A Comparative Study Of Custom CNN And MobileNetv2 For Binary Waste Classification Using Deep Learning

MSc Research Project
Masters in Data Analytics

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MSc Project Submission Sheet

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A Comparative Study Of Custom CNN And MobileNetv2 For Binary Waste Classification Using Deep Learning

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Abstract

The onset of significant environmental impact due to poor disposal of waste requires a new way that can facilitate waste classification in an efficient manner. This research paper looks into how deep learning models can be used in performing a binary classification of waste types through image-based information, to predict whether the waste is Organic or Recyclable waste. The main goal was to compare the performance of a Custom Convoluted Neural Network (CNN) to that of a pre-trained MobileNetV2 on the basis of the performance accuracy of the classification model in the dataset and the generalization abilities. It has a systematic approach that entails data preprocessing, design of the model, training, and testing. The two models were trained and evaluated based on the idea of a curated dataset, and the performance of the models was determined using various parameters like accuracy, precision, recall, and F1-score.

The Custom CNN model tested better with an accuracy of 92.24% compared to the MobileNetV2, which achieved 90.03% accuracy. The classification report indicated the excellence of Custom CNN in recalling the recyclable waste, but MobileNetV2 was consistent in recognizing both classes thematically. The results show that custom CNN architectures can perform better in the particular waste classification task, but MobileNetV2 is also a potentially attractive option to use in lightweight deployment settings. The study highlights the applied knowledge of deep learning in facilitating the implementation of intelligent waste management systems and more environmental sustainability. Future developments will involve multi-class classification, applying the model to edge devices, and into actual municipal waste handling systems.

1 Introduction

1.1 Background

The increased awareness of environmental deterioration and the lack of proper waste management have provoked the rise of interest in sustainable practices and technologies. The production of existing waste and recyclable waste has been greatly increased as the population of the world keeps growing, and urbanization keeps improving. The World Bank indicated that more than 2 billion tons of municipal solid waste are produced every year, with more than 33% not dealt with in a manner that is environmentally safe. The problem is especially intense in the developing countries, where the system to separate trash and recycling fails or is still in the development process.

Conventional waste sorting techniques are mostly of a manual nature in terms of human resources to man the effort and human discretion to perform sorting. Such approaches are not only time-consuming, prone to errors, and highly unhealthy for the workers. Furthermore, the poor disposal of waste results in contamination of the recyclable trash and utilization of more landfills, contributing more to environmental pollution and climate change. The solution to this problem, therefore, lies in the incorporation of artificial intelligence (AI) and computer vision, more specifically, the deep learning methods, into the process of streamlining and enhancing the classifiers of waste.

1.2 Justification for the Study

Machine learning and deep learning have become driverless by staging revolutions in the ways machines capture and condense images with a rich likelihood of accuracy. Particularly, Convolutional Neural Networks (CNNs) have shown incredibly high success rates as applied in diverse image classification scenarios such as medical diagnosis, face recognition, and object detection. Using such technologies to classify the waste has the possibility of minimizing human involvement, cutting the cost of operation, as well as boosting efficiency and accuracy of waste management activities.

Although some previous works have been carried out to classify the waste based on image processing, there are a lot of multi-class tasks that have a high inter-class confusion similarity issue, or the existing extraction of features lacks generalization ability. Further, some of the current models are computationally demanding and cannot be used in real time with low resources.

This study aims to fill this gap by comparing a model built with a customizable CNN and a transfer learning method, which utilizes MobileNetV2, a model to classify waste as organic or recycling the waste, as the binary switches. The research question is to find out the model that is more suitable in accuracy, speed, and generalization.

1.3 Research Gap

Even though deep learning has been used in many of the studies involving waste classification, very few studies have done a comparative study of custom CNNs and pre-trained models like MobileNetV2 in the specific context of a two-category classification. Moreover, a significant part of the literature available does not provide an end-to-end pipeline including data preprocessing, model evaluation, and graphical representation of performance. Lightweight, faster executable models that can be used in real-time and Low-Power applications, like embedded systems and edge devices to be installed in Smart waste bins are required.

This paper covers the above gaps by designing and testing two deep learning models on an open dataset, with comprehensive preprocessing, augmentation, and evaluation plans.

1.4 Research Questions

RQ: Can deep learning models effectively classify waste images into organic and recyclable categories?

In particular we will investigate how does the performance of a custom CNN compare with that of a pre-trained MobileNetV2 model for binary waste classification, and the trade-offs between model accuracy, training time, and computational efficiency.

1.5 Aim and Objectives

Aim

This research aims to develop and evaluate a deep learning-based image classification system using a custom CNN and MobileNetV2 to accurately distinguish between organic and recyclable waste for efficient real-world deployment using Python programming.

Objectives

- To review existing literature on the application of deep learning and image classification techniques in waste management.
- To collect and preprocess a publicly available image dataset representing organic and recyclable waste, ensuring data augmentation for improved model generalization.

- To design and implement both a custom CNN model and a transfer learning model using MobileNetV2 for binary waste classification, enabling a comparative analysis of their performance.
- To compare and evaluate the performance of the two models using metrics such as accuracy, precision, recall, F1-score, and confusion matrix.
- To identify the most suitable model in terms of classification accuracy, training efficiency, and potential for real-time deployment.
- To provide recommendations for integrating the selected deep learning model into automated waste sorting systems to promote sustainability and operational efficiency.

1.6 Organization of the Study

Figure 2.1: Thesis Structure

(Source: Self-created)

This research work is organized into seven chapters. In chapter 1, the research background, aims, and objectives are presented. Chapter 2 examines literature on the topic of deep learning, wastes classification, and transfer learning. Chapter 3 describes the research methodology and data treatment, and the model to be used. Chapter 4 contains details of the custom CNN and MobileNetV2 models in terms of design specifications. The implementation process is discussed in Chapter 5. In Chapter 6, the performance of the models is measured and compared. Last but not least, Chapter 7 closes the research segment by explicating findings and future research. This paper works towards the improvement of intelligent waste management utilizing deep learning of image-based classification.

2 Related Work

2.1 Introduction

An increase in the waste of the megacity and the low productivity of the manual sorting system have led to an inquiry about deep learning methods of automatic classification of waste. This literature review looks at innovations within the fields of custom CNNs, transfer learning, smart waste systems, and data development. It showcases new developments, assesses model performance, and lists the research gaps that exist to provide solutions to problem-free and feasible smart waste management in the future.

