recall and F1-score metrics yielded high values, underscoring the model's effectiveness in correctly predicting a significant proportion of the samples. Overall, this modified ResNet-50 model exhibits considerable promise for applications in waste management, including waste sorting and recycling, IoT-based waste management systems, and waste classification through mobile applications.

Introduction
Waste management poses a significant global challenge attributed to the rapid expansion of populations, industrialization, and urbanization [1]-[3]. As of the conclusion of 2020, the cumulative global production of municipal solid waste (MSW) had already exceeded a staggering 2.01 billion tons, and forecasts indicate that this figure will surge to 2.59 billion tons by 2030 and a monumental 3.40 billion tons by 2050 [4]. In the context of Nigeria, its urban centres were accountable for an estimated 16.8 to 25.3 million tonnes of MSW in 2020, and future predictions project this annual volume to escalate dramatically, potentially reaching 72.46 million tonnes by the year 2040 [5][6]. To grapple with this mounting challenge, the Nigerian government has initiated several strategies encompassing sanitation support, recycling endeavours via waste-to-wealth initiatives, and fostering opportunities for "wastepreneurs" [7]. Implementing automated waste sorting solutions holds the potential to significantly augment these initiatives, with computer-based systems employing deep learning techniques to distinguish and categorize various solid waste types.

Deep learning (DL) is a distinct domain within the realm of machine learning, that harnesses the power of artificial neural networks to derive intricate, high-level features from input data [8]. What sets the DL model apart is its innate capacity to discern intricate connections between input and output data while autonomously extracting features, ranging from uncovering fundamental patterns to advanced, multi-faceted patterns. This attribute prompts heightened robustness, scalability, and adaptability within deep learning algorithms [9]. In this DL domain, the Convolution Neural Network (CNN) technique excels in processing grid-like data structures, particularly images, and has demonstrated remarkable efficacy in tasks related to waste classification and management [10][11]. Its application is prominent in computer vision domains, encompassing tasks like image classification, object detection, and semantic segmentation.

CNNs have found practical applications in the realm of waste classification, effectively contributing to more efficient waste management systems. These neural networks can seamlessly integrate with IoT systems, enhancing waste monitoring and segregation processes. In [12], the SpotGarbage mobile app harnessed the GarbNet CNN model to identify and pinpoint instances of waste in real-world images. This model showcased its prowess with a mean accuracy of 87.69% when tested on the Garbage-In Images dataset. In [13], the MSWNet model, based on ResNet-50 and employing transfer learning, was employed to categorize municipal solid waste into four distinct classes, boasting an impressive accuracy rate of 93.5%. In [14], researchers explored various CNN models trained on the TrashNet dataset. After training for 100 epochs, the VGG16 network achieved a classification accuracy of 76.94%, while the Inception-ResNet-V2 model secured a commendable accuracy of 89%. With 150 epochs of training, the Densenet-169 and MobileNet models both yielded an 84% test accuracy. In the work presented in [15], the original ResNet-50 model underwent training on the TrashNet dataset for 250 epochs, culminating in an accuracy of 84.46%. This was compared with two enhanced ResNet-50 models: ResNet-50-A achieved an accuracy of 88.4%, while ResNet-50-B reached an impressive accuracy of 92.08%. The research in [16] delved into CNN models trained over 100 epochs for the classification of waste into six distinct classes, delivering validation set accuracies ranging from 91.9% to 94.26%. Among these networks, MobileNetV3 distinguished itself, achieving a remarkable classification accuracy of 94.26%, all while maintaining a compact storage size of 49.5 Mb. In a comprehensive analysis detailed in [21], eight CNN models were trained over 5, 7, and 10 epochs, with the results revealing that ResNet models excelled in achieving high classification accuracy. Specifically, ResNet50 attained an accuracy of 92.06% after 7 epochs, and ResNet101 reached an even higher accuracy of 92.38% after 10 epochs.

This research proposed a waste classification model through the modification of the ResNet-50 network architecture. The primary objective is to enhance classification accuracy while reducing the required number of training epochs. Employing the transfer learning methodology, the model's focus was on categorizing waste items into six distinct classes. To evaluate its performance, the modified ResNet-50 model underwent rigorous testing and was benchmarked against alternative CNN models. The experimentation and analysis were conducted utilizing the MATLAB 2022a platform.

