

Leveraging AI for Food Waste Sorting in
Urban Areas

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Bachelor of Science

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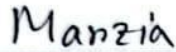
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Leveraging AI for Food Waste Sorting In Urban Areas

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Thesis submitted in fulfillment of the requirements
for the award of the degree of
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DEDICATION

Greet to my family whom I love, and who help me with love, encouragement, and inspiration, whence this constant faith in the dignity of labor always takes its source. The belief in myself has helped me to overcome challenges.

ABSTRACT

The current paper deals with management of urban food solid waste (FSW), which is the high-priority issue of health, environmental sustainability, and activities of cities. It is the nature of the issue brought into the limelight at sustainability courses that brings in questions about the inability to have a successful resolution. The problem is relatively simple, but at the same time it gets complicated due to the issue of scaling, contamination, and classification, which Noske and Funke display in their article on the sorting of glass beads in terms of color (Figure 009). In our laboratory experiment, we were able to see that manual sorting is rather tedious and time-consuming and energy-intensive, and this fact supports the necessity of automating the process. The paper will suggest a deep-learning-based solution to the problem of automatic labeling of food waste based on a large amount of high-resolution photographs taken in various urban conditions. The research approach is a novel and practical methodology with substantiated data. DenseNet201 was modified through transfer learning, large data augmentation, and balancing methods to remain general to overcome skewed data distributions. The dataset consists of more than 600 annotated images of five categories, which include buffet food waste, general food waste, restaurant food waste, vegetable waste, and wedding food waste that captures real-life conditions of waste in urban areas. After optimization, DenseNet201 was compared to InceptionV3, EfficientNetB2 and MobileNetV2, but trained with the same settings. DenseNet201 was found to be more precise and recall as well as achieve better validation accuracy with over 86 percent, being more accurate and reliable than the competing architectures, especially underrepresented classes. The suggested system has potential in application in smarter urban waste-management projects, university sustainability projects, and resource-optimization endeavors, which makes it a strong contender in a computer science capstone project.

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LIST OF SYMBOLS

$x, x_0, x_1, \dots, x_{l-1}$	Input features
l	Layer index
$Hl(\square)$	Transform function
y	Output feature map after processing input xx
$\text{Concat}(\cdot)\text{Concat}(\cdot)$ dimension.	Concatenation of feature maps along the channel dimension.
$\text{Pool}_{3 \times 3}(\cdot)$	3x3 pooling operation
$+$	Element-wise addition

LIST OF ABBREVIATIONS

AI	Artificial Intelligence
CNN	Convolutional Neural Network
FSW	Food Solid Waste
IoT	Internet of Things
MSW	Municipal Solid Waste
SDG	Sustainable Development Goals
TP	True Positive
TN	True Negative
FP	False Positive
FN	False Negative
TPR	True Positive Rate
FPR	False Positive Rate
TNR	True Negative Rate
FNR	False Negative Rate
DenseNet201	Densely Connected Convolutional Network (201 layers)
InceptionV3	Inception Network Version 3
EfficientNetB2	EfficientNet Model, B2 variant
MobileNetV2	MobileNet Version 2

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Appendix A : Dataset Availability

CHAPTER 1

INTRODUCTION

1.1 Background

The issue of urban waste management has become a burning issue in developed and developing nations due to the high rate of urbanization, population growth, and the changing consumption patterns. The volumes of municipal solid waste (MSW) and their increasing heterogeneity are especially acute in the emerging economies, where the scarcity of infrastructures and the unavailability of resources threaten the sustainability of the management practices (Hossain et al., 2023; Addas et al., 2024). An example is Bangladesh where the daily generation of per capita waste is increasing, and household garbage (mainly food and vegetable waste) is the major urban solid waste stream. Many cities are struggling with functional shortages, including the lack of regular collections, recycling centers, and optimal waste disposal, thereby leading to environmental pollution, health risks to the community, and citizen dissatisfaction with the local governments (Habib et al., 2021; Das et al., 2019). Traditional waste management methods namely the methods that are based on manual collection runs, periodic pick-ups and haphazard waste disposal are becoming ineffective to meet the size and diversity of the modern urban waste flow. These deficiencies create an environmental and community health risk, as well as an abstinence of possible economic benefits of resource recovery (Sulaiman & Wolniak, 2024). In addition, the fast changing lifestyle in the city, coupled with inadequate awareness programmes and behavioural inertia further increases the dumping habits and reduces citizen involvement in sustainable dumping methods. To these growing pressures, however, a clear shift toward technology-based waste management practices has been observed in recent years. The utilization of Internet of Things (IoT) devices has led to smart recycling receptacles that are equipped with sensors which constantly scan their fill levels and send the data to enable the optimization of collection paths. The given technological innovation allows municipal officials to limit operational expenses, decrease overflow cases and improve efficiency in general (Addas et al., 2024; Gopi et al., 2021). Simultaneously, cloud-based and mobile technologies have also

optimized the organization of collection schedules, the control of operations, and the involvement of citizens; however, challenges, such as the initial part of the infrastructure costs and difficulties in integrating the systems, continue to exist (Hossain et al., 2023). The frontier of this digital transformation is in artificial intelligence (AI) and deep learning methods, which allow automated waste classification, sorting, and optimization of the system (Singagerda et al., 2025; Celik, 2025). The current deep convolutional neural networks (CNNs) have demonstrated the high accuracy of image-based waste classification, which allows sorting in the sources or recycling plants in real time. More complex and heterogeneous tasks also have better performance due to hybrid and ensemble models that fuse feature representations of multiple architectures, including EfficientNet, InceptionV3, and DenseNet201 (Yogamadhavan and Mannayee, 2024; Celik, 2025). In addition, AI has also developed the process of planning and managing an entire waste stream in a city, including predictive analytics to collect and generate it and optimized routes to use vehicle fleets. Knowledge management and big data analytics are also increasingly seen as the key facilitators of the next generation of smart cities. The combination of past and live waste data allows city authorities to predict the patterns of waste generation, dynamically distribute resources, and mobilise communities to engage in recycling, waste minimization, and resource recovery programs to a greater extent (Sulaiman and Wolniak, 2024). The integration facilitates operational efficiency as well as full documentation, spreading of best practices and ongoing improvement of the process.

Although the potential of AI and IoT is strong, to achieve the maximum potential in the scope of waste management, it is necessary to address a variety of technical and social issues, including data privacy, the interoperability of systems, trust in the community and its inclusion in stakeholders (Hossain et al., 2023; Sulaiman and Wolniak, 2024). Considering the growing environmental, financial, and policy demands that are aligned with the Sustainable Development Goals (SDGs), the digital and community-based approach to urban waste management may be regarded as the most promising avenue to resilience and sustainability in addressing the future of waste management.