2.2 Introduction to Deep Learning in Waste Classification

The issue of waste management in contemporary urban society has gained particular importance due to the current increase in solid waste and the importance of sustainable methods. This old-fashioned method of sorting the used waste, where manual kk is highly relied upon, is ineffective, time-consuming, and more likely to make mistakes. Artificial intelligence and some specific ones in particular, deep learning integration, have presented themselves, in this case, as potent means of automating and optimizing waste classification tasks. The elements of deep learning, which are a branch of machine learning that learns complex structures of abstractions in the data, have been effective in image-based recognition problems and, therefore, can be applied to the problem of classifying the different types of waste materials (Dabhane, 2023).

The use of Convolutional Neural Networks (CNNs) specifically has gotten a considerable amount of exposure since these models learn spatial hierarchy in pictures, which makes them suitable for identifying visual patterns that can be related to various classes of waste, like plastics and organic food materials. As computational power and the availability of large-scale data have improved, researchers have devised many models that increase the classification accuracy, decrease computational cost, and make the models more generalizable in real-world applications.

2.3 Custom CNN Architectures for Waste Classification

The design of specific CNN models that can work with the specific properties of the images of wastes and produce the results needed in deep learning-based waste classification is another of the bases that have to be built into such a methodology. Dabhane (2023) tried to perform a thorough study in order to sort out organic and recyclable waste with the custom-made CNN models. The study entailed the process of collecting a dataset of labeled waste images, and a deep learning architecture that was designed and perfected through experimentation. Several hyperparameters were used to train and validate the model, and the findings generated demonstrated that a well-organized CNN could attain high levels of accuracy in categorizing waste into Boolean masses.

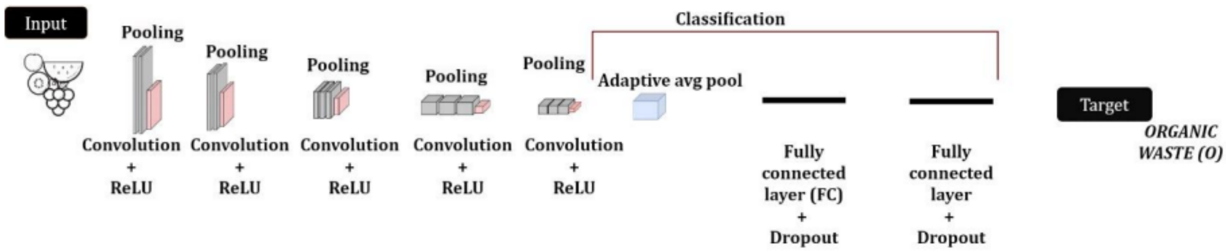

Figure 2.1: CNN architecture

(Source: Dabhane, 2023)

The importance of the architectural choices, like the number of convolutional layers, kernel sizes, and activation functions, was noted by Dabhane in his work. Furthermore, the paper also emphasized the necessity of data augmentation to reduce overfitting and build a robust model to be deployed to work in different lighting or background situations. The present study added starting points to the knowledge on establishing domain-specific applications of CNN models, including the classification of waste.

2.4 Transfer Learning and Pre-trained Models

Although custom CNNs are flexible and adaptive, training a deep network in the superior state relies on large-sized annotated datasets and extensive computational resources. In a bid to overcome this drawback, researchers have sought to use transfer learning, in which models trained on huge datasets, such as ImageNet, are fine-tuned to specific tasks.

A new deep learning framework for efficient classification of organic and recyclable waste, ICCDN-Net, was proposed by Islam *et al*. (2025). The architecture has used both custom CNN blocks and pre-trained layers to show the efficacy of the approaches that use domain-specific knowledge and generalized information on the visuals. The ECCDN-Net model performed much better in terms of classification than baseline CNNs, especially precision and recall. It also highlighted the advantage of exploiting ensemble strategies and a cross-channel feature extraction to boost the capacity of the model to recognize visually adjacent classes.

In the same vein, the backbone of the system proposed by Ahmed *et al*. (2023) was MobileNetV2, a lightweight and mobile-friendly model. It was able to lift the accuracy to high levels by tuning the pre-trained MobileNetV2 on a labeled waste dataset to keep the model computationally efficient to meet the needs of real-time applications. Their results are in favor of transfer learning in situations where there are limited computational resources and where fast deployment is necessary.

2.5 Deep Learning for Sustainable Waste Management

The application of AI in waste classification is well in line with their general sustainability agendas. Malik *et al*. (2022) have commented on how deep learning can unleash the power of intelligent waste sorting in the promotion of sustainable development. Several CNN models have been tested, such as AlexNet, VGG16, and ResNet50, and their performance in identifying, sorting waste based on recyclable, non-recyclable, and organic waste.