Convolutional Neural Network (CNN)

The Convolutional Neural Network (CNN) is a forward-feeding neural network comprising various layers, including the input layer, convolution layer, pooling layer, activation layer, fully connected layer, and output layer [2]. Within the activation layer, the Rectified Linear Unit (ReLU) function is applied to nonlinearly map the convolutional layer's output [11]. The CNN leverages its convolutional and pooling layers to automatically extract data representations or abstractions. Notably, images can be directly employed as input data for this type of neural network [8][18]. Consider an input feature map X with dimensions W×H×C and a convolution kernel or filter (ω) sized at F×F×C×K, where F represents the filter size, and K indicates the number of filters in the layer. The computations for the convolutional layer and pooling operations can be expressed using Equations 1 and 2, while Equation 3 defines the ReLU activation function, which transforms negative values to 0 while leaving positive values unchanged.

$$Y_{x,y,k} = \text{₳} \cdot \left(b_k + \sum_{m=1}^{F} \sum_{n=1}^{F} \sum_{c=1}^{C} \omega_{m,n,c,k} \cdot X_{x+m,y+n,c} \right) \quad (1)$$

$$PoolingLayer = average(Y_{x,y,k}) \quad (2)$$

$$\text{₳}_{ReLU} = \max(0, Y_{x,y,k}) = \text{ReLU}\,(Y_{x,y,k}) \quad (3)$$

Where: $Y_{x,y,k}$ denotes value at position (x,y) in the k-th output feature map after convolution; ₳ is the activation function (mostly ReLU); $\omega_{m,n,c,k}$ represents the value of convolution kernel (weight) at a specific position (m,n) within the kernel, for a particular input channel (c), and for the k-th output channel or feature map; X(x+m, y+n, c) denotes the pixel value at position (x+m ,y+n) in the input feature map for a particular input channel.

Transfer Learning

Transfer learning is a machine learning technique employed to build models for new tasks by utilizing pre-existing models as a foundational starting point [19]. It entails the transference of knowledge from one context to another, typically under differing circumstances. Figure 2 visually illustrates the concept of transfer learning. One widely adopted strategy involves the incorporation of pre-trained Convolutional Neural Network (CNN) models, which are subsequently fine-tuned with additional layers to adapt the network for the classification of new images. These pre-trained models, initially trained on extensive datasets like ImageNet, offer significant advantages in deep learning, particularly when dealing with limited datasets. In the realm of waste classification, the target domain pertains to the trash dataset, encompassing specific labelling tasks [18][19]. The objective of transfer learning is to harness the insights acquired from the pre-trained model, which was originally trained on ImageNet, and apply this knowledge to effectively learn the target probability distributions inherent to the trash dataset. In the context of this research, the approach adopted involves the modification of ResNet-50 using the principles of transfer learning.

ResNet-50 Model

ResNet [17], a distinctive CNN model, employs skip connections, also known as shortcut connections, to tackle the problem of vanishing gradients during backward propagation in deep networks. These skip connections enable certain layers to be bypassed in the backpropagation process. The ResNet-n model is constructed by stacking residual blocks, each containing n levels of convolutional layers and skip connections. ResNet models help mitigate the vanishing gradient issues that occur when the gradient becomes exceptionally small, resulting in minor updates to initial layers in deep neural networks and a prolongation of the training process [8].

In the case of ResNet-50, the model consists of 49 convolution layers and 1 fully connected layer, organized into residual (or convolutional) blocks distributed across 5 stages. Within each residual block, three convolutional layers of various sizes (1 × 1, 3 × 3, and 1 × 1) are employed, along with skip connections (refer to Figure 1) and batch normalization. Additionally, an average pooling layer is utilized to downsample irrelevant pixels, and the weights and biases of each neuron are propagated to the fully connected layer. The final convolutional layer connects to the fully connected layer through a global average pooling layer, and class predictions are generated using the SoftMax activation function, which identifies the class with the highest associated probability among the input data [17][18]. The mathematical expression for the SoftMax activation function is presented in Equation 4.

$$softmax\ function: \quad Ⱥ(x)_i = \frac{\exp(x_i)}{\sum_{j=1}^{K} \exp(x_j)} \tag{4}$$

Where: x denotes the input vector, x_i represents i-th entry value in the input vector; K is the number of classes in the multi-class classification, *exp* denotes the exponent