1.2 Problem Statement

The rapid urbanization and the increased population density has actually put the issue of food waste handling at the head of the campus café to-do list. The manual sorting of food waste is definitely a big pain, it is labor intensive and expensive, particularly when all the trash is mixed up with those strange and heterogeneous pieces that wind up in the incorrect bins. The common city-scale systems continue to use basic visual inspection or a straight up sensor that simply cannot sustain the available high-accuracy and scalability in the domain of a ton of real-world categories. The recycling, composting, and the alleviation of the burden on our landfill locations all basically rely on sorting food waste. However, it is the cutting-edge techniques that continue to struggle with mixed waste, excessively represented classes, and those that are just barely different sources of trash. Being a campus in a tight location where resources are constrained, there is a literal demand to have an automated system that can isolate domestic food waste with other urban sources and can just keep going when we are in need of scaling it. Therefore, this study is all about getting out of manual and legacy automatic waste classification. Our vision is to develop a state-of-the-art computer vision system based on deep learning, namely a new convolutional neural network to appropriately classify the different types of urban food waste in and around the campus.

1.3 Motivation

Hey, we need to consider the better way to deal with urban food waste in case we want to have sustainable development and a healthier city atmosphere, particularly in the areas with a large number of people. Manual sorting is usual but it is time-consuming, erroneous and the employees are left in sticky situations. There is nothing like wasted food everywhere - new sources, appearance, freshness - and this further complicates things, so you really should have some robots. Recently, large-scale deep learning and computer vision became extremely precise and scalable. This food waste sorting technology would have a beneficial effect on increasing productivity, reducing expenses, and increasing recycling. Separating different wastes automatically do not only benefit the recycling efforts of municipalities, but it also allows smarter city planning and resource management through the analysis of data. This paper is all about the association of the antique strategies of waste with fresh AI wizards. To achieve that feasible objective: smarter cities, cleaner surroundings and a more sustainable

future, we will train powerful deep learning models such as DenseNet201 and compare them to the best models in the game.

1.4 Significance of the Study

To an extent this work provides us with some viable practical and scholarly benefit in terms of dealing with trash in cities and adopting technology to keep the environment under control. The studies leading to a credible deep-learning model automatically sorting food waste directly address the inefficiency of traditional methods of sorting trash. The results of our tests on real city scenes indicate that deep learning can be used to significantly increase the accuracy of sorting and uptime reliability even in super variable urban environments.

The results are useful in a number of ways:

- **Reduced Recovery Rates:** When the trash is detected properly, the separation will be improved, and recycling and composting will not be as laborious, which will reduce the number of items that will end up in the landfills.
- **Operating Economics:** It reduces the cost of labor, maintains low rates of errors, and processes a vast and diverse stream of waste in the blink of an eye - hence, waste management in the city becomes more efficient and quicker over time.
- **PUBLIC HEALTH and Safety:** By minimizing human contacts, people can lower the threat of being in contact with nasty organisms and infecting people with contaminants.
- **Policy Implications:** The data on classification can assist govt folks to evaluate who is generating what type of waste, focus on interventions, and monitor the performance of the policies.
- **Generalization Potential:** With the architectural variety, we have made some rather attractive inferences and established a benchmark on an AI-driven waste-management study that can be used in more than a myriad of urban settings, wherever various forms of clutter are present.

Overall, this study places AI and sustainability as the major factors in creating stable, intelligent, and healthier cities, which provides us with instruments to clean urban environments with our thinking minds in action.

1.5 Research Questions

But what about a truly messy, noisy environment like the city, how do we design a deep-learning style computer-vision model that is able to recognize different types of urban food waste based on image data? What is the relative classification accuracy, precision and recall of DenseNet201 to InceptionV3, EfficientNetB2 and MobileNetV2 on the various types of food waste that we are handling? What are the key challenges of automated image-based waste classification in an actual city setting and how can we deal with them with the help of tricks such as data augmentation and class balancing? How does improved sorting accuracy affect the aggregate waste management, in terms of recovering more resources and increasing efficiency and enhancing the health outcomes of people? Is this model scalable and transferable to other cities to manage their own wastes and classify them accordingly?

1.6 Research Objective

To develop and train a convolutional neural network model (DenseNet201) that can successfully classify into various types of urban food waste in image format.

To compare the performance of our DenseNet201 with the state-of-the-art models like inceptionV3, EfficientNetB2, and MobileNetV2 with the same back-propagation and data-augmentation guidelines and test conditions.

To address the stereotypical issues in the garbage classification, e.g. the lack of data balance, inter-class similarity and other conditions of the images, by means of using progressive data augmentation and adaptive class weighting procedures.

Efforts to gauge the degree of enhancements of the classification accuracy, the precision and recall and the overall model robustness through the statistical analysis and comparison with benchmarks.

To test and confirm the developed methodology of the urban waste management

system in the real world and test its practical applicability and the possibility of the system to be scaled up to achieve better sorting, better recovery of resources, and sustainability..

1.7 Research Scope and Limitations

This work trains and analyzes deep learning models to categorize urban food waste based on the images with consideration of five classes. It also identifies the data, environment, and scope constraints that may interfere with generalization and practice.

1.7.1 Scope

This research is concentrated on the design, development and in depth analysis of DL computer vision models used to classify five broad urban food waste categories such as buffet, general/mixed sources, restaurant (i.e., non-dried), vegetable (with or without packing), and wedding based on a customized data of digital images collected in real metropolitan locations. The research also includes comparative models benchmarking, application of extensible data augmentation and class balancing procedures and detailed examination of such measures as accuracy, precision, and recall and F1-score. Despite the fact that the image-based classification can only be applied to controlled datasets, the study aims to provide a background to be incorporated in broader waste management activities and urban sustainability expansion.

1.7.2 Limitations

Limitations are the use of a single image dataset (but not all types of urban food waste), and only five classes of them (not a whole lot of them), not all being mixed or other foods, and only evaluated with static images (non-tested in real-time online environments or in multi-sensoric systems). We will have to extrapolate the model to new climates, expand and balance the data sets and refine the methodology to the real world.

1.8 Thesis Organization

I have divided this thesis into several chapters to help everyone have the entire picture of how we have done things, why we have chosen those ways, and our findings.

Chapter 1: Introduction

Here I will make the background, the reason we are bothered about this, the problem we are addressing and the objectives and the significance, the research questions, and what I limited the study to.

Chapter 2: Literature Review

This section reviews the previous studies on city waste management, the way humans employ image-based categorization, and the recent advances in deep-learning-based trash classification.

