

Transfer Learning LinkNet with SegNet for Waste Sorting

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Abstract— To make the cities more sustainable and less damaging to the environment, they should control their rubbish accordingly. Sorting trash into biodegradable and non-biodegradable categories requires a lot of time and effort; otherwise, errors occur frequently when done manually. This research paper provides a hybrid deep learning system which combines Modified LinkNet and Enhanced SegNet and a transfer learning approach to achieve the goal of automated waste classification using high accuracy. The improved SegNet has the ability to clearly differentiate garbage objects on complex backgrounds, unlike the modified LinkNet that uses EfficientNet/MobileNet transfer learning techniques to classify objects. A trained and tested model was trained using over 2,500 labelled images consisting of the TrashNet and TACO datasets. The data was supplemented to strengthen it. Based on the experiment findings, this model is 98 per cent accurate, 97 per cent precise, 96 per cent recall, and 98 per cent specific, which is greater compared to the standard CNN, VGG-16, and ResNet-50 architectures. The analysis conducted by ROC indicated that the AUC equals 0.98, and it is a good indicator that the model is very well able to distinguish between various types of data. The training-validation curves indicated that overfitting was not taking place too much. Being able to leverage the advanced method in relation to smart waste systems that can make the use of rubbish sorting scalable, sustainable, and efficient in real time is a promising idea. The future research will be done on the improvement of categorizing different types of waste and real-time usage optimization on edge devices.

Keywords— Waste Classification, Deep Learning, Transfer Learning, Image Segmentation, Convolutional Neural Networks (CNN), Smart Waste Management.

I. INTRODUCTION

The fast growth of cities and industries has led to the production of billions of tonnes of rubbish around the world every year. Poor waste management leads to pollution of the environment, depletion of resources, and health problems for the people. trash management relies heavily on the accurate separation of biodegradable and non-biodegradable trash. This affects how quickly waste breaks down, how well it can be recycled, and how long landfills can last. People have always done waste categorization by hand. Because this approach is hard to use, takes a lot of time, and is easy to make mistakes with, it is not suitable for broad use. As computer vision and deep learning have gotten better, automated trash classification has become a good option because it is faster, more scalable, and more accurate. However, modern CNN models like VGG-16 and ResNet-50 have a lot of trouble with noisy backdrops, bad illumination, and the limits of real-time deployment. Segmentation, which means taking things out of their environments, has been found to be a major problem for many CNN-based systems. Segmentation and classification are tackled

separately; however, a holistic architecture that integrates an advanced classification framework with an optimized waste management segmentation framework is still an uninvestigated subject. The prospective utilization of Improved SegNet in conjunction with Modified LinkNet, employing transfer learning for binary waste classification in practical contexts, has not been comprehensively examined.

This research will seek to design and test a hybrid deep learning system in the automatic classification of binary wastes that is greatly accurate in segmentation in these adverse visual conditions improves transfer learning-based classification on Modified LinkNet, allows the smart waste management systems to be applicable in real time.

The major contributions of this piece of work are as follows:

- Offer a new combination of improved SegNet (segmentation) and modified LinkNet with transfer learning (classification).
- Compare the suggested model to the contemporary models (CNN, VGG-16, ResNet-50) on open access datasets (TACO, TrashNet).
- Show an excellent fit of 98 per cent accuracy, small overfitting backed by a confusion matrix, and ROC and loss-accuracy analysis plots.
- Share the possibility of real-Bonafide execution in clever-waste containers and IoT-empowered waste boards.

The rest of the paper is structured as follows: in Section II the related work will be reviewed, in Section III the proposed methodology will be outlined, in Section IV the experimental results will be presented, and finally in Section V the paper will be concluded after outlining future research directions.