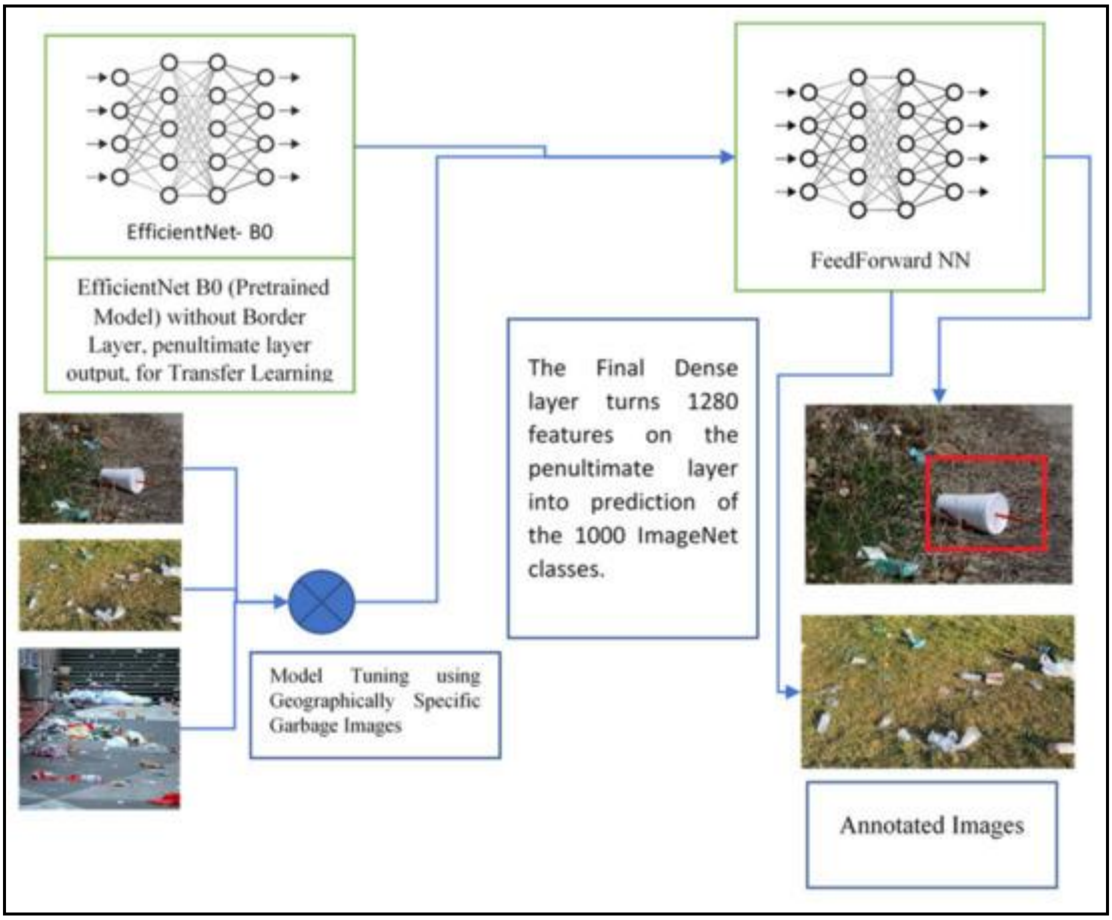

Figure 2.2: Image Localization Architecture Using Transfer Learning Model over EfficientNet-B0

(Source: Malik *et al*. 2022)

Their analysis showed that deep learning models had the potential to minimize landfill waste by allowing correct separation at source to the extent possible. Moreover, the significance of employing the model of image recognition in smart bins and municipal waste management systems was highlighted in the course of the study. Such models reduce human error and increase the speed of the sorting process, which promotes the principles of a circular economy and conserves the environment.

2.6 Smart Waste Systems and Real-Time Classification

The use of real-time classification systems has played a vital role in the creation of smart waste management infrastructures. Shourie *et al*. (2024) have developed an organic and recyclable waste classification system using VGG16 as a classification tool as part of a project of smart waste management. This was able to do because the researchers tested their model in a real-time environment with the help of embedded devices and still proved that it was possible to implement deep learning systems in edge-based computing environments.

Their paper solved the problems of latency, model compression, and the compatibility of hardware, and provides insight into the implementation of smart classification systems in a low-resource environment. Transfer learning with VGG16 allowed achieving a high level of accuracy with a short amount of training and supplemented the applicability of premade models in a real-time waste management system.

Reddy *et al*. (2024) also discussed a machine learning application to the landfill minimization problem. They used an intelligent system of classification based on both classic machine learning procedures and deep learning procedures, such as decision trees, CNNs, and random forests. CNNs were found to be superior to other algorithms in accuracy, scalability, and thus they are selected as more desirable in the automation of waste classification.

2.7 Dataset Challenges and Real-World Applicability

The provision and quality of datasets are one of the essential difficulties in the classification of wastes with deep learning. Most experiments are based on ad hoc-selected datasets, which do not provide sufficient diversity and size to allow solid generalization. Single *et al.* (2023) closed this gap with the introduction of the Real Waste, a large-scale, real-world data set intended to teach landfill waste classification. It has thousands of labeled images taken under different lighting and background situations, which makes it a good dataset to train and benchmark deep learning models.

Use of the Real Waste dataset made it possible to create models that were closer to the realities of real-world waste sorting. Single *et al.* highlighted that there is a requirement for new and standardized databases and benchmark procedures to enhance the comparability of research and independent verification within the field. They also advocated that academia, the government, and industry collaborate to ensure open-access repositories and better transparent models of their works.

Similarly, Sevinç and Özyurt (2022) also examined how the deep learning models perform in a variety of data sets and architectures. They tested models like DenseNet and InceptionV3 under recyclable waste classification, whereby the deeper architecture models with a skip connection proved to be better in complex classification assignments. Nonetheless, it was also reported by the authors as a drawback that increased training time and resources consumed, which makes model complexity an essential aspect of efficiency.

2.8 Deep Learning Architectures and Model Innovations

The field of automated waste classification is still being influenced by new improvements in deep learning architecture. Zhang *et al.* (2021) proposed a deep learning framework, the combination of the convolutional and residual blocks, which enhanced the classification accuracy. They used methods of preprocessing (background subtraction and noise filtering), which improved the quality of the image provided to the model.

The model had high performance on different classes of recyclable waste and exhibited powerful generalization skills. The work by Zhang *et al.* emphasized the role of architectural design in addressing the intra-class variations and the effect of preprocessing on model performance.

In a study by Narayan (2021), entitled DeepWaste, an application using deep learning to classify waste on mobile phones was created. Mobile application of the model. Hence, by combining the optics of scanning and categorizing waste on a smartphone, people would be able to participate in sensitizing life and citizen involvement in achieving sustainable waste management even when travelling. This paper has pointed out the importance of the user-centered design when coming up with intelligent classification systems, which are not only accurate but also easy to use by non-expert users.

2.9 Research Gaps

Although the state of deep learning relative to waste classification is advanced, some gaps are remarkable. The generalizability and robustness of the models are impaired by the lack of large, diverse, and real-world datasets, which constitutes a major limitation. In addition, issues of real-time implementation, including computational performance, energy requirements, and suitability for edge devices, are underdeveloped. Further, few studies have been conducted that look into ways to incorporate these AI-based models into already existing waste management infrastructures or have evaluated the socio-economic effects of these models. These gaps evidence the existence of a gap, which should further be explored to find scalable, efficient, and context-aware intelligent waste classification solutions.

2.10 Summary

The reviewed literature has the transformative nature of deep learning within automated waste classification. Ranging from custom CNNs, pre-trained networks, and real-time inference, there are many approaches that have been taken to increase the accuracy and efficiency in waste sorting systems. The smart combination of intelligent models, quality datasets, and smart deployment strategies can be used in potentially more sustainable and efficient waste management practices. Future research needs should push boundaries on working on limitations of the dataset, model explainability, and integration of AI-based systems in a large spectrum of waste management policies to ensure the creation of maximum social value.

3 Research Methodology

3.1 Overview of Research Procedure

This project employs an experimental approach to compare MobileNetV2 and a Custom CNN for binary waste classification. The steps include obtaining the dataset, preprocessing, data augmentation, developing the model, training the model, and evaluating the model. The aim is to identify a better model to classify waste as organic or recyclable. MobileNetV2 can transfer its learning to limited data and resources, which is based on previous results. Its methodology is reproducible and scientifically sound as it complies with the best practices in image classification based on deep learning, and measures the accuracy, generalization, and computational efficiency of the model via an identical, objective process.