Chapter 3: Methodology

In this section, I describe what I did to acquire the datasets and clean them, the steps of the experiment I have executed, the model designs, the data-augmentation techniques and the metrics that I employed to evaluate performance.

Chapter 4: Results and Discussion.

This section presents the statistics of my models and some competitors then goes into the accuracy, precision, recall, F1-score and the overall performance of all of it in sorting urban food waste.

Chapter 5: Conclusion and Future employment.

Lastly, I conclude the main lessons learned, contributions, and constraints and propose the next steps that could be implemented to continue this exploration and implementation.

The structure also facilitates the understanding of the flow of ideas by the readers and presents all the key points in a concise way.

CHAPTER 2

LITERATURE REVIEW

2.1 The Urban and Food Wastes in Bangladesh.

The rural-urban migration and urbanization in Bangladesh have been throwing a mountain of municipal and domestic garbage, in particular, food and vegetable waste (Ahsan et al., 2014; Das et al., 2019; Habib et al.). It is even more depressing to discover that the waste orgs are not only overworked, they are also incredibly slow (60-70% of home and city garbage is not picked up or it gets into open dumps). It is an issue of great significance to the health of the population, the state of land, water pollution, and greenhouse gases emissions (Alamgir et al., 2005; Matter et al., 2013). The key issues related to selective waste collection are the inability to monitor it, unrelated services, and the absence of money to procure improved collection equipment (Othman et al., 2013; Ahsan et al., 2014). Poor garbage collection leads the population to lose trust in the local government and this murders general involvement in sustainability benefits (Ahsan et al., 2005).

We are also failing to pay sufficient attention to the manner of consuming food, cultural habits and absence of concrete pieces of advice on how to preserve food. This only adds to the problem, as well as some unwanted preparation and purchases, be it event or marketing buzz; they usually boil down to trash (Tahmina Khatun & Hossain, 2024).

2.2 Social Economic and Behavioral Issues: Motivators of Waste Production.

The income earned by families, their educational qualifications, occupational categories, and family size determine the amount of waste produced by the household as well as their management (Tahmina Khatun & Hossain, 2024). It is often found that the adoption of waste segregation and recycling programs is also correlated with the level of education and financial capacity of households, as citizens with higher education and more financial resources are more likely to participate in waste segregation and recycling (Ahmed et al., 2023; Alamgir et al., 2005). The behavioral dynamics are not limited to the awareness campaign but include the beliefs of the individuals about the consumption and food wastes, and environmental factors. The

shopping behaviors, meal organization and sensitivity to education-based programs are all involved in the reduction of waste sources. Social stigma, apathy, the saying of out of sight, out of mind, and lack of recycling incentives are among the factors that often harm the community-based initiatives (Ahmed et al., 2023).

The research has shown that the active involvement and the actual connection between a waste decrease, the cleanliness of the community, and the health of individuals are important factors that encourage people to join campaigns and engage in sustainable activities (Alamgir et al., 2005; Tahmina Khatun and Hossain, 2024).

2.3 Urban Smart Waste and IoT in Bangladesh.

The introduction of intelligent waste management, especially that based on the Internet of Things (IoT) technology (where waste receptacles are networked, have ultrasonic sensing and data transmission features) has been found as a potentially effective paradigm to improve operational efficiency (Imran Hossain et al., 2023; Gopi et al., 2021). These systems promote the monitoring of the level of fill in real-time, the optimization of routes that a collection vehicle uses, instant feedback to the governing authorities, and predictive analytics of strategic planning (Kumar et al., 2017; Malapur et al., 2017). Early results of the urban pilot projects in Rajshahi, Dhaka, and other locations in Bangladesh have proven significant reduction in collections missed and overflow cases, better resource distribution, and prioritization of waste-management operations (Imran Hossain et al., 2023).

In addition to that, cloud-based management systems and mobile notification software have the potential to further encourage community involvement and integrate citizen actions with city collection schedules (Kumar et al., 2017; Malapur et al., 2017). Still, the initial capital cost related to the implementation of the technology, the ongoing issues of maintenance, and reliance on the effective digital infrastructure still constitute significant barriers to the widespread adoption of such solutions (Imran Hossain et al., 2023).

2.4 Deep Learning Development Applications to Solid Waste Classification.

Recent studies have shown that there has been considerable advancement in the automation of waste sorting by using deep learning (in particular, convolutional neural networks (CNNs)) to classify images of various waste objects (Yogamadhavan and Mannayee, 2024; Simarmata et al., 2023; Tang et al., 2024; Celik, 2025). Some of the

state-of-the-art models that are used include DenseNet201, InceptionV3, MobileNetV2, and EfficientNetB0 which are regularly reported to have accuracies above 90 percent. The state of art classification has been achieved with remarkably high precision, recall, and F1 scores with the further refinement of multi-layer feature fusion, ensemble, and hybrid architectural strategies, and has proven to be near perfect at classifying benchmark datasets (Celik, 2025; Yogamadhavan and Mannayee, 2024).

The implementation of data-augmentation schemes, transfer learning protocols, and adaptive-weight balancing plans prepare such models to overcome such issues like class imbalance, heterogeneity of photographic conditions, and intra-class similarity (Simarmata et al., 2023). Therefore, deep-learning methods are increasingly being researched to be integrated into the working smart waste-management systems.

2.5 Technical and Social Implementation Challenges

Nonetheless, there are several limitations that still exist. The high computational needs and requirement on big, well-annotation training databases are major challenges, especially in developing countries (Tuncel et al., 2025; Simarmata et al., 2023; Yogamadhavan & Mannayee, 2024). Many of the models are constructed and tested in controlled conditions but prototype performance can degrade under real world settings, such environment have a lot of lightning variation, scale ratio of objects and images research with occluded images (Celik, 2025).

Socially, it depends on community acceptance and how transparent and trustworthy the systems are as well as how they remain involved in system building (Imran Hossain et al, 2023; Kumar et al., 2023). Add to that limited financial capability and little or no digital infrastructure, and you begin to see how difficult it is to scale both IoT- and AI-driven solutions — particularly in such resource-constrained municipalities. Overcoming these challenges will require sustained resources, strategic investments and adapted public outreach that are tailored to the specific local setting (Ahsan et al., 2014; Imran Hossain et al., 2023).

CHAPTER 3

METHODOLOGY

Methodology

This paper gives recommendations on data set selection, preprocessing, model design, as well as the training plan in order to enhance the performance of food and waste image classification.

Dataset Preparation

One such dataset consisted of images of food and waste, which were assigned to five categories, such as the waste of buffet foods, general food waste, restaurant food waste, vegetable waste, and wedding food waste. The images were annotated and divided into 80 per cent and 20 per cent of training and validation respectively. To reduce the imbalance in the classes, class weights were calculated and added to loss function.