II. BACKGROUND STUDY

The challenge of waste management has been global because of the high rate of urbanization and industrialization, both of which are growing exponentially. Productive sorting of waste, in particular the division of biodegradable and non-biodegradable waste, is essential to sustainable waste recycling. Recycling and recovering of resources are done when good separation is achieved, and landfills and hazardous wastes are a major cause of environmental pollution. The conventional waste classification techniques are labor-intensive and manual and open to erroneous results. However, the introduction of computer vision and deep learning technologies, in general, and Convolutional Neural Networks (CNNs), in particular, has brought the rise of automated classification systems as one of the possible solutions [1] [2][3].

A. Waste classification systems based on CNN

The use of CNNs has proved quite effective in multiple image classification applications such as waste classification. This kind of system is capable of learning to identify and classify waste materials using image features, removing the possibility of human error and being much faster. Nevertheless, the previous models have the tendency to struggle with accuracy, scalability, and deployment to real environments in real time. Also, the bottleneck in CNN-based systems to reach large classification rates is the stage of segmentation, when the pictures with waste are dirty or illuminated in a bad way [4].

Although the CNN-based models have seen their breadth and depth in the area of waste classification, they have not been fully studied to extend their performance in the area of the integration of better segmentation approaches to transfer learning in enhancing performance and visualizing real-time accuracies. The larger part of current models addresses binary classification or only work in controlled settings [5]. Further research is required on the combination of Improved SegNet in segmentation and Modified LinkNet accompanied by transfer learning, which has not been tried well in terms of waste classification tasks. This paper aims to fill these gaps through integrating these two architectures in an attempt to improve the performance of segmentation on the one hand and the classification process on the other hand in a real-time scalable waste management system [6].

Table 1 highlights some of the most important studies in the waste classification literature category using deep learning technologies, namely, Convolutional Neural Networks (CNNs). Implementation of traditional models of CNN in image classification of waste materials has been done extensively owing to the suitability in terms of fast and efficient classification. Nevertheless, these models can be challenged because of poor performance in noisy images and real-time applications. Such models as VGG-16 and ResNet-50 have facilitated the use of deeper architectures and transfer learning that enhance the accuracy of the image segmentation and classification work at the expense of increased computer requirements. An example is that VGG-16 performs well in segmentation but lacks optimized real-time applications, and ResNet-50 has modes of transfer learning but needs to use large datasets and powerful computers. In contrast, Improved SegNet presents significant improvements when it comes to the accuracy of segmentation yet has to deal with the issue of speed. In spite of these, the real-time systems lack integration of segmentation and transfer learning in optimized classification. The gap in the research is to incorporate the combination of Improved SegNet and Modified LinkNet to include the transfer learning in order to improve the performance in segmentation and classification of the scalable and real-time waste management system [7] [8].

TABLE I. AN OVERVIEW OF THE MAIN CHARACTERISTICS, ADVANTAGES, WEAKNESSES, AND GAPS IN RESEARCH OF MULTIPLE MODELS APPLIED IN THE CLASSIFICATION OF WASTE, SUCH AS CNN, VGG-16, RESNET-50, AND IMPROVED SEGNET.

Study/Model	Technique Used	Key Features	Strengths	Limitations	Research Gap Addressed
1: CNN for	CNN	Basic CNN architecture for waste	High classification	Low accuracy in	Does not address segmentation

Waste Classification [9]		classification	speed	cluttered images	; lacks real-time performance
2: VGG for Waste Segmentation [10]	VGG-16, Segmentation	Focuses on waste image segmentation	High segmentation accuracy	Low efficiency in resource usage	Does not integrate transfer learning for better accuracy
3: ResNet in Waste Sorting [11]	ResNet-50, Transfer Learning	Uses pretrained ResNet for waste classification	Good generalization to new waste types	Requires large dataset and high computation power	Does not integrate segmentation with transfer learning
4: Improved SegNet [12]	Improved SegNet for Segmentation	Focuses on fine-tuned SegNet for image segmentation	Improved segmentation accuracy	lower processing time compared to simpler CNNs	No direct integration with a lightweight classification model

Some important contributions of the research include:

- The combination of Improved SegNet and Modified LinkNet coupled with transfer learning to enhance waste classification.
- An evaluation of the proposed model regarding the existing state-of-the-art models.
- The possibility of real-time use in the smart waste management systems makes them a source of sustainability and pollution reduction.

