Classifying Real Waste: A Deep Learning-Based Approach to Multi-Class Image Classification

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***Abstract*—Efficient and effective waste management depends on the accurate classification of waste. As improper waste management affects the global ecosystem, it is important to detect and classify waste material accurately. To overcome the challenges such as scalability and human error faced by traditional methods, this paper presents deep learning models for the classification of real waste materials. The objective is to develop effective classification models capable of accurately categorizing wastes into distinct classes for efficient waste management. The study analyses MobileNetV3, ResNet152, DenseNet121, and ConvNeXt models' performance in waste classification. The RealWaste dataset with labelled image data is used in this research. The research methodology follows the Knowledge Discovery in Database (KDD), encompassing data collection, preprocessing, model training, evaluation, and result analysis. The evaluation results show the effectiveness of the proposed methods in accurately classifying real waste materials, therefore contributing to improvement in waste management practices. Using the dataset MobileNetV3 and ResNet152 show an accuracy of over 85%. On the other hand, DenseNet121 and ConvNeXt show better accuracy over 95%.**

Keywords– waste classification, deep learning, transfer learning, waste management, RealWaste

I. Introduction

Effective waste management is a crucial challenge in today's world. Tons of trash are produced daily, and managing it all can be difficult. Improper management of waste causes significant risks to the ecosystem and human health, arising from harmful byproducts found in wastewater [1] and methane present in the gas emitted from landfills [2]. An essential aspect of waste management is waste classification according to their properties. It further helps differentiate the wastes into recyclable and non-recyclable. Wastewater and landfill gases both depend on the amount of organic material in the waste. [3] shows how different types of waste composition and operations performed in the landfill can affect the quality of Landfill leachate (any liquid that, in the course of passing through matter, extracts soluble or suspended solids). Another paper [4] shows landfill gases depend on the quantity of the organic material present in the waste. The presence of food can increase it to 4% whereas the presence of wood shows a 65% reduction in the result. The above-mentioned harmful pollutants and gases generated from the waste get released into the water, air, and soil. This causes a lot of air and water pollution. The greenhouse gas methane that is generated from organic waste decomposing contributes majorly to global warming as well as climate change. Therefore, accurately classifying waste is important for more efficient management and reducing environmental impact.

Traditional methods of waste classification often rely on visual inspection, weighing and measurement, and manual sorting. Visual inspection involves a visual accessing process to identify and classify waste based on its composition. Weighing and measurement determine the quantity of waste and its physical properties. Manual sorting includes the physical separation of waste into different categories by humans. Although these methods are less expensive, they are time-consuming and labor-dependent. Therefore, there is a chance of human error which can lead to inconsistency in the classification. Machine learning models can be implemented to address these challenges and classify the waste by automating the process. These models can analyze visual data through computer vision to categorize different types of waste based on their characteristics [5]. Deep learning architecture such as Convolutional Neural Networks (CNNs) can also be used in waste classification. It performs very well in waste classification due to its ability to extract features efficiently from the images of waste. It learns hierarchical representations of the features and provides accurate classification [6]. As CNNs can handle large amounts of data it is suitable for classifying large image datasets. These models can capture intricate patterns from the images because of their feature extraction capability. The convolutional layers can identify edges and other characteristics that help the network to classify accurately. Pooling layers help to reduce spatial dimensions and improve waste classification efficiency.

Although deep learning models show promising results in waste classification, a few challenges are present. Few deep learning models don't perform accurately for a wide range of materials and sometimes the prediction is not accurate for materials that are not in perfect shape. As improving accuracy in waste detection is the main objective, this paper explores the application of deep learning architectures for image-based real waste material classification.

The research question in this paper, "How effectively can deep learning-based image classification techniques be used for classifying different types of real waste?" focuses on developing accurate classification models capable of distinguishing between different types of waste. This paper proposes four deep-learning models applied to the RealWaste dataset that covers various classes of landfilled waste. This dataset gives a visual insight into various waste materials generated in real life. The RealWaste dataset consists of images of different types of waste materials such as glass, metal, plastic, cardboard, etc. There are a total of 4752 images in the dataset with a resolution of 524 × 524 captured from Whyte's Gully Waste and Resource Recovery Centre's landfill site. It is located in Wollongong, Australia where municipal waste items are mixed and contaminate each other [7]. Images are properly labelled according to different categories. The RealWaste dataset was introduced to help in developing a robust model to sort and manage waste.

This paper explores four deep learning models such as MobileNetV3, ResNet152, DenseNet121, and ConvNeXt on the RealWaste dataset to classify the waste. This study aims to evaluate the model's performance in accurately detecting and classifying different kinds of wastes captured in landfill environments. A comparative analysis of these four models will be done and the best performed model can be chosen from the study. Through the model analysis, this paper also aims to provide insights into the limitations of the models that have not performed up to the standard in waste classification.

The subsequent sections of this paper are described as follows: The Related Work II section discusses the reviews of previous papers related to the research question. Next, the Methodology III section includes a detailed overview of the data preprocessing and applicable models with their implementation details to the RealWaste dataset. Then, the Evaluation and Results IV section shows the results of the models. Finally, the Conclusion and Future Scope V provides a summary of the research and indicates future possible improvement of the research.