Data Augmentation

Rotations (maximum 40), zooms (maximum 30), shifts (maximum 20), shearing (up to 20), and horizontal flips were added to images as well as rescaling pixel values to the range [0, 1].

Model Architectures

Four convolutional neural network models were considered: DenseNet201, MobileNetV2, InceptionV3 and EfficientNetB2. The feature extractor was DenseNet201 and the global average pooling layer, which is then used with a dropout rate of 0.5 and 0.3. Transfer learning was used in comparative trials by initializing the custom models with ImageNet weights.

Training Strategy

All the models used the categorical cross-entropy as the loss function and the Adam optimizer with a learning rate of $1/10^{-4}$. Training was done until 50 epochs to prevent

overfitting using early stopping and model checkpointing. ReduceLROnPlateau scheduler was used to vary the learning rate when it was being trained.

Transfer Learning and Fine-Tuning.

Transfer learning was used, where the top layers were first trained, and the final 30 layers were then unfrozen to be further fine-tuned once the initial convergence had been reached.

Evaluation Metrics

Measurement of model performance was done based on validation accuracy, confusion matrix analysis, precision-recall curves and class-wise classification reporting in terms of final validation accuracy and average precision score.

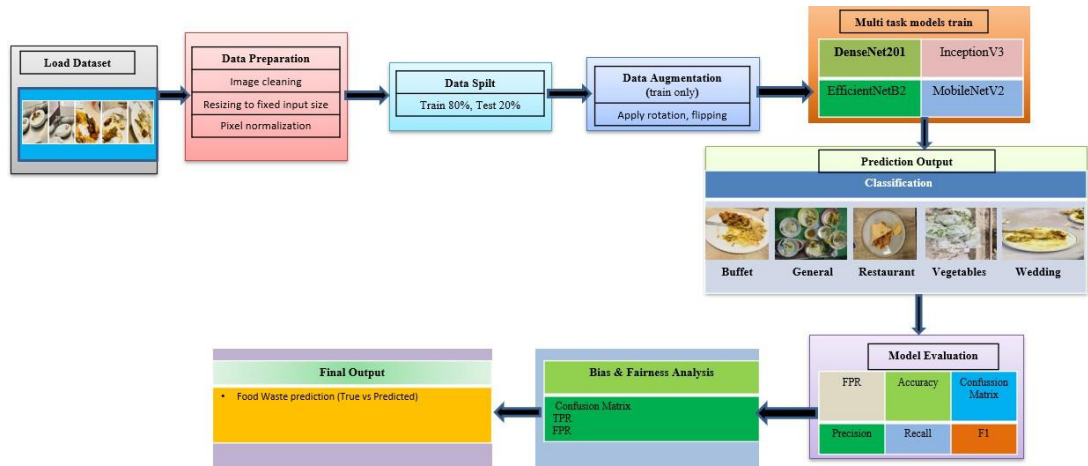


Figure 2.2.1 Workflow Diagram

3.1 Data Collection

The main basis of this investigation is based on the creation of an extensive and representative image bank that is focused on area classification of food and refuse. The publicly available datasets, online image archives, and in some cases, shot using a camera provided the sources of the static images to ensure that a wide range of real-world conditions of wastes is covered. The images were subjected to careful examination and they were then given to one of the five different categories Food Waste General, Wedding Food Waste, Buffet Food Waste, Vegetable Waste, or Restaurant Food Waste.

The images in the datasets were filtered by quality and relevance to obtain quality model training; copies and low-quality images were then cut off. The purpose was to compile a balanced data set that would represent the large spectrum of visual features occurring in different waste situations. Specific focus was given to the aggregation of variability in illumination, background context and presentation of waste, which allowed models to be more robust with regards to generalization when faced with unseen data.

The compiled set of data appears as the base upon which other steps of data preprocessing, data augmentation, and classification experiments that will be

discussed in this work are to be done.

3.2 Data Preprocessing

3.2.1 Data Cleaning & Study

A preliminary study was conducted to determine the extent and validity of the data. The images with low resolutions, irrelevant material or duplication were filtered out. However, the classes and possible biases were analyzed both visually and using the exploratory statistics.

3.2.2 Data Splitting

A primary examination was done to determine data completeness and credibility. Low-resolution images, meaningless content and duplications were deleted. Visual analysis and exploratory statistics were used to determine the distribution of classes and possible biases.

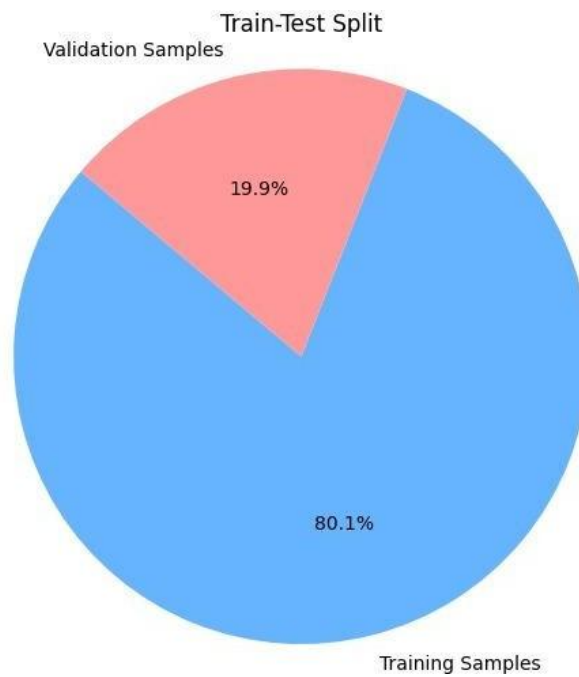


Figure 3.2.2 Train-Test Split pie-chart

3.2.3 Resizing:

All pictures were scaled to the default input size that is required by modern deep learning architectures, i.e. 224 x 224 pixels. This is done to provide consistency and compatibility among the convolutional neural network architectures used through uniform resizing..