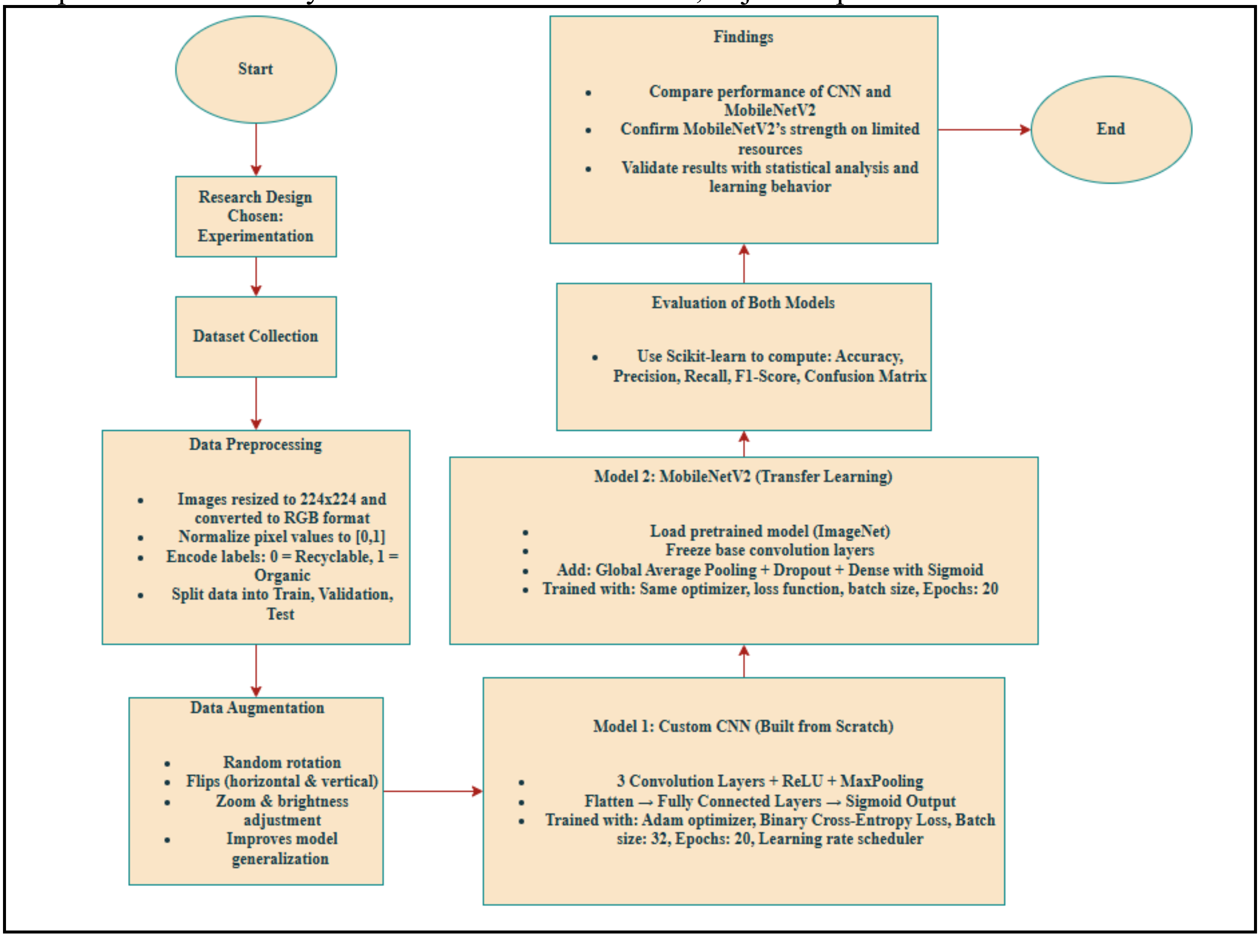

Figure 3.1: Experimental Workflow for Binary Waste Classification Using Custom CNN and MobileNetV2

(Source: Self-created)

3.2 Dataset Description and Collection

The data used in this research is publicly available waste classification data obtained on Kaggle, consisting of organized and recyclable waste labeled pictures. The data is not biased and has good-quality images that enable deep learning models to train and be tested reliably. About 2,5000 images were utilized, with nearly the same number of images belonging to each of the classes to eliminate biases during the training. Each of the pictures initially varied in resolution and format. All pictures were scaled to a specific size (224x224 pixels) and put in the RGB format to stay consistent and compatible with the models. The dims were selected due to the fact that they are the standard input sizes of models such as MobileNetV2, as well as custom CNNs.

3.3 Data Preprocessing and Augmentation

The dataset was subjected to thorough preprocessing before the model training. This involved normalization of pixel values between the range of [0, 1] and encoding of categorical labels to binary values of 0 (recyclable) to 1 (organic). Furthermore, the dataset has been partitioned into training and evaluation, validation, and test sets with 80:10:10 proportions in order to have a fair evaluation and avoid over-fitting (Moutsis et al. 2023). Data augmentation was implemented as a means of augmenting the variety of training samples and to enhance model generalization. Such effects were reached through random rotations, horizontal and vertical flips, as well as zooming and adjusting brightness. This not only emulated real-world differences in waste image capture circumstances but also improved the resilience of both models under test.

3.4 Custom CNN Architecture Design

The scratch CNN based on PyTorch was created. It has three convolution layers, after which ReLU activation functions and max-pooling functions are used. Convolutional layers perform feature extraction based on the spatial features of the given input images, and the pooling layers perform dimensionality reduction as well as minimizing the number of floating-point operations during the computation. The convolutional block is followed by the flattening of the feature maps and two fully connected layers. The last layer has a standard activation of sigmoid, which is used to give binary classification (Li et al. 2022). A random weight was used to initialize this custom model, and it was trained with the Binary Cross Entropy loss and the Adam optimizer. An adaptive learning rate was also used, where the learning rate was dropped based on stagnation in performance using a learning rate scheduler. The batch size was 32, and the model was trained on a regular Windows 10 computer with 8 GB of RAM and an Intel i5 processor for 20 epochs.

3.5 MobileNetV2 with Transfer Learning

A pre-trained architecture of a deep neural network called MobileNetV2 was chosen to be used in transfer learning on ImageNet, as it is lightweight and efficient. The source model was already with locked convolutional layers and did not lose its feature extraction skills which it had acquired. A second layer of classification was added including global average pooling layer and dropout layer to prevent over-fitting, and dense with version of sigmoid activation layer. The use of transfer learning allowed transferring the previously learned visual patterns to the model and helped to shorten training time and the number of resources required. In 20 epochs, the model parameters were optimized on the training set under the use of the same loss function, optimizer, and batch size used during the custom CNN (Nnamoko *et al*. 2022). Transfer learning proved to be especially useful since the repository is moderately sized, and the available research equipment is not very considerable.