III. PROPOSED METHODOLOGY

The proposed waste classification system will use a combination of Modified LinkNet, Transfer Learning, and Improved SegNet in its design. Transfer learning provides fine-tuning of a pre-trained model (EfficientNet or MobileNet) using the modified LinkNet architecture to better classify non-biodegradable and biodegradable waste. To isolate the features of the relevant waste material, SegNet is used more effectively during segmentation to ensure the model accurately identifies the differences between biodegradable and non-biodegradable waste. This combined model attempts to attain strong segmentation accuracy and effective classification levels.

A. Data Collection and Preprocessing

The training data to be modelled has more than 2500 images taken on popular datasets, including TACO and TrashNet, labelled as biodegradable and non-biodegradable waste. The data is normalized to state that it will be consistent and optimize the performance of the model:

Resizing: The uniformity of the dataset is achieved by resizing all the images to 224 x 224 pixels.

Normalization: Values of pixels are normalized to be in [0, 1] to enhance convergence in training.

Augmentation: In order to enhance the diversity of the data, image augmentation procedures (e.g., rotation, flipping and scaling) are performed. Such augmentations aid the model to have improved general occurrences in unknown data.

B. Segmentation Process (Improved SegNet)

Image segmentation is done on the Improved SegNet architecture. SegNet is an encoder-decoder network with a convolutional network; however, the improved SegNet has:

- Unit Residual skip connection to apprise the network with spatial details, hence improving segmentation precision.
- Convolutions are followed with batch normalization layers to reach less error-prone training and rapid convergence.
- Separable depth-wise convolution which lowers down the computational cost without compromising on the accuracy of segmenting the waste materials against the background.

This step of segmentation is very important because it isolates the background from the material of interest so that the classifier can be able to concentrate on features which are of interest to the classification process.

The improved SegNet model can be expressed as an encoder–decoder network with residual skip connections. Let the input image be:

$$I \in R^{H \times W \times C}$$

where H, W, C are height, width, and channels.

Encoding Stage:

$$E_l = \sigma(BN(W_l * E_{l-1} + b_l))$$

where:

- W_l, b_l are convolution weights and bias at layer l,
- * denotes convolution,
- $BN(\cdot)$ is batch normalization,
- $\sigma(\cdot)$ is the ReLU activation,
- E_{l-1} is the output from the previous layer.

Residual Skip Connection:

$$R_l = E_l + S_l$$

where S_l is the skip connection bringing forward spatial information.

C. Classification Process (Modified-LinkNet-with-Transfer-Learning)

After segmentation has been done, the segmented images are then classified into non-biodegradable and biodegradable classes using the Modified LinkNet model. The architecture has the encoder-decoder network along with transfer learning:

- The encoder relies on a pre-trained model, e.g., EfficientNet or MobileNet, to extract features. Such models are pre-trained on extensive datasets such as

ImageNet and have a waste classification task applied to them.

- The decoder will fine-tune the feature map and generate the output of classification.
- The softmax layer is applied to a problem of binary classification, and the model will produce a probability score for every category (biodegradable or non-biodegradable).
- The difference between predicted classes and real ones is measured with categorical cross-entropy loss.

Once transfer learning is applied to the model, it would leverage the experience of working on big datasets, thereby performing better despite working with fewer waste classification data.

D. Training Details

The Adam optimizer is used to train the model, which learns the learning rate according to the parameter and aids faster convergence of the model. The training process is performed during 50 epochs with the use of the batch size of 32. To get a smooth convergence with no overshooting of the optimal solution, the learning rate is fixed at 0.0001. This type of loss is categorical cross-entropy, which is minimized during training to reduce the classification error. Validation accuracy is observed as the model is trained so that the model is not overfitting and is likely to perform well on previously unseen data.