II. Related Work

In classifying multiple types of waste various authors did many research works. This section goes through the previous studies on model implementation that were implemented for waste classification, as its classification is a serious environmental issue. Studies have proposed their models using machine learning and deep learning techniques and most of the studies have utilized the power of Convolutional Neural Networks (CNN). According to the study [8], it proposes two new benchmark datasets i.e., detect-waste and classify-waste with labels in which this study has categorized mostly all of the waste categories such as bio, glass, plastic, and metal, paper, non-recyclable waste, and miscellaneous wastes. The study has proposed a two-stage detector model which can be used for background detection which was done by using EfficientNet-D2 and EfficientDet-D2 for multi-class waste classification. The results of this study have achieved a precision of 70% for the detection of wastes and an accuracy of around 75% which was a decent accuracy but not that good. The study [9], has employed the TrashNet dataset on which it utilizes deep learning models such as DenseNet121, DenseNet169, InceptionResnetV2, MobileNet, and Xception architectures along with Adam and Adadelta optimizers in their architectures for the classification of waste. In this study, the Adam optimizer has outperformed as compared to the Adadelta optimizer. As the TrashNet dataset size was limited, data augmentation was performed to enhance the accuracy of the models which resulted in higher accuracy of the model and the reason mentioned was due to less data.

In the study [10], deep-learning models VGG-16, InceptionResNetV2, DenseNet121, InceptionV3, and MobileNetV2 were utilized for the classification of real waste that was trained on unadulterated materials and some of the samples were collected from the landfill site. They trained these samples of the images on DiversionNet and achieved an accuracy of 49.69% which was a very low accuracy for the model. Further, the study also utilizes the newly formed RealWaste dataset and trained the model with InceptionV3 and Densenet121 which have achieved a better accuracy of around 89.19% and outperformed all the other models that were trained on the Real Waste dataset. All the models, that were trained on DiversionNet, did not perform well. Similarly, there was another study [11] in which the researchers utilized automated detection of waste with the use of Convolutional Neural Networks (CNN) models such as VGG, Inception, and ResNet were trained on the TrashNet dataset. However, this study combined the Inception and ResNet models and achieved an accuracy of around 88.6% which outperformed all the other models.

Another study [12] utilized a dataset of approximately 156,362 images that have binary classes of wastes i.e. biodegradable and non-biodegradable waste. This study utilizes the greyscale and RGB images of wastes on 3 different architectures of Convolutional Neural Networks (CNN) where both types of images were used for training the architectures. As a result, it was found that the third architecture consists of a fully connected layer, then a convolutional layer, and then another fully connected layer. The third architecture of the network outperformed the other two architectures with a classification accuracy of around 82.7% for RGB images and approximately 81% for greyscale images respectively. Another research [13] was done in which the researchers utilized Convolutional Neural networks (CNN) for the CNN-based feature extraction from the images and Graph-LSTM for the detection of waste, two deep learning techniques were utilized for the waste classification on a belt conveyor in the waste collection systems. The CNN model was used for the training for the classification of the six classes i.e., cardboard, metal, glass, plastic, paper, and organic waste. The proposed model has achieved higher accuracy, higher precision and recall value.

This research study [14] presented a waste classification model named DarkWaste. As the name suggests the main idea of this study was to classify the waste in low light. This study focused on resolving the issue of less training data and for that, they employed an Illumination Conversion method for the generation of low-light images and the study has utilized an improved version of the CovNeXt network combined with the YOLOv5 for the waste classification. For the validation of this proposed model, they have tested this model on a self-built dataset of the real world. The results of this study state that the proposed model outperformed all the other models such as Faster R-CNN, Swin Transformer, and YOLOv5 with a mAP of 77.88% and precision of 84.13% and the fastest among all these models. Similarly, another research [15] was done where the study utilized the ConvNeXt as a backbone model for the effective and efficient classification of wastes. In this study, they utilized this model for the classification of the four classes of wastes in which they employed 1660 labelled images for training the ConvNeXt model and got the mAP of 79.88%. But when tested on the test set, it shows that Mask R-CNN network with ConvNeXt outperformed all the other models such as Swin Transformer, ResNet50, and YOLOv3. Another study [16] was presented in which the proposed model utilizes ConvNeXt_tiny as a backbone network and added channel attention and spatial attention to this CNN-based architecture to improve the efficiency of the model for the extraction of features from the images of the garbage. To enhance the classification accuracy, researchers did some hyperparameter optimization in which they chose PolyLoss as a loss function and optimized some model parameters with transfer learning to improve the accuracy. At the time of validation of this proposed model, the model's performance shows extremely well with an accuracy rate of 97.36%, precision of 97.51%, and recall value of 95.51%.

Similarly, another research study [17] presented deep learning and computer vision techniques for the classification of 6 classes of wastes such as glass, metal, paper, plastic, cardboard, etc. In this research study, researchers have utilized Inception-v3 for the classification of the wastes and achieved a training accuracy of 92.5%.

In the research done in [18], the study presented a methodology for automated waste classification using deep learning techniques instead of doing the classification of wastes manually. To achieve this goal, this study proposed a Convolutional Neural Network (CNN) which was DenseNet121 in which they have optimally fine-tuned the architecture by utilizing the genetic algorithm to the fully connected layer of DenseNet121 for the classification of waste trained on the TrashNet dataset for enhancing the performance of the CNN model. The models achieved a higher accuracy which shows the effectiveness of the genetic algorithm. Similarly, another research was done in [19] which has built a new waste dataset i.e. NWNU-TRASH which was better than the other public waste datasets available. Based on this dataset, the study has proposed a DenseNet169 model which was pre-trained on the ImageNet large dataset, and the parameters of this model were fine-tuned and applied to this newly built dataset which resulted in an accuracy of 82% for the classification of waste.