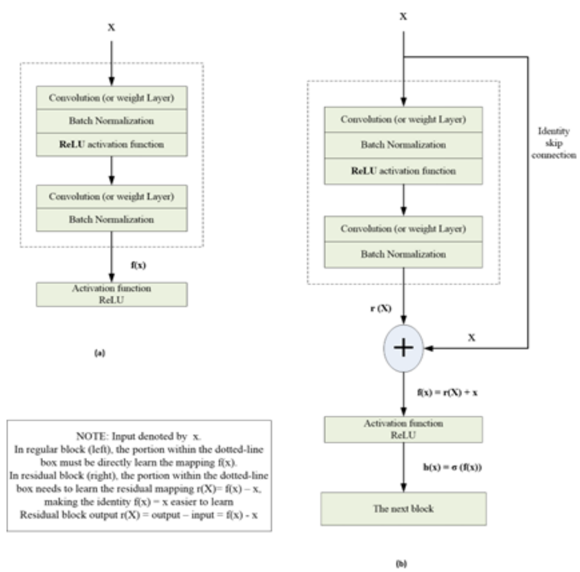

Figure 1: Regular CNN block and residual learning block

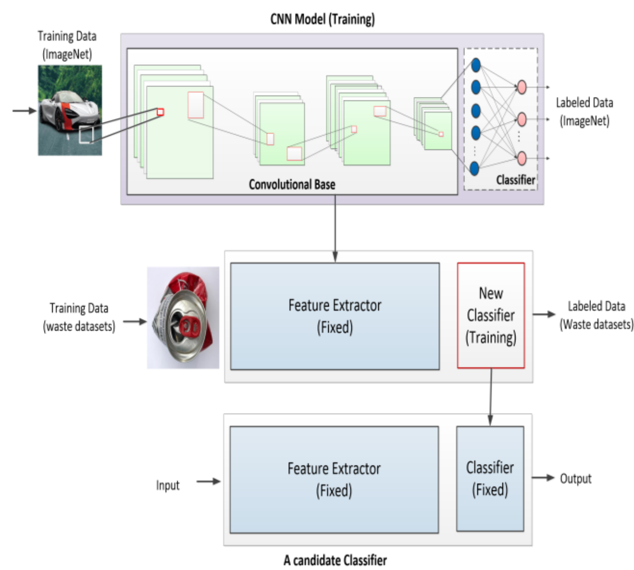

Figure 2: Transfer learning concept

The modified ResNet-50

This research proposed a ResNet-50 model modified for the classification of solid waste into six distinct categories, aimed at facilitating the recycling of materials. The adoption of a transfer learning approach allowed for the efficient transfer of pre-trained parameters, streamlining the training process. The process involved the utilization of the pre-existing ResNet-50 model, which was loaded into MATLAB version 2022a and subsequently fine-tuned to align with the specific classes within the dataset. The modifications encompassed several steps, including the adjustment of the input image size to [512,384,3], the integration of two fully connected layers (designated as fc1_2048nodes and fc2_2048nodes), followed by ReLU activations (relu1 and relu2), and the incorporation of dropout layers configured with a dropout rate of 50% (dropout1_0.5 and dropout2_0.5). To tailor the network for the classification of waste into six distinct classes, a third fully connected layer (fc3_6class) was added, followed by the application of the softmax function to yield probabilistic classification outcomes. This modified ResNet-50 architecture was subsequently trained using MATLAB. The training algorithm is presented in detail in Table 1.

Data and Experiment setup

The research utilized the TrashNet dataset [20], a widely recognized open-source dataset designed for waste classification tasks, as the basis for training and assessing the modified ResNet-50 model. Data augmentation was applied to enhance dataset diversity, mitigate the risk of overfitting, and improve the model's capacity to generalize effectively. The TrashNet dataset was partitioned into two subsets: a training set and a validation set, distributed at a ratio of 75:25. The training set was employed to train the model's weights, whereas the validation set evaluated the model's performance. Training the model involved multiple epochs, specifically 7, 15, and 30, with the model's performance meticulously assessed using a range of evaluation metrics.