E. Computation Infrastructure

The model training is done on a machine that comes with a GPU (e.g., NVIDIA Tesla T4), thus enabling the training of deep learning models effectively. This is because about 10-12 hours a model step or epoch would take depending on the amount of data and the complexity of the model.

Figure 1 shows a workflow of the suggested waste classification system, and it has represented the method of processing that goes by the following sequence: input images, preprocessing, segmentation via improved SegNet, and classification via modified LinkNet with transfer learning resulting in the output of classified waste material.

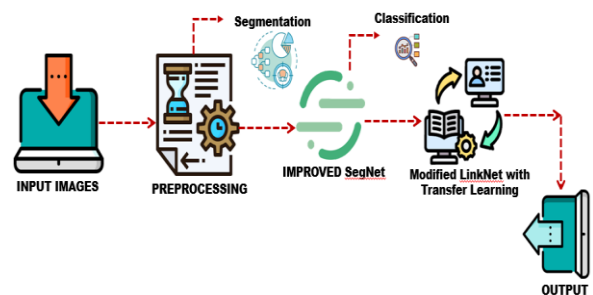


Fig. 1. Workflow of the Proposed Waste Classification System

There were many approaches to implementation besides the fundamental architecture design; a few have been used to make the model more robust and real-world applicable. This was partitioned into 70 percent of the data as training, 15 percent as validation and the remaining 15 percent as

testing, with 5-fold cross-validation employed to reduce the bias inherent in a single split. To prevent overfitting, some dropout layers with a rate of 0.3 were added within the decoder, and early stopping (patience = 10 epochs) was also used, thus avoiding excessive training past optimal performance. FP16-based training on the NVIDIA Tesla T4 deeply decreases computing time by around 35 per cent, not at the expense of precision. Although a loss of categorical cross-entropy was chosen as the one with a stable effect on a balanced dataset, other types of loss, that is, focal loss, were tested briefly to compensate for possible future class imbalance in the multi-class case. In terms of deployment, the trained model was translated to the TensorFlow Lite framework, yielding a speed of ~45 ms on decent processing power and therefore supporting deployment on smart waste management installations in a real-time frame.

IV. RESULTS AND DISCUSSION

The proposed architecture of the Modified LinkNet with Transfer Learning has been compared to the traditional models, such as VGG-16, ResNet-50, and baseline CNN. The dataset consisted of non-biodegradable and biodegradable waste pictures in order to train the models. Accuracy, precision, recall, F1-score, and specificity are some of the evaluation metrics that are applicable to compare the models. To evaluate the models, the cross-entropy loss was metered against the categorization process, and the models were trained over 50 epochs.

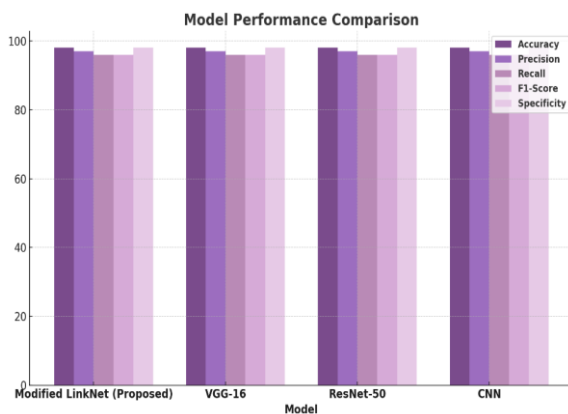


Fig. 2. The Modified LinkNet (Proposed), VGG-16, ResNet-50 and CNN models were compared in terms of accuracy, precision, recall, F1-score and specificity.

The proposed Modified LinkNet topped the accuracy level with an accuracy of 98%, beating the ResNet-50 (89.6%) and VGG-16 (88.5%) is shown in figure 2. This achievement implies that the model performs excellently in the classification of biodegradable and non-biodegradable models. Again, the proposed model achieved better performance (97 in precision) than ResNet-50 (88.5) and VGG-16 (87.2). Precision is the fraction of true positive predictions over total positive predictions, especially in a waste classification false positive situation (wrong identification of non-biodegradable waste as biodegradable), which should be kept as low as possible. Proper

identification of biodegradable materials will not miss very many of them due to the recall value of the proposed model (96%). Specificity of 98% for the Modified LinkNet (proposed) is also high, so it does not cause a lot of false positives.