Another research was done in study [20], which presents a CNN-based architecture to classify trash into multiple categories. In this, they have employed the EfficientNet-B0 architecture which was pre-trained on the ImageNet large image dataset. This study proposed the EfficientNet-B0 by tuning the model for the specific demographic regions. This study proposed a model that was fine-tuned with transfer learning for the classification of waste into multiple categories. When this proposed model was experimented with the dataset, the result showed that this model takes fewer input parameters and provides better accuracy of 85%. This was better than that of other EfficientNet-B3 models which indicates the improvement in the classification of region-wise trash images. Similarly, another research was done in study [21] for the detection and classification of garbage using a newly proposed deep learning-based machine vision system in which the study has proposed an improved MobileNetV2 architecture in which the performed principal component analysis (PCA) for minimizing the dimensions of the last fully connected layer. To classify garbage waste into multiple categories, such as hazardous waste, kitchen waste, and recyclables, those involved in this study improved parameters such as CBAM, PCA, and transfer learning. As a result, the proposed model achieved a precision of 90.7%, which was better than that of the original MobileNetV2.

Finally, research was conducted in [22] for recyclable waste recognition using deep learning-based models. This study combined the results of a self-monitoring component test with a residual network (ResNet)-based classification model. When compared to other models on the TrashNet dataset, the proposed model obtained a precision of 90.84%. The TrashNet dataset, which was utilized for this research, was quite limited in size and did not allow any model to be generalized. Therefore, we used the Real Waste dataset, which included a high number of images, for our study.

In conclusion, waste classification is an essential environmental problem that has been thoroughly researched using deep learning and machine learning methods. Research has shown that decent performance in waste classification can be achieved by Convolutional Neural Networks (CNN) based models such as DenseNet, ResNet, and MobileNet. The complexity of waste classification, dataset quality, dataset size, and the need for manual waste image annotation are some of the drawbacks of the present techniques. This study utilizes MobileNetV3, ResNet152, DenseNet121, and ConvNeXt because the previous studies where these models were employed showed good results. So, the main goal here is to increase the model's performance in waste classification by fine-tuning its input parameters. Also, certain limitations have been addressed in this study, i.e., the size and quality of the training and testing dataset and the challenges faced in the classification of the waste mentioned above.

III. Methodology

This project utilizes the data that has been retrieved from the UC Irvine Machine Learning Repository for waste classification. The methodology for waste classification follows the systematic approach of Knowledge Discovery in Databases (KDD) which is the method of extracting meaningful and useful knowledge from data [23]. KDD follows the steps that include data collection, followed by data preprocessing, model transformation, model implementation, and model evaluation. These steps form the foundation for the completion of the project. Figure 1 shows the representation of the KDD flow in the project.

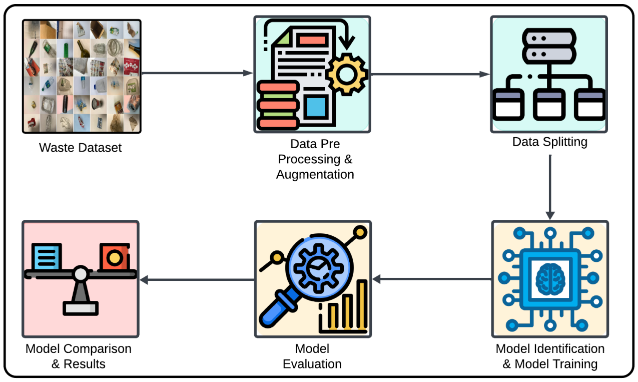

Fig. 1: KDD Flow of the project

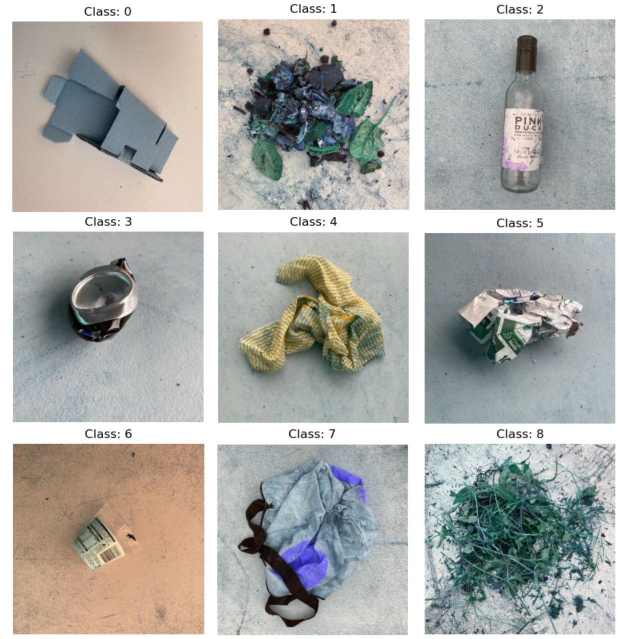

Fig. 2: Waste Data Classes

A. Collection of Data

The dataset used for this project consists of a set of diverse waste data in the form of images sourced from the UC Irvine Machine Learning Repository [24]. The categories present in the dataset include Cardboard, Paper, Plastic, Textile Trash, Food Organics, Vegetation, Glass, Metal, and Miscellaneous Trash which are assorted into classes. Figure 2 represents the total 9 categories classified from 0 to 8. The dataset is not divided into train and test sets initially. The dataset needs to be split in the later stages to train the model.

B. Data Pre-processing

The data collected from the repository needs to undergo data pre-processing and data augmentation to increase the robustness of the models that will be used.

The data pre-processing techniques used here include image resizing and batch normalization. The image resizing technique makes sure that the dimensions of the images are consistent throughout ensuring compatibility with the models used. Resizing the images also enhances performance by reducing the possibility of overfitting and computational complexity thereby lowering the training time [25]. The initial size of the sourced images is 524x524 which are resized to a constant dimension of 256x256. Batch normalization is an essential process used to improve the data quality of the image batch that will be fed to the machine-learning model and enhance the performance of the model [26]. It scales the data to a similar distribution and minimizes feature bias within the classes present.