3.2.4 Parameters and hyperparameters:

Table 6.1 Parameters and hyperparameters

Parameter/Hyperparameter	DenseNet201 (Proposed)	InceptionV3	EfficientNetB2	Mobile NetV2
Base Architecture	DenseNet201	InceptionV3	EfficientNetB2	Mobile NetV2
Pretrained Weights	ImageNet	ImageNet	ImageNet	ImageNet
Input Size (pixels)	480 × 480	480 × 480	480 × 480	480 × 480
Top Layer Removed	Yes	Yes	Yes	Yes
Global Average Pooling	Yes	Yes	Yes	Yes
Dropout Rates	0.5, then 0.3	0.5, then 0.3	0.5, then 0.3	0.5, then 0.3
Dense (FC) Layer	512 (ReLU), then 5 (softmax)	512 (ReLU), then 5 (softmax)	512 (ReLU), then 5 (softmax)	512 (ReLU), then 5 (softmax)
Batch Size	16	16	16	16

Loss Function	Categorical crossentropy	Categorical crossentropy	Categorical crossentropy	Categorical crossentropy
Optimizer	Adam	Adam	Adam	Adam
Learning Rate	10^{-4}	10^{-4}	10^{-4}	10^{-4}
Epochs	Up to 50 (early stopping)	Up to 50 (early stopping)	Up to 50 (early stopping)	Up to 50 (early stopping)
Early Stopping	Patience 10, restore best weights	Patience 10	Patience 10	Patience 10
ReduceLROnPlateau	Factor 0.5, patience 5	Factor 0.5, patience 5	Factor 0.5, patience 5	Factor 0.5, patience 5
Model Checkpoint	Save best only	Save best only	Save best only	Save best only
Data Augmentation	Rotation, shift, shear, zoom, flip	Same	Same	Same
Validation Split	0.2 (20%)	0.2 (20%)	0.2 (20%)	0.2 (20%)
Fine-tuning	Last 30 layers trainable (after stage 1)	Last 30 layers trainable	Last 30 layers trainable	Last 30 layers trainable
Class Weights	Computed for imbalance	Computed	Computed	Computed

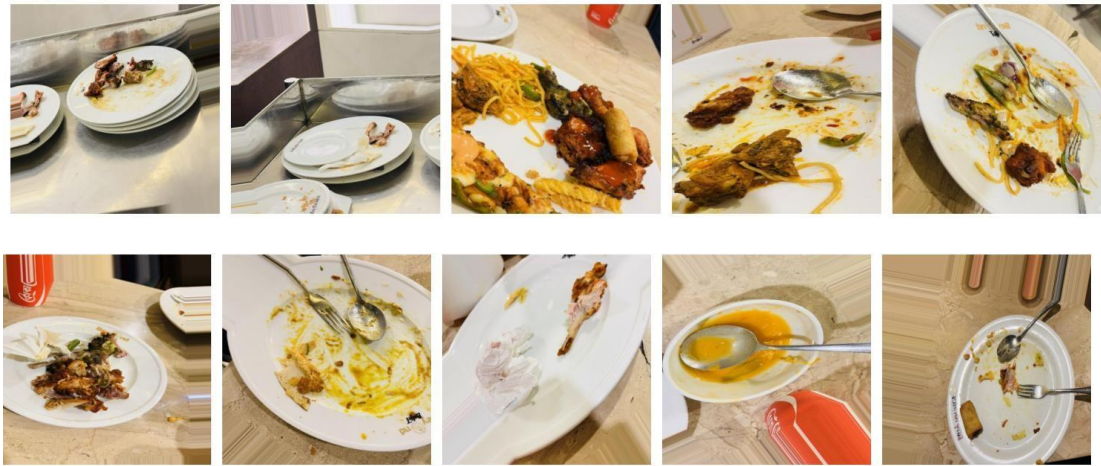


Figure 3.2.4 Sample of Dataset

3.2.5 Normalization

Images have been standardized and allow pixel values to be scaled and convergence of training models to occur. The values of all the pixels were rescaled to fit into the range $[0, 255]$ (maximum pixel value of the majority of the images). This process has the benefit of reducing differences in brightness and contrast in the pictures.

3.2.6 Data Augmentation

The training set was artificially increased in size thus increasing the robustness of the model by using augmentation techniques, which involved random rotations, zooms, horizontal and vertical shifts, shearing, and horizontal reflections. As empirical evidence shows, a scheme of ten fold augmentation would have significant positive outcome, as it allows the model to generalize better and, therefore, the amount of overfitting becomes less significant.

3.2.7 Label Encoding

The class labels were coded in numbers to be used in the training. Within the framework of multi-class classification, the labels were one-hot, which made each image a binary vector that shows its categorical membership. Most deep-learning systems which use categorical prediction require such encoding scheme.

3.3 Models

3.3.1 DenseNet201

DenseNet201 is a type of deep convolutional neural network that is characterized by a number of layers and a unique dense connectivity scheme (201). The input of each layer is contributed by all the prior layers in the same block thus boosting feature reutilization, maintaining fine grained features, and alleviating the vanishing gradient problem, which is common with immensely deep networks. This architecture is easier to train and gives higher performance in comparison with the traditional convolutional networks.

DenseNet201 is architecturally similar to other DenseNets consisting of four dense blocks separated by transition layers that reduce feature map sizes. Inside the dense blocks, feature maps of all the previous layers are concatenated and the network reuses the features and reduces redundancy. Common ones include batch normalization, ReLU activation, convolutional operations, bottleneck layers and transition layers that perform convolution and pooling to accomplish down-sampling. The network is then completed by global average pooling and then fully connected layers with softmax often used in the classification.

The dense connectivity of DenseNet201 allows the passing of gradients and preservation of features, which makes it especially effective in tasks that are sensitive and multi-scale, such as biomedical imaging, forensic science, and various computer vision problems. It is extensively adaptable to transfer learning, and can be specialized to specialized uses. It can also be improved by introducing new modifications (i.e., the dropout layers and hybrid models, i.e., integration with LSTM or capsule networks).