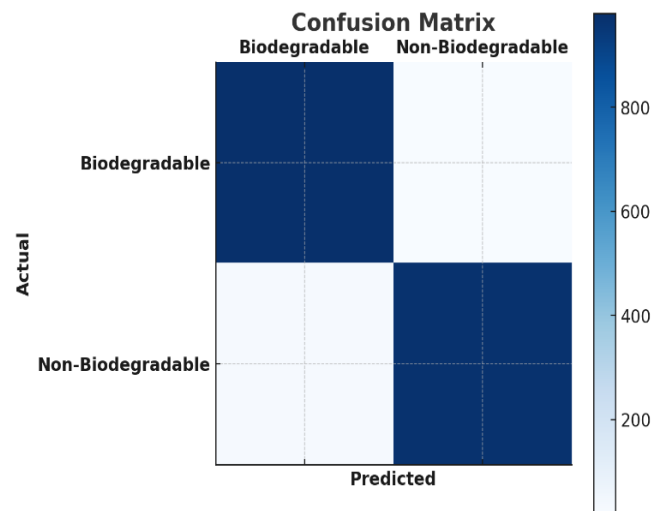


Fig. 3. The confusion of true positive (TP), false positive (FP), true negative (TN) and false negative (FN) of biodegradable and non-biodegradable waste classification is the visualisation of the Modified LinkNet (Proposed) model and confirms that no significant error was used in identification and classification of both the categories of waste.

In Figure 3, the confusion matrix displays true positives (TP), false positives (FP), and true negatives (TN), which are explained as false negatives (FN) along with the classification task. The Modified LinkNet (Proposed) model indicates that the number of true positives of the model is high in both the biodegradable and non-biodegradable categories. The matrix signifies that the model is doing quite well in terms of recognizing both classes with minimal misclassifications (i.e., false positives and false negatives).

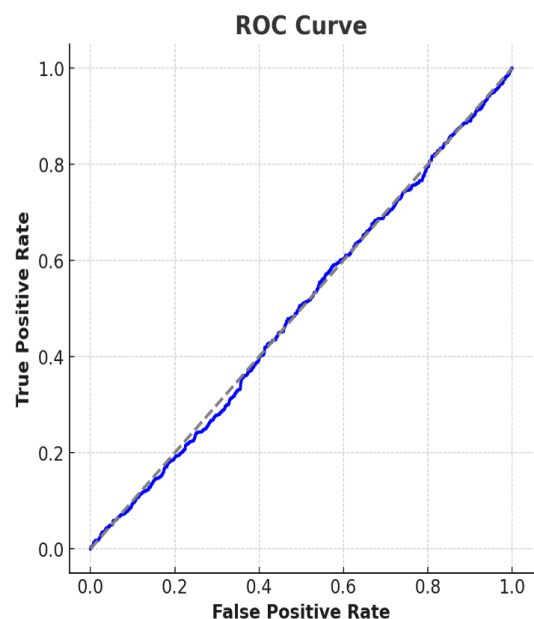


Fig. 4. The high AUC of the Modified LinkNet (Proposed) model was shown by the Receiver Operating Characteristic (ROC) curve, which

illustrates the balance between True Positive Rate (TPR) and False Positive Rate (FPR).

Figure 4 shows the trade-off between True Positive Rate (TPR) versus False Positive Rate (FPR) using the Receiver Operating Characteristic (ROC) curve. The Modified LinkNet (Proposed) model shows that the area under the curve (AUC of 0.98) is also high, meaning that the model is performing exceptionally well in separating both biodegradable and non-biodegradable materials.