The data augmentation technique is used to enhance the shape and size of the image. This technique generates a modified version of existing data and solves the issues of input data variation and data overfitting [27]. The input data are rescaled, flipped, and randomly rotated to introduce variability in the orientation of the images which can be seen in Figure 3. The image is rescaled to 1/256, meaning each pixel in the image is divided by 256, which effectively scales the values to a range between minimum and maximum pixel values. The images are flipped along the horizontal and vertical axis as well. The images are also randomly rotated at 0.2 times the maximum rotation range and this can bring variability in the trained data. Along with this the augmentation also includes random affine transformations and color jitter with brightness, contrast, and saturation being manipulated.

C. Model Transformation and Implementation

The process of model transformation includes the use of pre-trained machine-learning models and then fine-tuning the models as per the requirement for waste classification. The pre-trained models that have been used here are ResNet152, MobileNetV3, DenseNet121, and ConvNeXt, and the reason for considering these models is justified in the related work section II. These models can capture the relevant features and information from the image data.

1) MobileNetV3: MobileNetv3 is used as a pre-trained model trained on Imagenet weights. The base model is loaded and the model customization is done to create an appropriate model for the specific requirement. For fine-tuning, the last 6 layers are removed and the trainable parameters of the model are set to false to block the base model weights from changing. The model customization includes the use of dropout layers for overfitting prevention. Dropout layers will randomly drop a portion of input data to prevent potential overfitting. Then

Fig. 3: Augmented Data

global average pooling and batch normalization are performed to reduce dimensions and normalize previous layer activation to improve the stability and performance. After using global average pooling and normalization, a further dropout layer is added to maintain regularization. Finally, a softmax activation function is implemented on the dense layer of the model for classification purposes. This is followed by the process of compilation of the model which is performed using Adam Optimiser with a learning rate of 0.00125. This learning rate is considered after multiple trials and errors. A loss function of Sparse categorical cross-entropy is implemented as well, as the class indices are labeled as integers. The evaluation metric in consideration is accuracy. The model is expected to run on a maximum epoch of 50 however with the use of a learning rate scheduler and early stopping, the model stopped after 15 epochs giving the best result. The Early stopping patience is considered as 4 which determines the number of epochs the training process will continue in the validation loss without any improvements. The model is now trained on the training data and its performance is evaluated over the validation dataset for several epochs.

2) ResNet152: The pre-trained ResNet152 model is also implemented and trained on ImageNet weights. The fully connected layers are removed from the top, and base model layers are set to freeze to block the model weights. The model customization also includes a dropout layer added to the previous layer output, with a dropout rate of 0.5. This states that 50% inputs will be randomly set to 0 for each training iteration. The output is then flattened into a 1-dimensional array. The Rectified Linear Unit activation function (ReLU) is applied to the dense layer with 128 neurons and returns a value if the input is positive, and it returns zero. This function brings sparsity to the model and removes the vanishing gradient issue. A softmax activation function is implemented on the dense layer of the model for classification purposes where each output represents the input probability of a particular class. Adam optimizer is used to compile the model with a learning rate of 0.0001, considered after multiple trials. Sparse categorical cross-entropy is implemented as a loss function for integer-labeled class indices. The model is trained on the training dataset and is expected to run for 20 epochs with an early stopping constraint. The patience of 2 is considered to prevent model overfitting. The early stopping allowed the model to converge in about 8 epochs.

3) DenseNet121: Next, the DenseNet121 pre-trained model is used in this project. Here for definition, the model is used with the help of 'Pytorch' using the 'torchvision' module. The model is pre-trained on the ImageNet dataset and the weights associated with that training are kept as it is. The gradients are then frozen so that the pre-trained weights are not retrained. As usual, the classifier is then replaced by a custom new classifier in this project. Here the classifier is replaced by the help of a linear layer. The new linear layer has the same number of input features as the original DenseNet121 classifier however the output features are set to the number of classes present in the dataset used within this project. This helps the model to adapt to the new data and classify the test images according to that. The training is done with an Adam optimizer and a 'ReduceLROnPleateau' scheduler. The optimizer helps to update the model parameters based on the gradients computed during the backpropagation. Backpropagation and optimization are both done step by step within the code. The project also implements running loss tracking so that the training and validation losses are tracked during the training phase. The learning rate helps to determine the step size that is updated during the updation of the parameters. The learning rate is set to 0.0001 in this case. The 'betas' parameter controls the exponential decay rates for the first and second-moment estimates also known as the mean and variance of the gradients. There is no callback for early stopping for this model and is trained for 10 epochs.

4) ConvNeXt: Finally, the ConvNeXt pre-trained model is used here in the project. The model implementation is quite similar to the DenseNet121 implementation. Just like the above model, the 'torchvision' module of the 'Pytorch' is implemented. The pre-trained weights on the ImageNet dataset are all frozen and are not trained further in this model. The classifier is replaced by a Linear layer that has 768 input features and output features of 9. Here 9 is just the number of classes this project data deals with. This is a fully connected layer in the ConvNeXt model. The bias is set to True for this layer. Similar to the DenseNet121 model, this model also runs for 10 epochs where the Adam optimizer is used and the ReduceLROnPleateau scheduler is used. The learning rate is set the same as DenseNet and the betas value are 0.9 and 0.999. Besides this, the weight decay is set to 0. The ConvNeXt model is trained for 10 epochs as well similar to the DenseNet. The backpropagation and the optimizer step help the model to generalize better overall during the training phase.