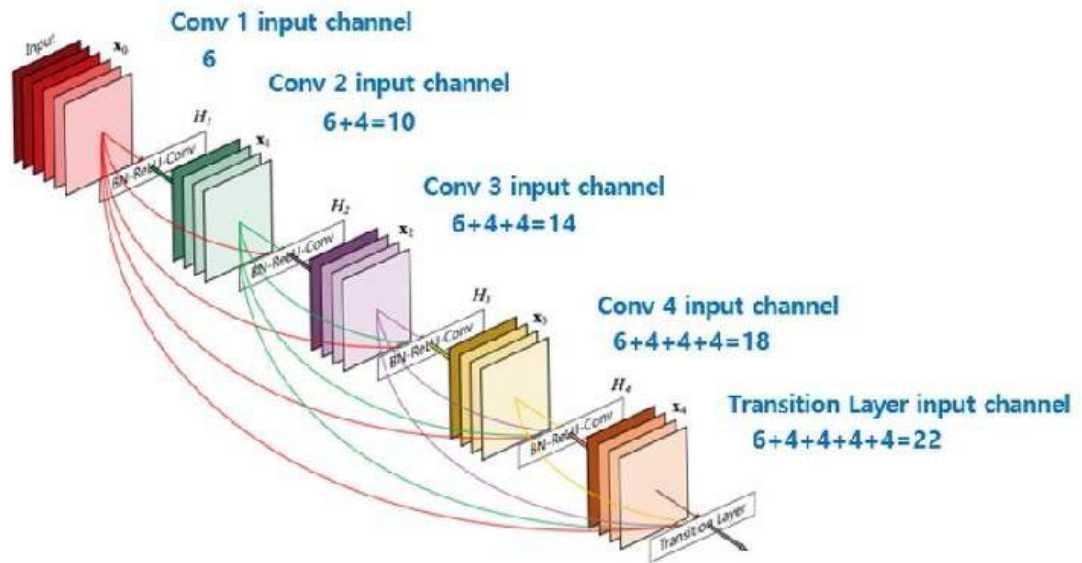


Figure 3.3.1 Diagram of DenseNet201 Model

Formula & Equation

Dense Connectivity (DenseNet Core Equation):

$$x_l = H_l([x_0, x_1, \dots, x_{l-1}])$$

3.3.2 InceptionV3

InceptionV3 is an advanced deep convolutional neural network, whose main design was intended to be used in image recognition and classification. It is the third variation of the Inception family of CNN models created at Google. The model is also known due to the simultaneous application of several parallel convolutional layers with different kernel sizes which allows capturing a rich set of features at multiple spatial scales of input images with high efficiency.

The structure is divided into three main parts: the stem which comprises the first layers which carry out downscaling and preprocessing of input data, the body, which includes several Inception modules, which carry out parallel convolutions and pooling tasks, and the head, which includes the last classification layers, such as fully connected layers and a softmax output. InceptionV3 has a set of architectural novelties, including factorized convolutions (breaking larger convolutions into smaller ones, e.g., 1×3 and 3×1) and the use of asymmetric convolutions, as well as batch normalization. All of these methods result in minimized computational cost with no or increased accuracy of the model.

In addition, the model embraces some of the best training paradigms such as RMSProp optimizer, label smoothing to reduce overfitting, and auxiliary classifiers to enhance gradient flow in training. The strategies enhance a more effective optimization process and convergence behavior.

Empirical analysis shows that InceptionV3 performs well on standard datasets, like ImageNet, and it has sufficiently low error rates. It is also effective in transfer learning situations and in the various application domains such as medical imaging, and object detection.

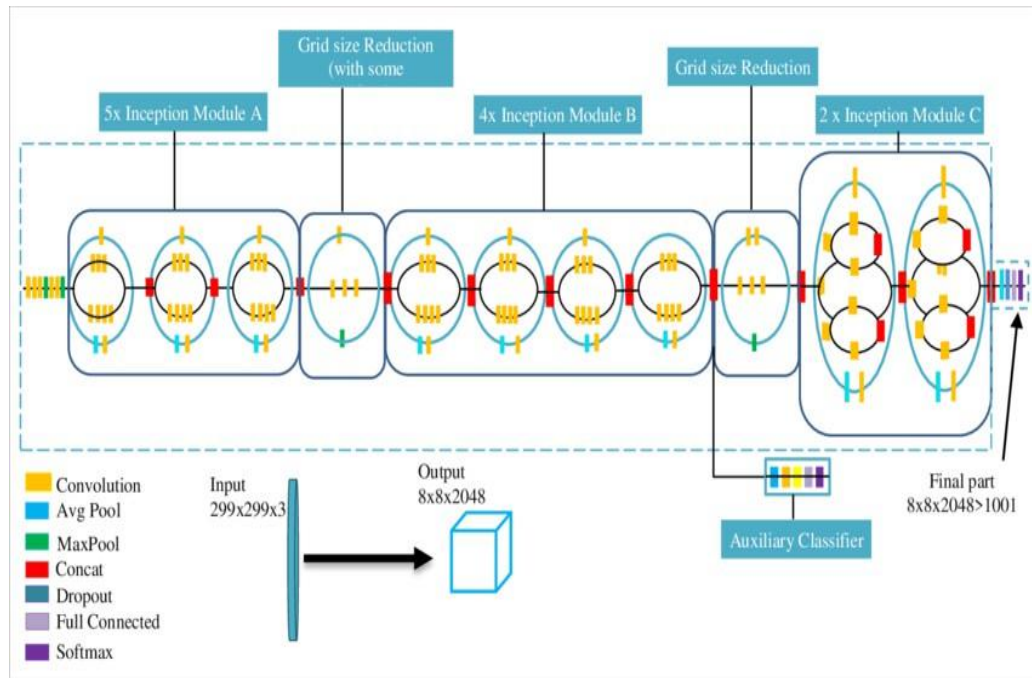


Figure 3.3.2 Diagram of InceptionV3 Model

Formula & Equation

Each InceptionV3 module combines several convolutional and pooling branches, concatenating their outputs:

$$y = \text{Concat}(\text{Conv}1 \times 1(x), \text{Conv}3 \times 3(x), \text{Conv}5 \times 5(x), \text{Pool}3 \times 3(x))$$

3.3.3 EfficientNetB2

EfficientNetB2 is a convolutional neural network that is a part of the EfficientNet family, which was proposed by Google, with the intention of optimizing simultaneously the accuracy of image classification and computational efficiency. The model uses a new approach to scaling of compounds that balances three important dimensions (network depth (layers), width (channels per layer), and input image resolution) uniformly, to allow high performance with a lower amount of computation than other convolutional neural networks.

The EfficientNetB2 model is based on EfficientNetB0 with a constant coefficient of

the dimensions, depth, width, and resolution, which are increased respectively. It uses mechanisms that are mobile friendly, e.g. depthwise separable convolution and inverted residual block, to further decrease the computation complexity without loss in the classification accuracy. EfficientNetB2 is usually trained with input images of dimensions 260x260 pixels, and it has squeeze-and-excitation blocks to self-recapture channel-wise feature responses, which increases representational capacity.