3.6 Evaluation Metrics and Techniques

In order to quantify the sufficient work of both models, some of the classification measures had to be used, such as accuracy, precision, recall, F1-score, and a confusion matrix. Based on the predictions made on the test dataset, the values of these metrics were computed using the help of the scikit-learn library. Accuracy was used to measure overall correctness of the predictions, precision measured how the predictions on positives were correct, recall assessed how well the model identified all relevant instances, and F1-score gave a harmonic mean of precision and recall (Rojas et al. 2021). The confusion matrix was also able to give more data on the specific kind of errors that each model was more likely to make, that is, whether the model was more prone to errors that would classify recyclable products as organic or the other way round.

3.7 Summary

This paper experimentally contrasts Custom CNN and MobileNetV2 in an attempt to classify waste in binary categories using a 2,5000 (approximately) balanced image dataset on Kaggle. Data were preprocessed, augmented, and separated into training data, quantity of data, and test sets. CNN was developed from scratch, whereas transfer learning was adopted in MobileNet V2. The same settings were used to train and test the models based on accuracy, precision, recall, F1-score, and confusion matrix. MobileNetv2 was effective even with limited computing resources, and learning curves were also used to ensure that there was no overfitting and convergence behavior.

4 Design Specification

The current project concerns the design and testing of two approaches to deep learning, Custom CNN and pre-trained MobileNetV2, in a binary waste classification (organic vs. recyclable) dataset. Both of the models were trained and tested on a Kaggle dataset of around 2,5000 labeled images with PyTorch. Its implementation occurred on a Windows 10 system with 8GB RAM and an Intel i5 CPU; as such, restrictions in hardware influenced model design. MobileNetV2 uses transfer learning to create efficiency, and the Custom CNN was designed with the aim of benchmarking performance. The objective was to evaluate precision and computational appropriateness with limited resources.

Custom CNN Model Architecture

The CNN was developed in PyTorch, without the use of pre-trained models. It is made up of three convolutional blocks, each block consists of a convolutional layer and a ReLU activation, and a max pooling layer. The convolutional layers are set out to obtain spatial features in the input images, and the max pooling layers help to decrease the number of spatial dimensions to reduce the required computation and to permit generalization by considering the most salient features.

The convolutional stages are followed by flattening and then two fully connected (dense) layers. The last output layer contains the sigmoid or non-linear statistical unit that carries out a binary classification by producing a probability value that can be used to decide whether the given image is organic or recyclable (Raschka et al. 2022). Random weights were used to initialize the network, and the model was trained with the Binary Cross Entropy as a loss function and the Adam optimizer that has adaptive learning rate behavior. Furthermore, a learning rate scheduler was applied to decrease the learning rate when no improvement in model performance was observed. Training of this model was carried out with an epoch of 30 and a batch size of 32.

Transfer Learning MobileNetV2

MobileNetV2 is the second one, which uses transfer learning to benefit from pre-trained weights that are developed on the large dataset of ImageNet. In this configuration, the convolutional core of MobileNetV2 was constrained to conserve the feature extraction qualities. This platform was topped off with a bespoke classification head. This head consisted of a Global Average Pooling layer to reduce the number of features and a Dropout layer to cope with overfitting, followed by a Dense layer with sigmoid activation as an output layer in order to perform the binary classification (Nnamoko et al. 2022). The application of transfer learning is especially beneficial in cases when the size of the data is not very large, since it allows achieving faster convergence and obtaining better performance using fewer computing resources. The last model was trained straining 15 epochs with the same optimizer, loss function, and batch size as the custom CNN. This enabled us to fairly compare the performance of models, as well as cut down significantly on training time.

Framework and Libraries

The PyTorch library was extensively utilized in the project to design the model, train, and even evaluate it. Other libraries used were torchvision to do image transformations and use pretrained models, matplotlib, and seaborn to visualize, and seaborn to compute performance measures such as accuracy, precision, recall, F1-score, and error matrix. Overall, a well-designed custom CNN model was used as a supplement to a low-weight but strong MobileNetV2 pre-trained model. Each architecture was optimized and tested on the same environment to provide true fairness in comparing its effectiveness in performing the task of classification of binary waste.

5 Implementation

During the implementation stage, the final development and testing of two deep learning models, Custom Convolutional Neural Network (CNN) and MobileNetV2, were performed to have an effective solution to the given problem. The idea was to develop a sensible image classification system that can sort wasteful photographs in terms of organic and recyclable images with a sturdy pipeline that can contribute to the reproducibility and computational viability. The models were built under the PyTorch open-source deep learning framework, which attains flexibility in terms of building, training, and testing any neural network. The contents of the waste classification dataset, obtained at Kaggle, were about 2,5000 images that were categorised as training, validation, and testing data. These images were cropped and augmented using the torchvision. The transforms module of PyTorch also executes operations like resizing the images, normalizing them, rotating, flipping, and cropping the images to enhance the generality of the model and help prevent overfitting (Raj et al. 2023).

In Custom CNN, a very basic approach was created with various convolutional layers, ReLU activation, max pooling, and fully connected layers. The model was then trained with an Adam optimizer and a cross-entropy loss function, and the test results were measured by the indicators of accuracy, precision, recall, and F1-score. In parallel, MobileNetV2 is a lightweight convolutional network pre-trained on ImageNet that was fine-tuned with the use of transfer learning. The last layer of classification was also changed to match the objective of binary classification. Similar hyperparameters were also used in training this model to have a fair comparison. These two models were trained and tested on a Windows 10 computer with 8GB of RAM and using an Intel i5 processor. Because of hardware constraints, there were only limited training epochs (557 per model), and the batch size was not too large to cause memory overflow. Model performance was monitored through the usage of Matplotlib to visualize such models as loss plots and accuracy records (Novac et al. 2022).

Products of the implementation were the trained models, performance metrics (confusion matrix, classification report), and visual analytics of the comparison of the behavior of the two approaches and their accuracies. The eventual outcomes indicated that MobileNetV2 excelled over the custom CNN in accuracy and speed of inference, demonstrating that transfer learning is effective when the dataset has limited amounts and when computing resources are restricted. The overall implementation provided a practical application in the field of automated waste classification by converting the design specifications into practical models.