D. Model Evaluation

Model evaluation is done using machine learning metrics to assess the performance of the waste classification model. The model while training rigorously evaluates the result obtained from the validation dataset. The dataset is initially divided into train and test subsets as mentioned in the data preparation phase. This allows the model to use the validation subset to continuously check up on the training phase so that the model does not overfit. The loss generated while training is calculated using the categorical cross-entropy cost function. The accuracy metric is also used to evaluate the model while training for both training and test data subsets. Once the training is complete the model is then evaluated with the use of different metrics such as accuracy, precision, recall, and AUC curve. These evaluations are further discussed in the next section IV. The trained models are evaluated using both quantitative and qualitative methods. Quantitative evaluation involves assessing model performance on test data using standard evaluation metrics. Qualitative evaluation includes a visual inspection of model predictions and identification of areas for improvement.

IV. Evaluation and Results

The evaluation depicts the effectiveness of the approaches used to accurately classify and categorize the waste materials. The trained models achieved high accuracy in classifying the waste classes.

The MobileNetV3 shows robust performance with precision, recall, and F1-score metrics ranging from 0.83 to 0.98 across all 9 waste classes as can be seen in Figure 4. The overall accuracy of 91% shows the model's effectiveness in accurately classifying the waste classes. The correct number of classifications for each class is depicted in the correlation matrix with a heatmap in Figure 5. The line graph in Figure 6 depicts the model accuracy increase. Figure 7 shows the decrease in the loss while training the MobileNetV3 model. This loss is monitored during the training phase so that the loss doesn't exceed too much even though the accuracy keeps increasing. This helps the model to be trained without getting overfit on the dataset.

The precision, recall, and F1-score metrics for ResNet152 exhibited varying performance for waste classes. The metric

MobileNetV3 Classification Report:

	precision	recall	f1-score	support
Cardboard	0.85	0.88	0.87	33
Food Organics	0.98	0.94	0.96	47
Glass	0.97	0.89	0.93	44
Metal	0.84	0.96	0.89	75
Miscellaneous Trash	0.83	0.83	0.83	42
Paper	0.95	0.88	0.91	60
Plastic	0.91	0.89	0.90	103
Textile Trash	0.86	0.86	0.86	28
Vegetation	0.98	0.98	0.98	43
accuracy			0.91	475
macro avg	0.91	0.90	0.90	475
weighted avg	0.91	0.91	0.91	475

Fig. 4: MobileNetV3 summary

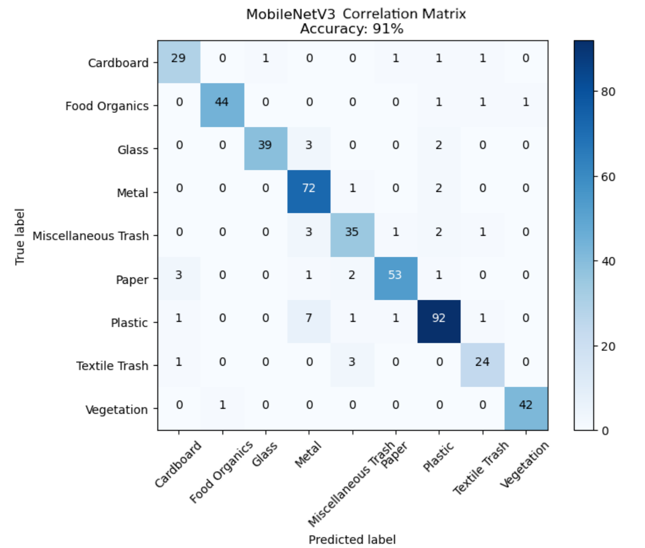

Fig. 5: Correlation matrix for waste classes using MobileNetV3

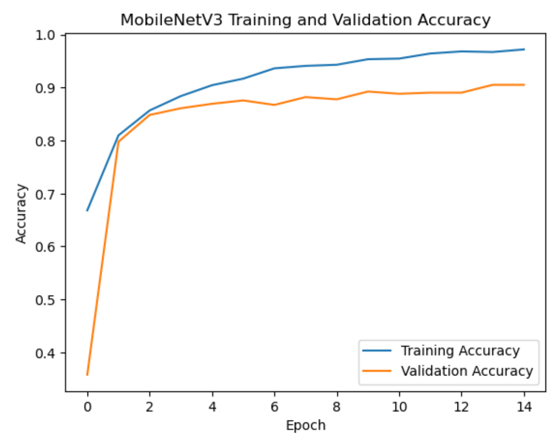

Fig. 6: Accuracy for MobileNetV3

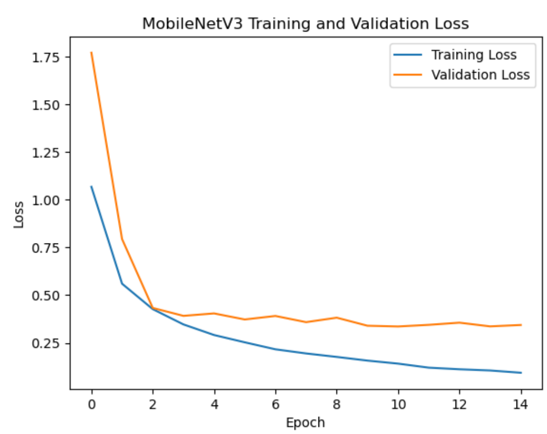

Fig. 7: Loss for MobileNetV3

ranges from 0.70 to 0.96, where certain classes like Vege-

ResNet152 Classification Report:	precision	recall	f1-score	support
Cardboard	0.86	0.91	0.88	33
Food Organics	0.95	0.87	0.91	47
Glass	0.92	0.75	0.82	44
Metal	0.73	0.93	0.82	75
Miscellaneous Trash	0.70	0.74	0.72	42
Paper	0.84	0.88	0.86	60
Plastic	0.89	0.79	0.84	103
Textile Trash	0.96	0.79	0.86	28
Vegetation	0.95	0.98	0.97	43
accuracy			0.85	475
macro avg	0.87	0.85	0.85	475
weighted avg	0.86	0.85	0.85	475