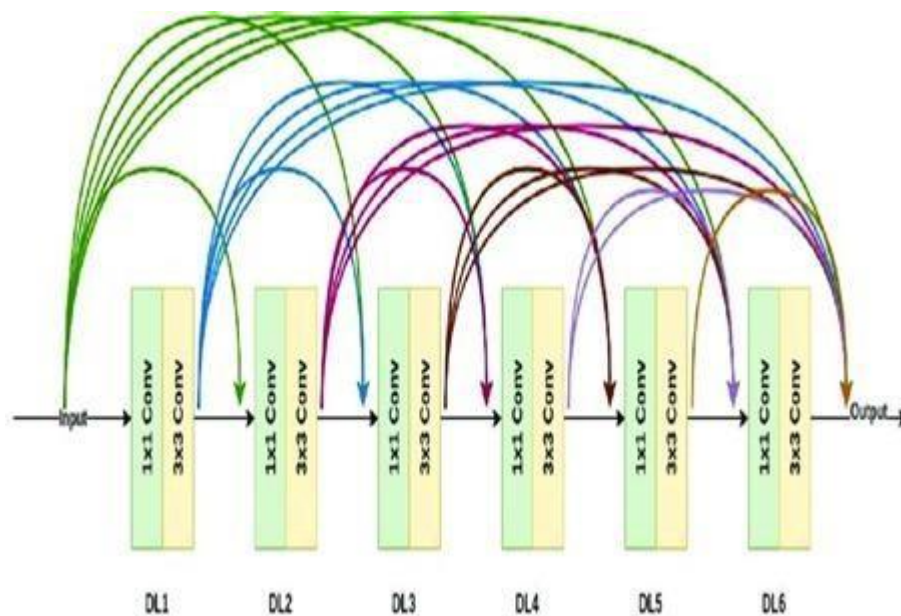


Figure 3.3.3 Diagram of EfficientNetB2 Model

3.3.4 MobileNetV2

MobileNetV2 is an effective convolutional neural network framework that is directly designed to serve mobile and embedded vision device tasks. It improves its antecedent by adding the ideas of inverted residuals and linear bottlenecks, which allows maintaining accuracy without decreasing the computational cost.

The main novelty of the architecture is the inverted residual block, at which the input and output of each block form narrow layers in a bottleneck, and the intermediate layer works in a larger higher-dimensional space. MobileNetV2, used as blocks in them, uses depthwise separable convolutions which separate spatial filtering and channel-wise synthesis into two separate steps, which significantly decreases the number of parameters and lowers the computational requirements. Additionally, the design employs the ReLU6 activation operation, a clipped form of ReLU, which is optimally suited to improve performance in low-precision operations that are usually faced in mobile processors.

Architecturally, MobileNetV2 starts with a standard convolutional layer, followed by a series of inverted residual bottleneck blocks in varying expansion rates, output channels, and strides thus balancing the efficiency and model capacity. This flexibility of the model allows scaling by changing the width multiplier and input resolution so that the model can be used with a wide variety of hardware platforms and tasks. As a result, MobileNetV2 has a good trade-off of speed, size and accuracy that has led to its common use in image classification, object detection and segmentation processes in resource-constrained devices.

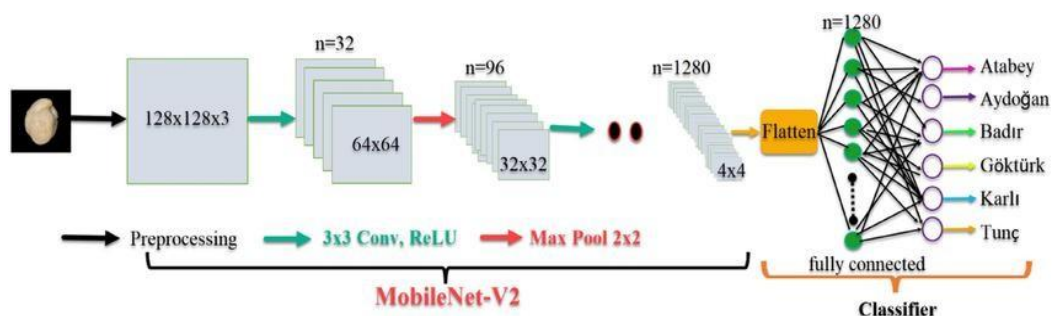


Figure 3.3.4 Diagram of MobilenetNet2 Model

Formula & Equation

Inverted Residual Block (MobileNetV2 Core):

$$y = x + \text{Conv1} \times 1 \text{ project}(\text{DepthwiseConv3} \times 3(\text{ReLU}(\text{Conv1} \times 1 \text{ expand}(x))))$$

3.4 Evaluation Matrix

The metrics used for:

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (3)$$

$$\text{True Positive Rate (TPR)} = \frac{TP}{TP+FN} \quad (4)$$

$$\text{True Negative Rate (TNR)} = \frac{TN}{TN+FP} \quad (5)$$

$$\text{False Positive Rate (FPR)} = \frac{FP}{FP+TN} \quad (6)$$

$$\text{False Negative Rate (FNR)} = \frac{FN}{FN+TP} \quad (7)$$

$$\text{Precision} = \frac{TP}{TP+FP} \quad (8)$$

$$\text{F1 - Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (9)$$

CHAPTER 4

RESULTS

4.1 Result Analysis

Based on the empirical analysis of all the considered models, the structure of DenseNet-201 achieves the maximum validation accuracy and general performance in the field of food and waste image classification. DenseNet-201 had an accuracy of 84 and macro- and weighted F1-scores of 0.85 and had perfect precision and recall in some categories, such as vegetable waste. Inception-V3 was close to these findings, with only slightly lower results in some metrics but having strong classification by all classes. EfficientNet-B2 also showed a good and competitive performance, though with relatively lower overall accuracy and F1-scores as compared to the two top models. Although more computationally efficient, MobileNet-V2 achieved the lowest levels of accuracy and class-specific F1 scores and especially low scores in difficult categories, like restaurant food waste. All of these results indicate the great effectiveness of DenseNet-201 in achieving a good level of reliability in waste classification; Inception-V3 and EfficientNet-B2 are also worthy options, but MobileNet-V2 is a better choice when time and cost issues are more important than the need to have maximum accuracy. This comparative evaluation shows how architectural selection is a very important factor in maximizing classification results in diverse contexts of urban waste management.