6 Evaluation

6.1 Experiment 1: Custom CNN

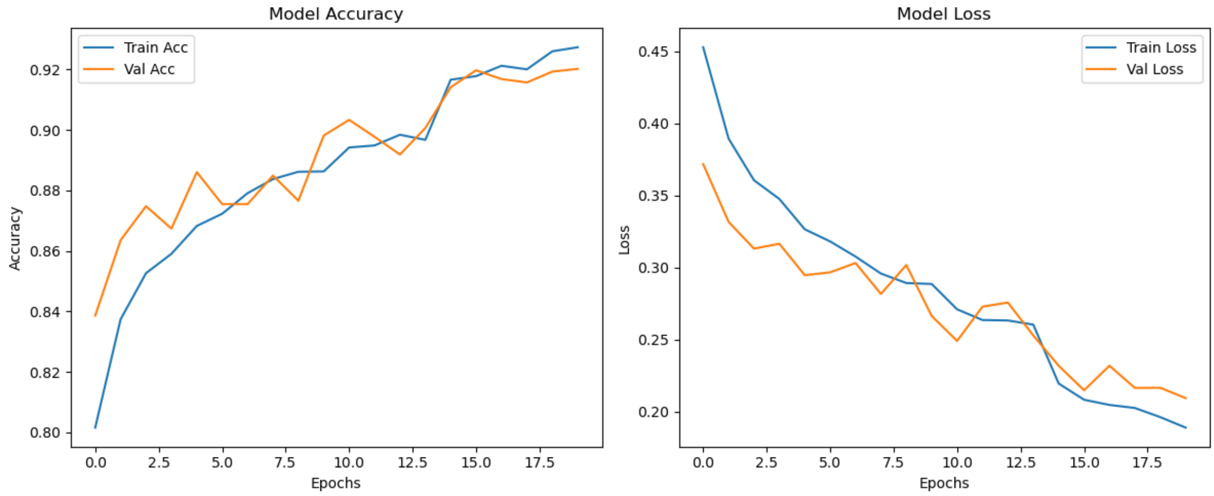

Figure 6.1: Training Performance for Custom CNN

(Source: Self-created)

The deep CNN model exhibited a good progression in learning within 20 epochs. First, the model reached the best result of 80.1% accuracy, and then gradually reached 92.7% and 92.0% accuracy on training and validation data, respectively. There was a substantial reduction in the training and validation loss of 0.45 and 0.37 to 0.19 and 0.21, respectively, which indicated successful convergence and no overfitting.

Accuracy curves (left chart) display consistent gains, and there are minor deviations between training and validation, which indicates good generalization. Combined with stable loss as seen in the loss curves (the right plot), it shows no deviation between training and validation loss.

A further reduction in learning rate at epoch 15 (0.001 to 0.0002) further fine-tuned the model and made it perform and/or be stable in additional ways. These findings indicate that the designated CNN framework was effectively architected to classify binary waste since it was deep relative to regularization (e.g., dropout), and it showed the advantages of using learning rate scheduling to achieve maximum accuracy.

```
75/75 [==============================] - 18s 231ms/step - loss: 0.2416 - accuracy: 0.9224

 Test Accuracy: 92.24%
```

```
75/75 [==============================] - 16s 208ms/step

Classification Report:
              precision    recall  f1-score   support

     Organic       0.89      0.97      0.93      1300
  Recyclable       0.97      0.86      0.91      1096

    accuracy                           0.92      2396
   macro avg       0.93      0.92      0.92      2396
weighted avg       0.93      0.92      0.92      2396
```

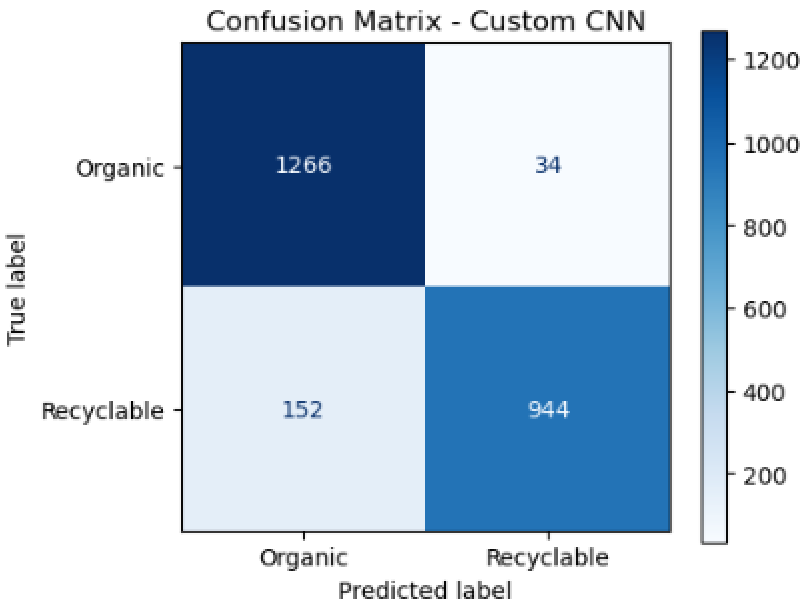

Figure 6.2: Confusion Matrix and Classification Report Interpretation

(Source: Self-created)

The CNN model created by customizing achieved a good test accuracy of 92.24, making it a strong generalization, transferring power across the unseen data. The confusion matrix reveals that of the 1300 tests conducted using organic samples, only 34 were incorrectly identified, leaving 1266 to be accurate. When compared, 944 out of 1096 items recyclable were properly challenged, with 152 items being misidentified as organic. This implies that the model has a higher performance when used to predict organic waste compared to recyclable products.

The classification report backs up this observation. Organic waste had a high score of 0.97 recall and 0.89 precision, which indicates that the model can predict most of the organic instances, but also makes some false positive predictions. Recyclable waste had a high precision of 0.97, and the recall was slightly lower at 0.86, as more of the cases of recyclable waste had been overlooked. All the scores, F1-score overall, macro average, and the weight average were 0.92, indicating consistent and balanced classification of both classes.