Fig. 8: ResNet152 summary

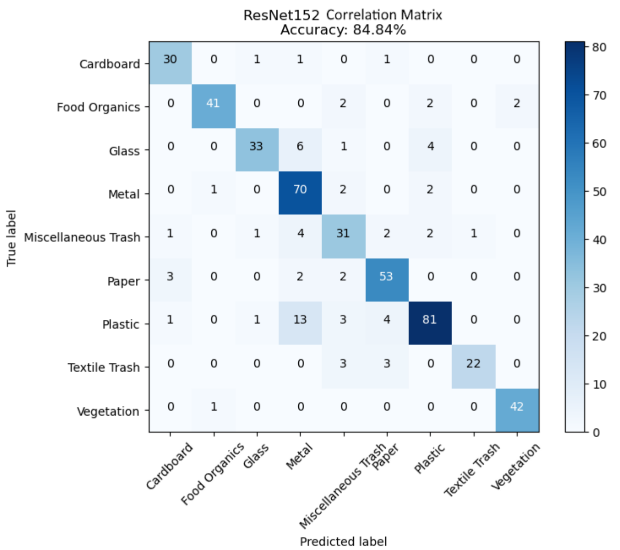

Fig. 9: Correlation matrix for waste classes using ResNet152

tation and Food Organics showed high precision and recall scores as seen in Figure 8. The overall validation accuracy is 84.84%, indicating its ability to classify waste materials correctly. The correct classification for each class is depicted with a heatmap in the correlation matrix as seen in Figure 9. Figure 10 shows the line graph with an increase in model accuracy and Figure 11 shows the validation and training loss. ResNet152 model shows promise in waste classification tasks, with potential applications in real-world waste management systems. Upon checking both the confusion metrics, it was also found that ResNet152 performed quite better for some classes such as cardboard and vegetation even though it has lower overall validation accuracy than MobileNetV3.

The DenseNet121 resulted in the precision, recall, and F1-score metrics ranging from 0.92 to 1.00 with an overall model accuracy of 97.27%, as shown in Figure 12. The DenseNet121 model accuracy line plot is shown in Figure 13. The line plot in Figure 14 shows the decreasing loss over time with each training epoch. The training accuracy obtained is pretty well. The test and validation accuracy also rises pretty well, however, is slightly lesser than the training accuracy which is about 2.7%. Overall, the model generalizes quite well

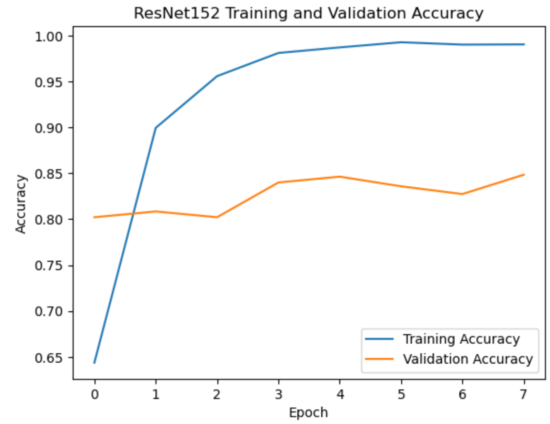

Fig. 10: ResNet152 Accuracy

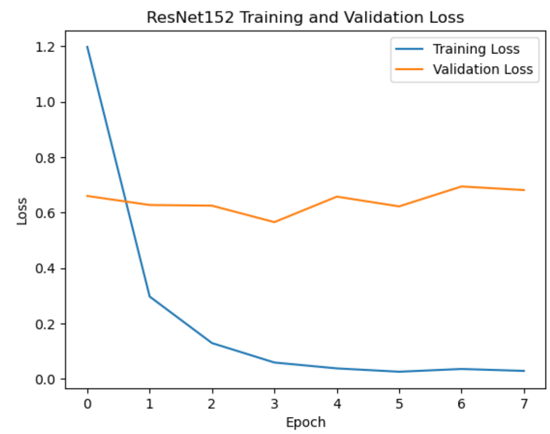

Fig. 11: ResNet152 Loss

Classification Report for DenseNet121:	precision	recall	f1-score	support
Cardboard	0.99	0.99	0.99	76
Food Organics	0.92	1.00	0.96	79
Glass	0.98	0.99	0.98	91
Metal	0.98	0.96	0.97	166
Miscellaneous Trash	0.92	0.96	0.94	83
Paper	1.00	0.98	0.99	104
Plastic	0.98	0.97	0.98	184
Textile Trash	1.00	0.99	0.99	77
Vegetation	0.99	0.93	0.96	91
accuracy			0.97	951
macro avg	0.97	0.97	0.97	951
weighted avg	0.97	0.97	0.97	951

Fig. 12: DenseNet121 Summary

compared to the first two models. The correlation matrix with heatmap for DenseNet121 is depicted in Figure 15 similarly as well. The difference is quite evident here in that there are a few more mistakes here when compared to ConvNeXt. However, the model overall performs way better than the first two models, ResNet152 and MobileNetV3.