The evaluation metrics encompassed the confusion matrix, accuracy, recall, precision, and F1 score, which were instrumental in effectively gauging the model's performance. These evaluation metrics not only provided insights into the model's performance but also facilitated comparisons with diverse algorithms. The confusion matrix was employed to visually represent the model's classification of each waste type. It encapsulated metrics such as True Positive (TP), False Positive (FP), False Negative (FN), and True Negative

(TN). These metrics, derived from the confusion matrix, were utilized to calculate the accuracy, precision, recall, and F1 score, as described in Equations 5 to 8.

$$\text{Accuracy} = (TP+TN)/(TP+TN+FP+FN) \quad (5)$$

$$\text{Precision} = TP/(TP+FP) \quad (6)$$

$$\text{Recall} = TP/(TP+FN) \quad (7)$$

$$\text{F1-Score} = (2\ (\text{Precision} \times \text{Recall}))/(\text{Precision}+\text{Recall}) \quad (8)$$

Table 1: Algorithm for Training the proposed model

Input: Training set (images and corresponding labels)
Output: confidence scores (Validation images, corresponding labels, and confidence score)

1. Modify the pre-trained ResNet50
   - Load the pre-trained ResNet50 model.
   - Adjust the image input size of the model to dimension [512-by-384-by-3] and replace the learnable layers according to the pattern: fc1, relu1,dropout1, fc2, relu2, dropout2, fc3, softmax,classOutput
2. Prepare dataset: apply data augmentation and split into training set (75%) and validation set (25%). Augmentation: rotation [-45 45], scaling [1 2], translation [-10 10], reflection [1 1].
3. Set the training parameter: the optimizer (sgdm), training mini-batch size (20), number of epochs (7, 15 and 30 respectively), initial learning rate (0.001), and validation frequency (50).
4. Training phrase: Evaluate the model on the training dataset (image and label),
   - Train the modified model on the training dataset using the specified training options. Repeat for the specified number of epochs.
     - Forward pass: calculate the predicted probabilities and the cross-entropy loss for the predicted label.
     - Backward pass: Compute the gradients of the loss for the model parameters (weights and biases) and update the parameters.
   - Evaluate the final loss.
5. Validation phrase: compute the model's inference on new, unseen data (validation dataset)
   - Input validation dataset into the modified model. In MATLAB, this is done while training the model.
   - Compute the accuracy of the model by comparing the predicted labels with the validation labels.
6. Evaluate the performance of the model using the evaluation metrics.

RESULTS AND DISCUSSION

Table 2 below presents the classification accuracy and error values after applying the modified ResNet-50 on the TrashNet dataset for 7, 15 and 30 epochs. Table 3 presents the evaluation metrics of the modified ResNet-50 model for each solid waste class. The modified ResNet50 was compared with AlexNet, GoogleNet, MobileNetV2, and ResNet-50 using the steps specified in the algorithm (steps 2-6) in Table 1. The validation accuracy results of this comparison are presented in Table 4.

Table 2: Accuracy and error values for the modified ResNet-50

Model	Epoch	Training Accuracy	Validation Accuracy	Training Error	Validation Error
Modified ResNet-50	7	95.4665%	93.6508%	4.5335%	6.3492%
	15	97.2588%	98.0952%	2.7412%	1.9048%
	30	99.6837%	94.6032%	0.31629%	5.3968%

Table 3: Performance of the modified ResNet-50 based on the evaluation metrics (epoch =15)

Solid waste class	Accuracy	Precision	Recall	F1_Score
Cardboard	0.9984	1.0000	0.9901	0.9950
Glass	0.9857	0.9531	0.9760	0.9644
Metal	0.9968	0.9808	1.0000	0.9903
Paper	0.9952	0.9932	0.9865	0.9898
Plastic	0.9873	0.9828	0.9500	0.9661
Trash	0.9984	0.9714	1.0000	0.9855

Table 4: Accuracy values of the modified ResNet-50 compared to other CNN models.

CNN models	7 epochs (%)	15 epochs (%)	30 epochs(%)
AlexNet	64.127	78.4127	81.5873
GoogleNet	89.6825	89.8413	91.1111
MobileNetV2	89.3651	90.7937	91.746
ResNet50	91.4286	92.0635	92.6984
Modified ResNet50	93.6508	98.0952	94.6032

From Table 2, the modified ResNet-50 model demonstrated the highest classification accuracy of 98.09% for the images in the validation set and a training accuracy of 97.53% after 15 epochs. This indicates that the proposed model has good generalization ability and the model's ability to learn and capture new unseen data and patterns for waste classification. The model also made accurate predictions for most validation samples. The proposed model's performance in predicting solid waste samples was evaluated using accuracy, precision, recall, and F1-score metrics as presented in Table 3. Across all the distinct classes, the model consistently delivered outstanding accuracy values, spanning from 0.957 to 0.99984. The precision values observed for each class were equally impressive, encompassing a range from 0.9531 to 1.0000. This signifies that the model exhibited remarkable precision in its ability to correctly classify samples, maintaining a very low rate of false positives. Furthermore, the model displayed a notably high recall rate, indicating its capacity to effectively identify a substantial proportion of true positives. Also, the F1_score rate, which considers both precision and recall, presented high values. These outcomes underscore the model's exceptional proficiency in accurately predicting positive samples within each class. Figure 3 shows the confusion matrices of the original ResNet50 and the modified ResNet-50.