6.2 Experiment 2: MobileNetV2

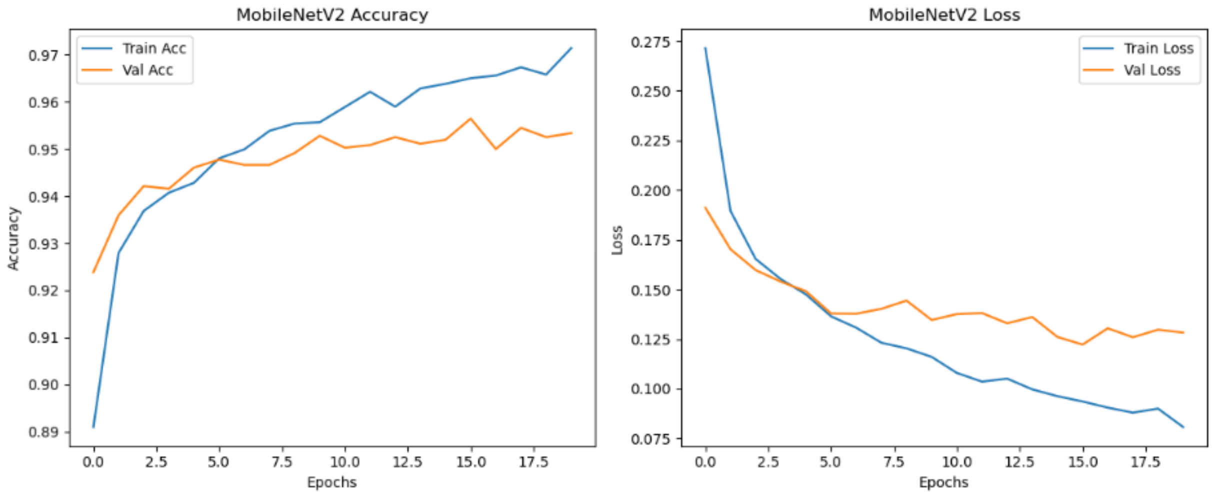

Figure 6.3: Training Performance for MobileNetV2

(Source: Self-created)

MobileNetV2 transfer learning model showed a stable, high performance at 20 training epochs. The model began with training accuracy of 89.1 and validation accuracy of 92.4, which were immediately increased to final training accuracy of 97.1 and validation accuracy of 95.3. This implies good learning and generalization. The Levels of the training loss dropped steadily from 0.2715 to 0.0807, and validation loss levels dropped as well 0.1911 to 0.1283. Even though a loss difference between the training loss and validation loss occurred after epoch 10, this difference did not change, which showed no overfitting.

Smooth convergence is confirmed by seeing the activity of accuracy and loss curves, and these measurements are gradually decreasing. Fine-tuning included reducing the learning rate between 1e-4 and 2e-5 on the last epoch. The model shows both high and stable validation accuracy across the training, which proves that MobileNetV2 is an optimal solution to the binary-level waste classification since comprehensive speed, accuracy, and generalization are achieved with reliability, especially when time and training resources are limited.

```
75/75 [==============================] - 42s 556ms/step - loss: 0.2428 - accuracy: 0.9003

Test Accuracy (MobileNetV2): 90.03%
75/75 [==============================] - 44s 571ms/step

Classification Report (MobileNetV2):
              precision    recall  f1-score   support

     Organic       0.86      0.98      0.91      1300
  Recyclable       0.97      0.80      0.88      1096

    accuracy                           0.90      2396
   macro avg       0.91      0.89      0.90      2396
weighted avg       0.91      0.90      0.90      2396
```

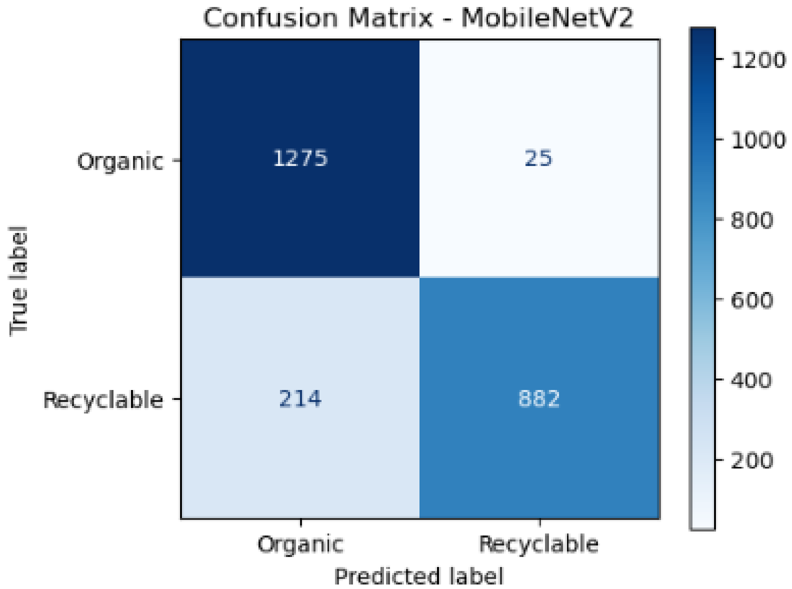

Figure 6.4: Confusion Matrix and Classification Report Interpretation

(Source: Self-created)

The MobileNetV2 model reached a test accuracy of 90.03 percent on the binary waste classification task, which suggests good generalization power. The evaluation of the classification report has depicted that the model has performed better in the identification of the organic waste, with its precision value of 0.86 and recall value of 0.98, leading to a good F1-score of 0.91. In the case of recyclable waste, the model received a precision of 0.97, a low recall of 0.80, which gives an F1-score of 0.88. It implies that, as much as the model was very accurate in the recyclable waste prediction, it had a significant number of missed actual recyclable cases. The confusion matrix shows that the images of organic waste have been accurately predicted; on the other hand, a high number of images of recyclable waste are mispredicted as organic. The discrimination of these is why the recall of the recyclable class is lower. In general, the model has a good run, although it can be improved in recyclable waste detection due to a better balance of data or more training tactics.