The ConvNeXt result summary shows precision, recall, and F1-score values between 0.97 and 1.00 across all the waste categories. The overall model accuracy of around 99% indicates

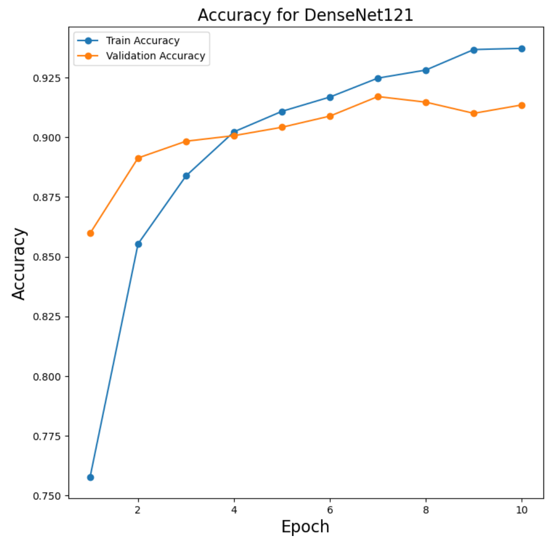

Fig. 13: DenseNet121 Accuracy

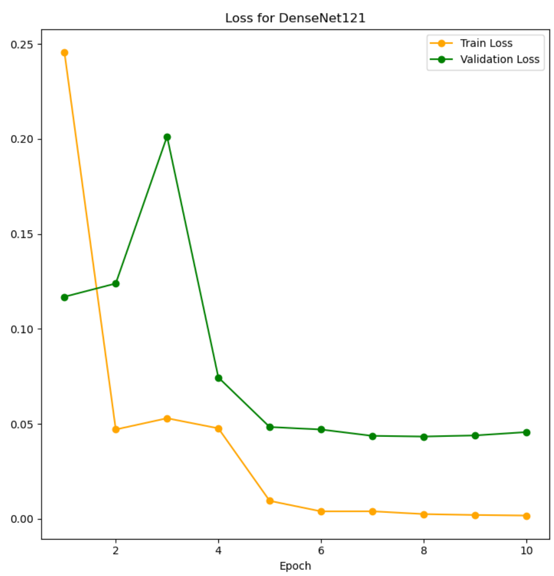

Fig. 14: DenseNet121 Loss

the model's effectiveness which can be seen in Figure 16. The accuracy growth for both the training and validation subsets while training the ConvNeXt model is shown in Figure 17. As seen within the results, the training and validation results of ConvNeXt have acquired the best results so far. The ConvNeXt model acquired a 98.95% accuracy over the test dataset. The validation loss goes down to around 0.045 and the net training time taken to train the model is about 209.0m. The loss line plot shows perfectly in figure 18 the decreasing loss over time with each training epoch. The model generalizes pretty well. The confusion matrix for ConvNeXt is depicted in figure 19. Here the correct classification for every class is depicted within the matrices.

The output for all the models is depicted in the table below in Table I. From this table, it can be understood that the models

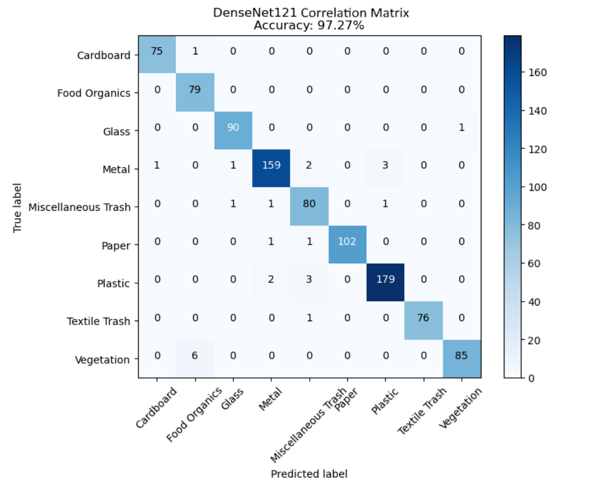

Fig. 15: Correlation matrix for waste classes using DenseNet121

Classification Report for ConvNext:

	precision	recall	f1-score	support
Cardboard	1.00	1.00	1.00	76
Food Organics	0.96	1.00	0.98	79
Glass	1.00	1.00	1.00	91
Metal	0.99	0.97	0.98	166
Miscellaneous Trash	0.98	1.00	0.99	83
Paper	0.99	1.00	1.00	104
Plastic	0.99	0.99	0.99	184
Textile Trash	1.00	1.00	1.00	77
Vegetation	1.00	0.97	0.98	91
accuracy			0.99	951
macro avg	0.99	0.99	0.99	951
weighted avg	0.99	0.99	0.99	951

Fig. 16: ConvNeXt Summary

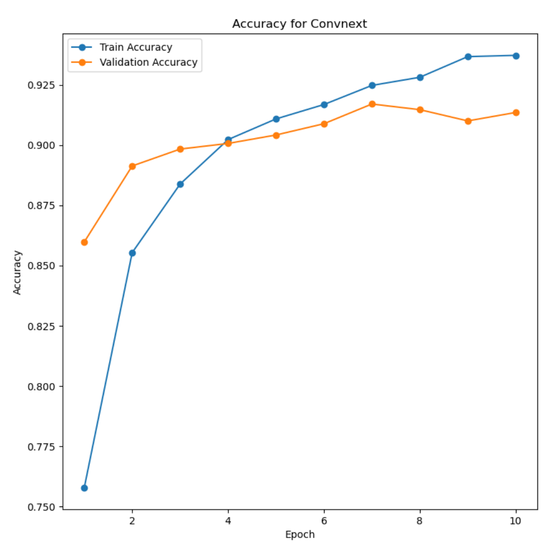

Fig. 17: ConvNeXt Accuracy

ConvNeXt performs the best and DenseNet121 performs the second best. Both the models have very high accuracy however the loss has decreased substantially for the ConvNeXt model in this case. The training accuracy is pretty high for all the