The results in Table 4 show that, for each training epoch, the modified ResNet-50 model achieved the highest classification accuracy among the other CNN models. Figure 4 and Figure 5 show the bar charts for validation accuracy and error values for the models. After training for 15 epochs, the modified ResNet50 model demonstrated a significant performance advantage over other models. It exceeded AlexNet by a notable 19.69%, GoogleNet by 8.26%, MobileNetV2 by 7.31%, and ResNet-50 by 6.04%. This substantial lead in accuracy underscored the modified ResNet50's exceptional performance in solid waste classification. The comparison plots for training accuracy, training loss, validation accuracy, and validation error for all the models after training for 15 epochs are presented in Figures 6 to Figure 9 respectively. When the epoch was increased to 30, there was a marginal accuracy improvement across most models (see Table 4). However, the modified ResNet50 model experienced a slight decrease of 3.5% in accuracy. This suggests that the modified ResNet50 had reached a point of stability and further training may not yield significant improvements in accuracy. Nevertheless, it maintained a higher position compared to other models even after this decrease in accuracy.

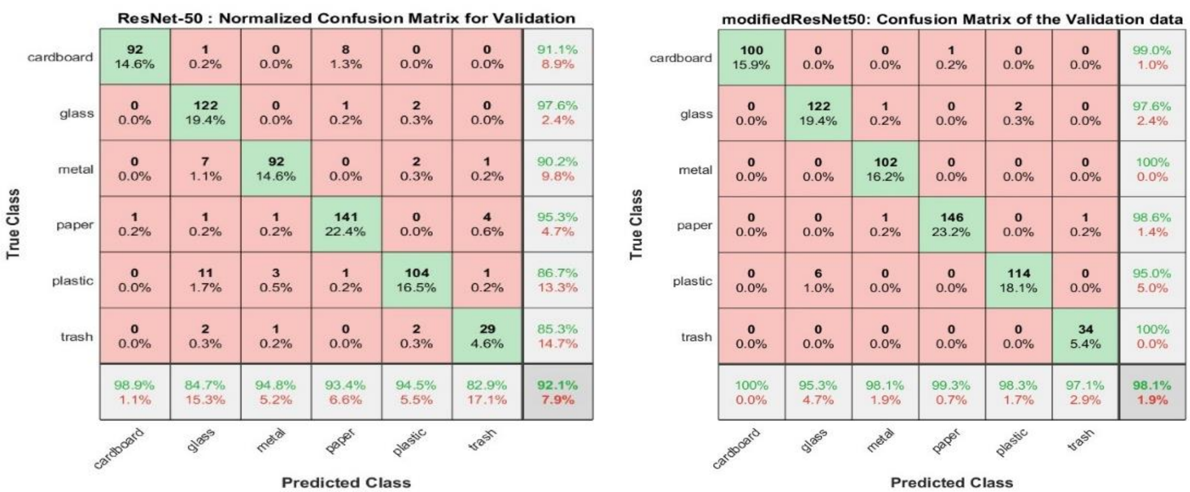

Figure 3: Confusion matrices of the original ResNet-50 and the modified ResNet50

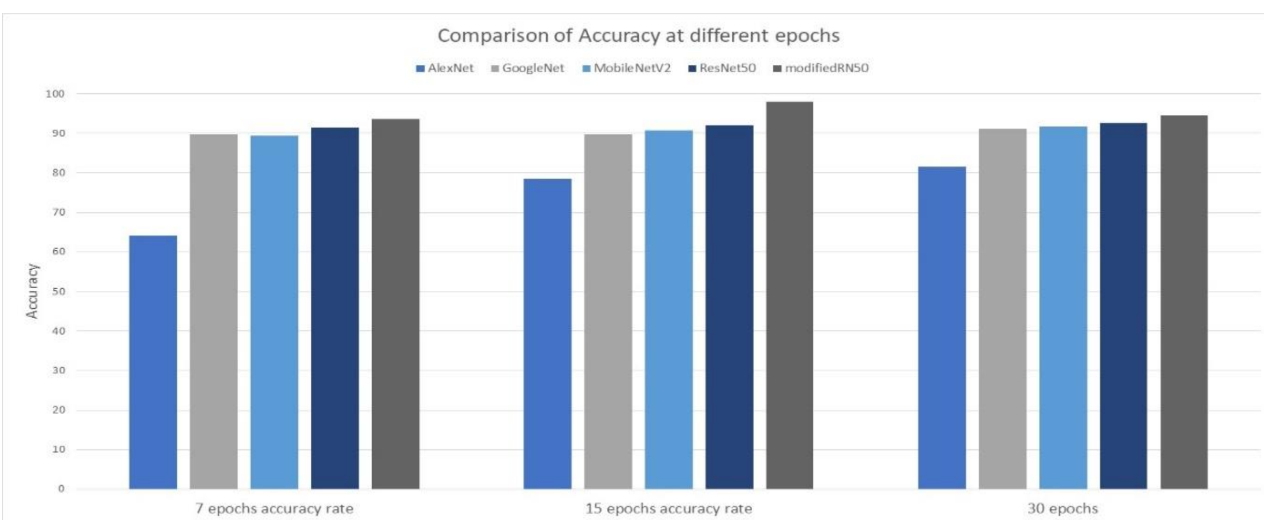

Figure 4: Classification Accuracy Comparison for the CNN models after training for Epoch=7, 15 and 30

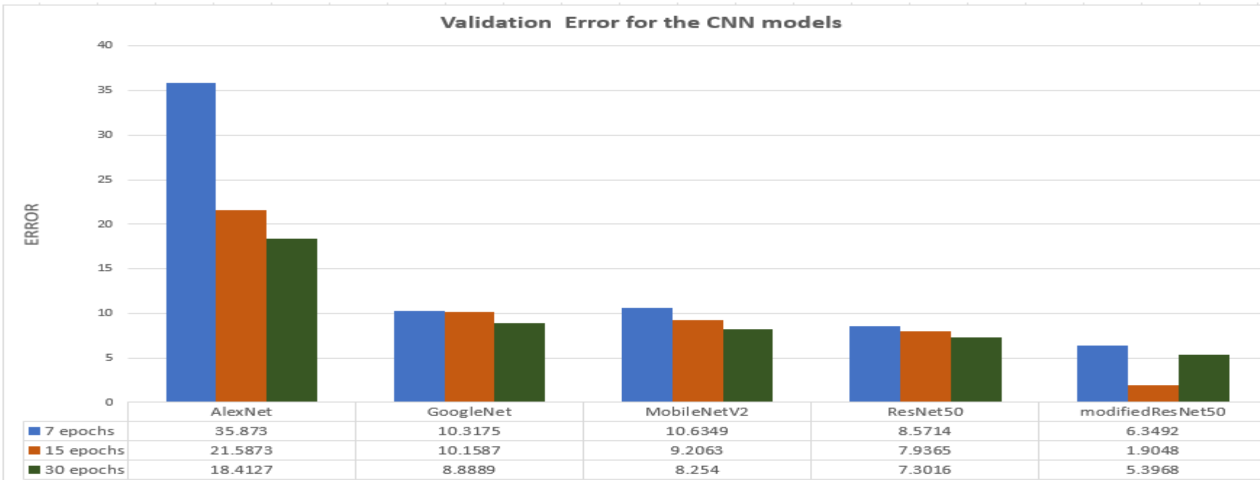

Figure 5: Validation errors for the CNN models

Figure 6: Training Accuracy plot for the CNN models (Epoch =15)