6.3 Discussion

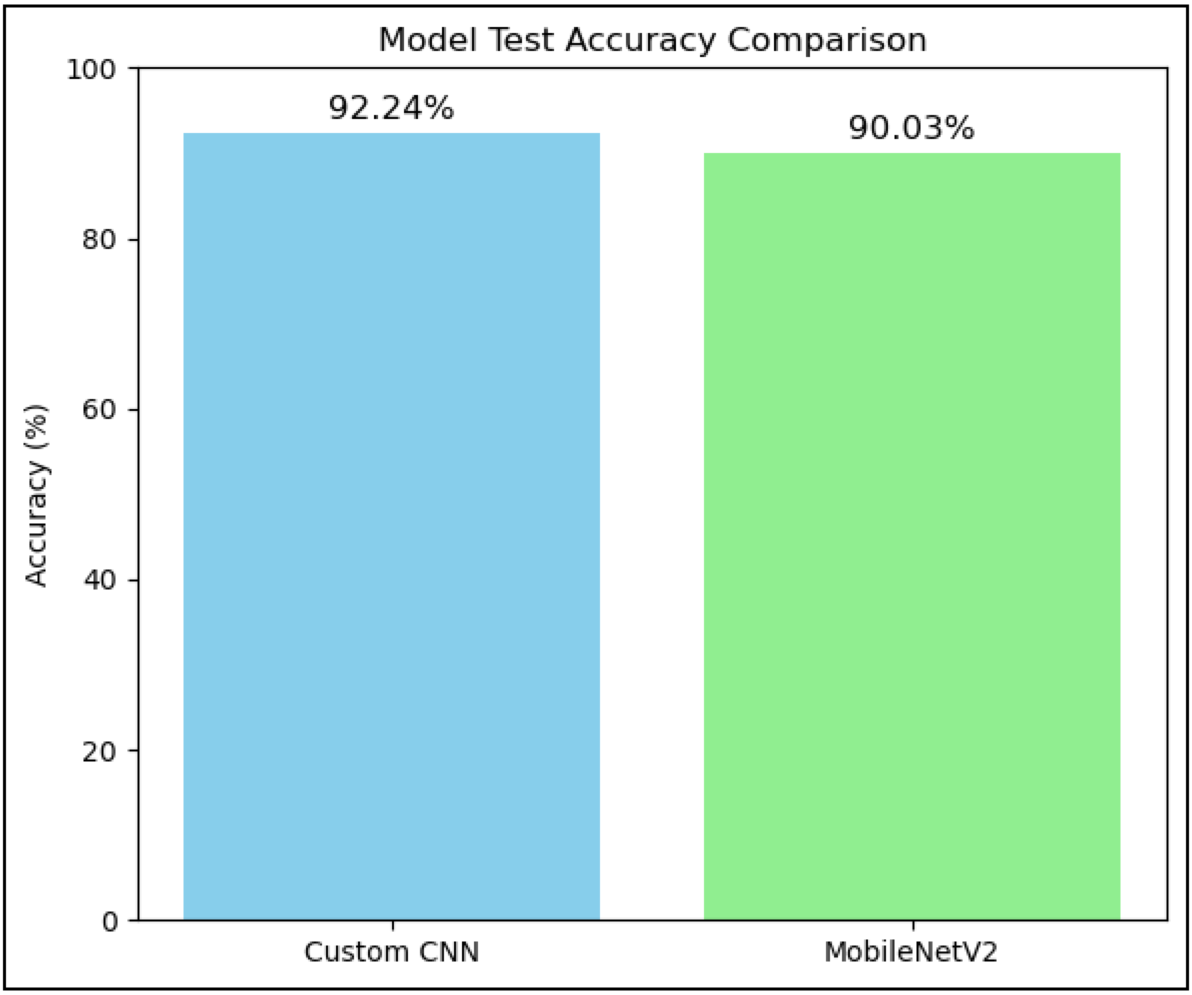

Figure 6.4: Model Test Accuracy Comparison

(Source: Self-created)

The bar chart shows a comparison of the accuracy of two models, Custom CNN versus MobileNetV2, regarding the classification of wastes as per their type, that is, binary. Custom CNN has a higher accuracy of 92.24 percent compared to MobileNetV2, whose accuracy is 90.03 percent. Despite the high classification ability of both models, the Custom CNN model is able to produce a slightly better performance. It indicates that the architecture suggested by the authors of custom architecture could be more optimised for the particular dataset utilised throughout this task. The difference is small, but potentially it can impact application that has a need for greater precision and reliability. Generally, the two models are effective, although Custom CNN has a slight superiority in accuracy.

The findings of this research emphasize the comparative efficiency of two convolutional neural network models, Custom CNN and MobileNetV2, in the classification of bin waste. Custom CNN was more successful than MobileNetV2 because 92.24% test accuracy was better than 90.03%. The difference, albeit slight, points to the fact that the custom design and training strategy that was employed in the case of the Custom CNN was more effective at learning characteristics pertinent to waste images (Amin *et al*. 2021). The fact that it also has dropout layers and a scheduler that modulates a learning rate may also have helped with generalizing the model and decreasing overfitting in the custom model. Based on the classification reports, it was observed that the Custom CNN performed well in both organic and recyclable waste classes, that is, there was a well-balanced precision and recall value by the Custom CNN model. The comparison of its performance to that of MobileNetV2 indicated that its recall value representing recyclable waste was significantly better, which implies that it was more sensitive to detecting recyclables, which is paramount in practice when it comes to national recycling programs. MobileNetV2 was rather accurate but less computationally efficient, so it was faster to train because of the lightweight architecture. Nonetheless, the fact that its recall of recyclable waste is 0.80 means that it could overlook some pertinent cases, which could make recycling more ineffective.

The learning curves of the two models indicated stable learning without large indications of overfitting, confirming the suitability of the used hyperparameters. A marginal yet meaningful difference in performance between the models is evidently confirmed by viewing the comparisons of the test accuracies visually (Jin *et al*. 2023). In summary, both models are appropriate to use in classifying the waste, but out of all the scenarios, the Custom CNN is better in instances where the accuracy of classification is of importance, whilst MobileNetV2 can be used where there is not so much access to resources.

7 Conclusion and Future Work

7.1 Conclusion

The proposed research also sought to examine the performance of a deep learning model, namely, Custom Convolution Neural Network (CNN) and MobileNetV2, in binary waste classification, in this case, distinguishing between recyclable and non-recyclable waste. Some research goals were envisaged to be a custom CNN design and training, to examine MobileNetV2 as a lightweight model of pre-training, and to compare their accuracy and classification capability. These were achieved through the study and provided the prescribed implementation, performance analysis, and a comparative study of the two models. The most important conclusions were that the Custom CNN performed a bit better than MobileNetV2, as it proved to have higher test accuracy (92.24% vs. 90.03%) and that it had a better recall of the recyclable contents. These findings make it clear that architectures can be customized to be able to obtain a call classification of higher precision, particularly when the data is geometrically aligned to the task. Nonetheless, the use of transfer learning using MobileNetV2 was a competitive and resource-efficient alternative, which proved that it is possible to use transfer learning in limited conditions.

The practical outcome of this study is that in smart waste management systems, it is efficient to automate the sorting process, and recycling can be increased with the help of automated classification, manual labour can also be reduced, and the environment can also be maintained. Although the study is successful, it is not without limitations: the size of the dataset was rather small, and evaluation was done in only the binary setting.

7.2 Future work

Future work to consider would be extending the model to support the handling of multi-class categories of waste with real-time images of varying environments. Moreover, there may be the potential to process sensor or metadata data (e.g., location, frequency of waste type) in order to increase the context awareness of the model. Investigating edge deployment solutions using optimized lightweight frameworks such as MobileNetV3 or EfficientNet-Lite may be helpful to operationalize it in under-resourced urban or rural environments. In addition, a successive research project may consist of partnering with municipal or smart city organizations in order to test and verify the models in practice and assess their effectiveness, and improve them to be applied at a large scale and in the commercial environment.

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