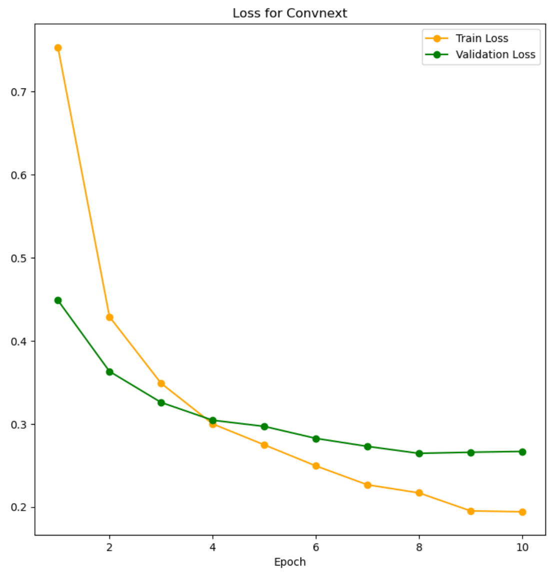

Fig. 18: ConvNeXt Loss

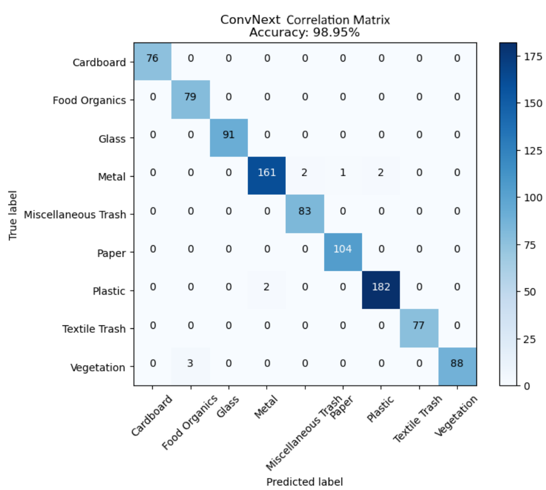

Fig. 19: Correlation matrix for waste classes using ConvNeXt

models with above 90%. However, the validation accuracy is what's changing and is the right evaluation metric for all the models. The validation and training loss are also mentioned within the table to check the probability of error that could be possible while making predictions with the models.

A random image from the internet has been used to check the accuracy of the two best-found models, DenseNet121 and ConvNeXt. On passing the image of cardboard, the models DenseNet121 and ConvNeXt show an accuracy of around 97.8% and 99.9% respectively in predicting the object as can be seen in Figure 20. This shows how efficient the two models are and has the capability of accurately categorizing any waste image.

V. Conclusion and Future Scope

This report presents a comprehensive study of models for image-based multiclass waste classification using deep learning. This study provides an automated solution for waste classification and makes a significant impact on the future handling of landfill wastes. The use of deep learning models namely MobileNetV3, ResNet152, DenseNet121, and ConvNeXt shows a promising result for classifying and streamlining wastes which is a big improvement over traditional manual

```
DenseNet121_0 Prediction: Cardboard
Cardboard          : 0.978295            prob: 97.83%
Food Organics      : 0.000001            prob: 0.00%
Glass              : 0.000098            prob: 0.01%
Metal              : 0.020550            prob: 2.06%
Miscellaneous Trash: 0.000024            prob: 0.00%
Paper              : 0.000902            prob: 0.09%
Plastic            : 0.000128            prob: 0.01%
Textile Trash      : 0.000001            prob: 0.00%
Vegetation         : 0.000001            prob: 0.00%
--------------------------------------------------------
ConvNext Prediction: Cardboard
Cardboard          : 0.999707            prob: 99.97%
Food Organics      : 0.000001            prob: 0.00%
Glass              : 0.000001            prob: 0.00%
Metal              : 0.000133            prob: 0.01%
Miscellaneous Trash: 0.000007            prob: 0.00%
Paper              : 0.000142            prob: 0.01%
Plastic            : 0.000001            prob: 0.00%
Textile Trash      : 0.000000            prob: 0.00%
Vegetation         : 0.000009            prob: 0.00%
```

Fig. 20: Prediction from random image

	MobileNetV3	ResNet152	DenseNet121	ConvNeXt
Training Accuracy	0.9722	0.9904	1.0000	0.9996
Training Loss	0.0931	0.0292	0.0009	0.0023
Validation Accuracy	0.9053	0.8484	0.9727	0.9895
Validation Loss	0.3436	0.6816	0.0942	0.0642
Epoch Count	15	8	10	10

TABLE I: Model Comparison

processes showing improved accuracy and efficiency.

Future work related to this study has an immense possibility of improvement and advancement on how waste materials are dealt with. Based on the study, more intricate patterns within an image can be identified by working with more dense convolutional layers with increased learnable parameters. Introducing further data augmentation techniques like cropping, contrast, saturation, colour augmentation, brightness, dimensional shifting, and grayscaling, can bring more features within the data thereby increasing the information to identify minute details. More advanced fine-tuning of the models can better handle all sorts of real-world situations. Vision transformers can also be implemented as it is an effective technique with way more learnable parameters and can handle images of varying resolutions without any complex preprocessing. Integrating deep learning with robotics can create an ensemble automated sorting mechanism that can set an industry-standard in the future. With the absence of human intervention, the efficiency and accuracy of machines will be very high which can have a significant business impact on the recycling and reuse industry. By integrating sensors and gadgets, real-time data can be fed into deep-learning models to increase operational efficiency and deployed in multiple waste management stages. The ensemble of sensor data and waste classification data can help assess the environmental impact of waste management thereby facilitating more sustainable approaches.

With advanced technological improvement, the future of our world appears green with the potential of a more sustainable and nature-friendly approach to dealing with waste materials.

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