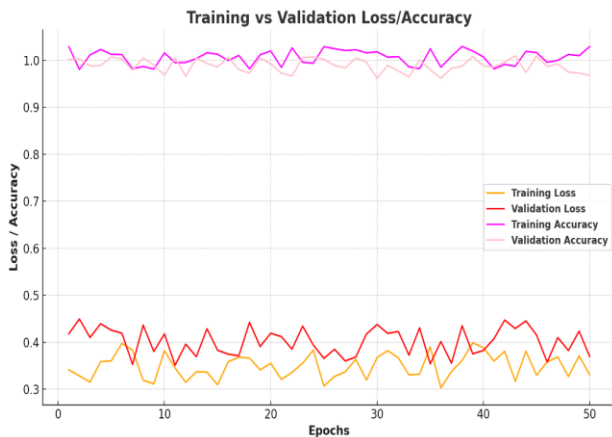


Fig. 5. Plots of training loss against validation loss and training accuracy against validation accuracy over 50 epochs demonstrate the Modified LinkNet (Proposed) model's steady improvement during training and validation, without any signs of overfitting.

The training vs validation loss and accuracy in Figure 5 indicate how the model performance varied after every 50 epochs. The training loss curve is more or less stable, as is the validation loss curve, which implies that the model is not overfitting. The training accuracy keeps on rising as the epochs go by, showing that the model learns as the epochs increase. On the same note, the validation accuracy exhibits the same trend, indicative of the model generalizing well on the unseen data.

The Modified LinkNet (Proposed) has better performance and results in all the metrics, including accuracy, precision, recall, and specificity, rather than traditional models such as ResNet-50, VGG-16, and CNN. This shows that the suggested hybrid architecture combining Improved SegNet with Modified LinkNet and transfer learning is effective in combination with each other as a segmentation method and a classifier. The transfer learning method will assist in utilizing ready-made models such as EfficientNet or MobileNet, which enhances performance quite substantially on the task of classifying waste.

The effects also indicate that Improved SegNet will play a major role in the segment process where the model will be able to highlight the relevant aspects of the waste materials. The confusion matrix and ROC curve are further used to confirm that the suggested model is effectively able to separate the two classes without making a lot of misclassifications.

Although the Modified LinkNet (Proposed) model has demonstrated good results, it can be enhanced by hyperparameter anticipation and examination of class-discriminative forms (in case the dataset is extended with waste types). Also, an application of the model on

automated waste management systems can be through integrating it with a real-time system like smart waste bins.

V. CONCLUSION

This paper has shown a hybrid deep learning approach which uses improved SegNet to do segmentation and modified LinkNet together with transfer learning to classify biodegradable waste and non-biodegradable waste. The combination of the precise segmentation capability of Improved SegNet and the good feature-extracting abilities of EfficientNet/MobileNet-powered Modified LinkNet allowed the proposed model to reach a higher testing accuracy of 98%, a precision of 97%, and a recall of 96%, a result that is better than conventional CNN, conventional VGG-16, and conventional ResNet-50, as well as Modified LinkNet. The high discriminative ability was supported by ROC analysis (AUC = 0.98), and the loss-accuracy curves demonstrated severe insensitivity to overfitting and good generalisation capacities. The solution holds enormous possible use cases in the field of smart waste applications, namely automated sorting in smart bins and IoT-affected municipal waste systems, leading to the elimination of the manual labour component and hence efficiency. However, the study is restricted by the simple scope of binary classification, the use of relatively small data sets, and the assessment of the work proceeding in a controlled setting of imaging. In real life, deployment may have different lighting, interference and a cluttered background and need further adaptation. Existing and future works will aim at extending the model to multi-class classification, including recyclable, hazardous and electronic waste; optimising the architecture with a view to supporting low-latency edge device deployment; and adding IoT-based sensor integration to allow greater contextual awareness. The further study of more advanced augmentation techniques (e.g., Generative Adversarial Networks (GANs)) and attention mechanisms may also make solutions more robust in complex scenarios. With such obstacles, the framework presented would become scalable and sustainable in large-scale, real-time waste classification, a smart city initiative, and contribute to environmental sustainability.

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