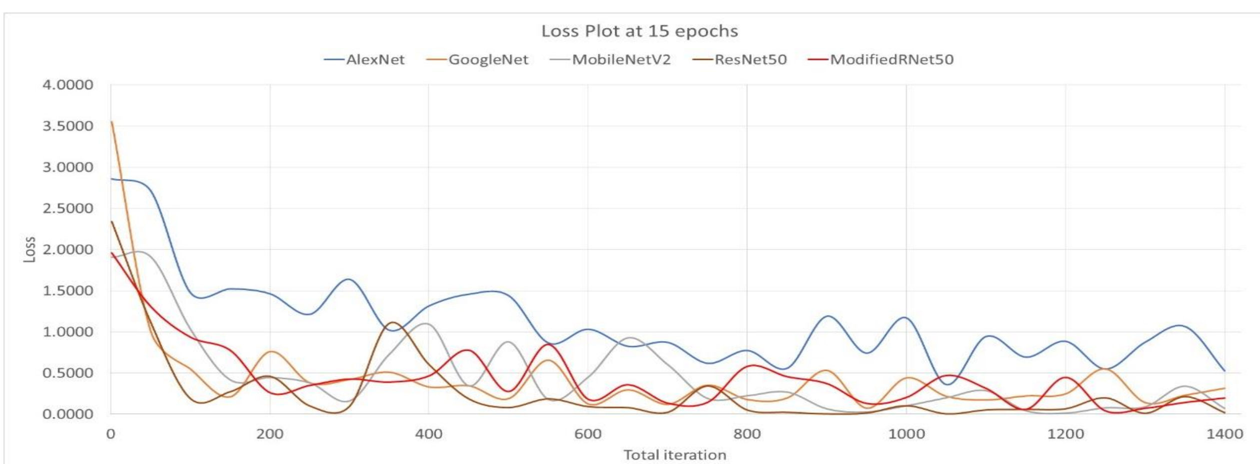

Figure 7: Training Loss plot for CNN models (Epoch = 15)

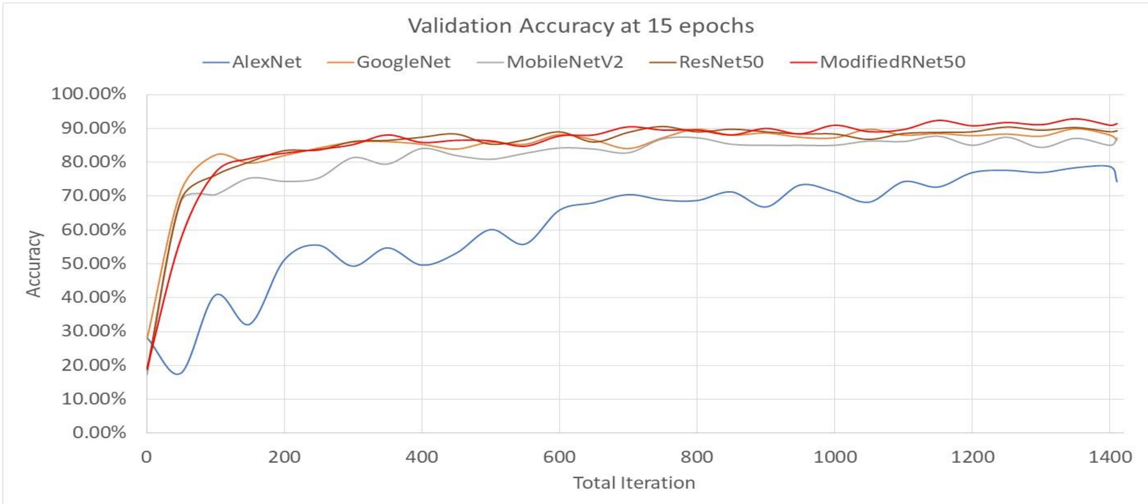

Figure 8: Plot for Validation Accuracy for CNN models (Epoch = 15)

Conclusion

This study employed a modified ResNet-50 model to effectively categorize solid waste into six distinct classes. Comparative evaluations were conducted to assess the model's performance after undergoing training for 7, 15, and 30 epochs, leveraging the TrashNet dataset partitioned into 75% for training and 25% for validation. By implementing the transfer learning approach, the original pre-trained ResNet-50 model was fine-tuned to adapt to our specific dataset, a process that reduce training time and yield promising outcomes. The MATLAB 2022a platform was instrumental in importing pre-trained CNN models, facilitating the training process, and conducting comprehensive assessments utilizing critical evaluation metrics including confusion matrix, accuracy, recall, precision, and F1-score. The modified ResNet-50 model exhibited remarkable accuracy, precision, recall, and F1-score when predicting solid waste samples. It demonstrated a low false-positive rate, high recall rate, and impressive F1 scores, affirming its potential for precise waste sample prediction. As a future direction, its application could be extended to more extensive datasets and incorporated into physical devices. Additionally, comparisons with other models with and without transfer learning approach. The proposed model holds significant promise for the field of waste management, particularly in the context of IoT-based sorting systems designed to identify and categorize waste, thereby enhancing recycling endeavours.

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