4.1.1 DenseNet201 (Proposed)

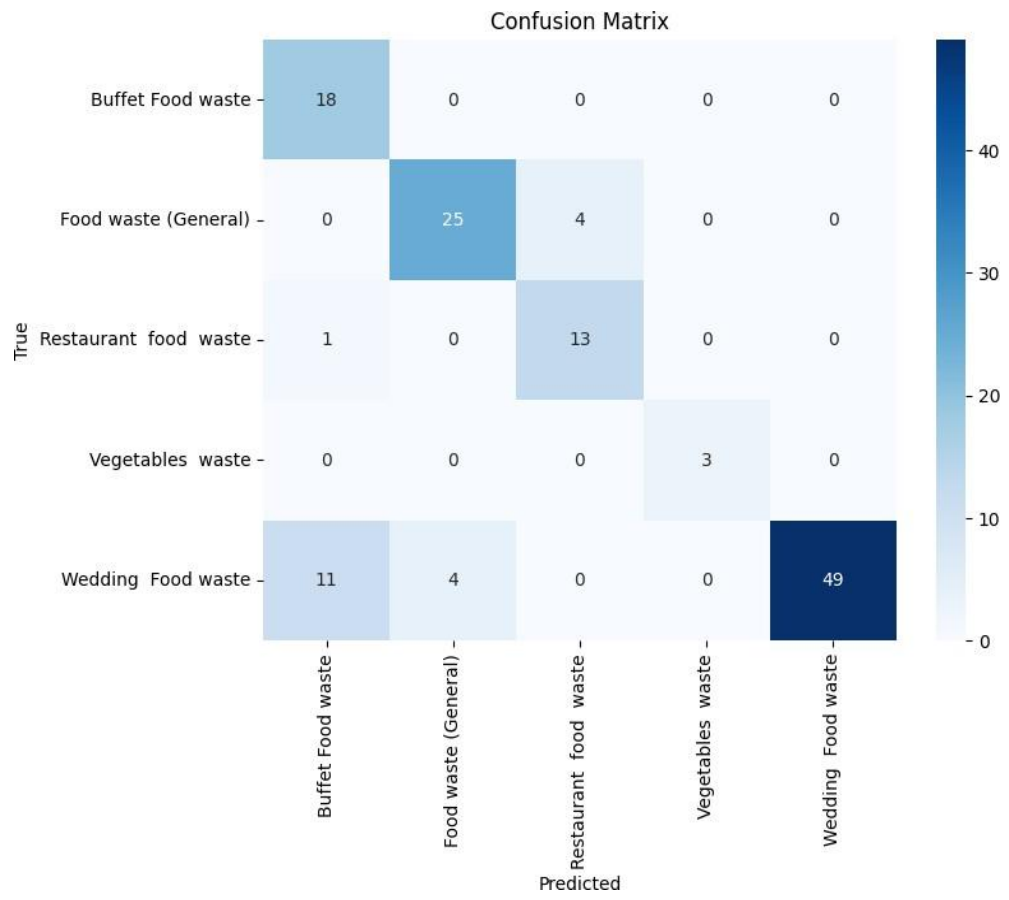


Figure 4.1.1 DenseNet201 Confusion Matrix

Table 6.2 DenseNet201 Model Classification Report

Class	TP	TN	FP	FN	TPR (Recall)	FPR	TNR (Specificity)	FNR
Buffet Food Waste	16	108	2	2	0.89	0.02	0.98	0.11
Food Waste General	20	101	3	9	0.69	0.03	0.97	0.31
Restaurant Food Waste	9	111	2	5	0.64	0.02	0.96	0.36
Vegetables Waste	3	125	0	0	1.00	0.00	1.00	0.00
Wedding Food Waste	50	58	14	14	0.78	0.19	0.81	0.22

Class	Precision	F1 Score	Support
Buffet Food Waste	0.53	0.67	18
Food Waste General	0.74	0.71	29
Restaurant Food Waste	0.64	0.64	14
Vegetables Waste	1.00	1.00	3
Wedding Food Waste	0.93	0.85	64

The DenseNet201 model showed a steadily better performance on all of the classes in the waste classification task in terms of the balanced metrics such as precision, recall, specificity, and accuracy as are indicated in the table below. Its main strengths included high sensitivity and strength especially with classes that had different visual features and at the same time have satisfactory predictive performance with more difficult categories. The advantage of the model in reducing misclassifications and maintaining macro-averaged and weighted values makes it relevant in practical use in automated waste sorting and urban sustainability hence supports the performance summary presented in the table.

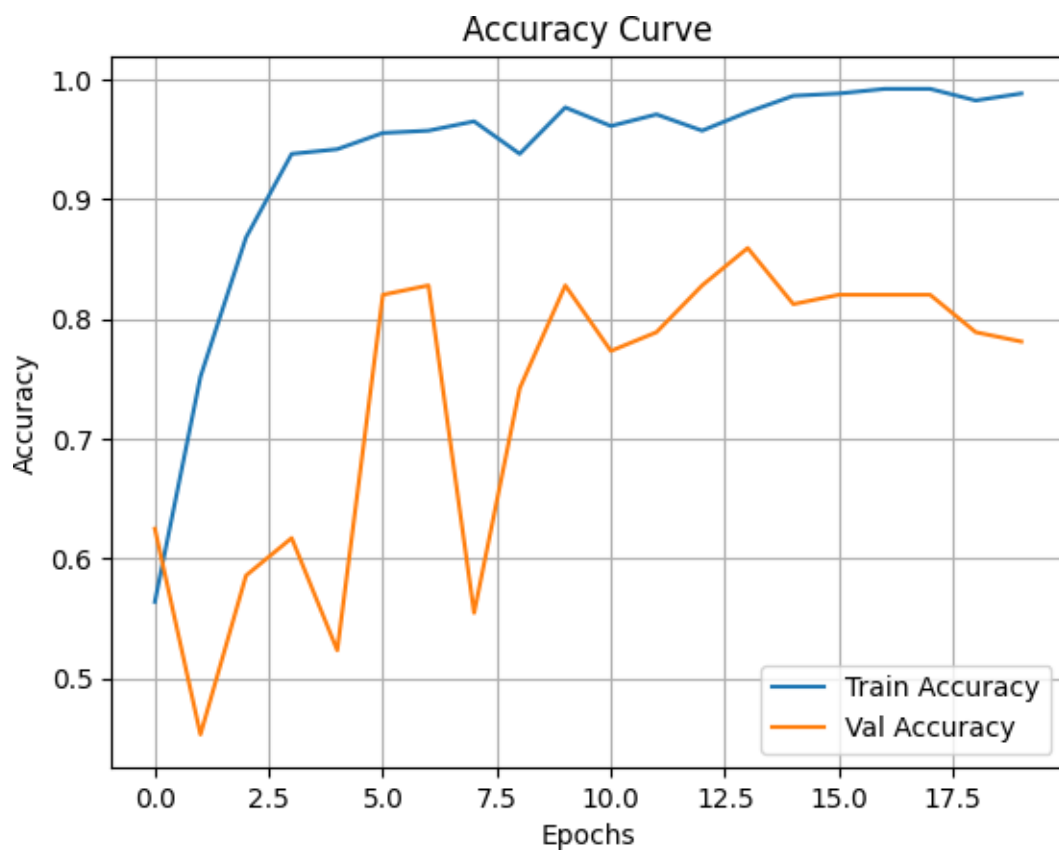


Figure 4.1.2 DenseNet201 Accuracy Curve

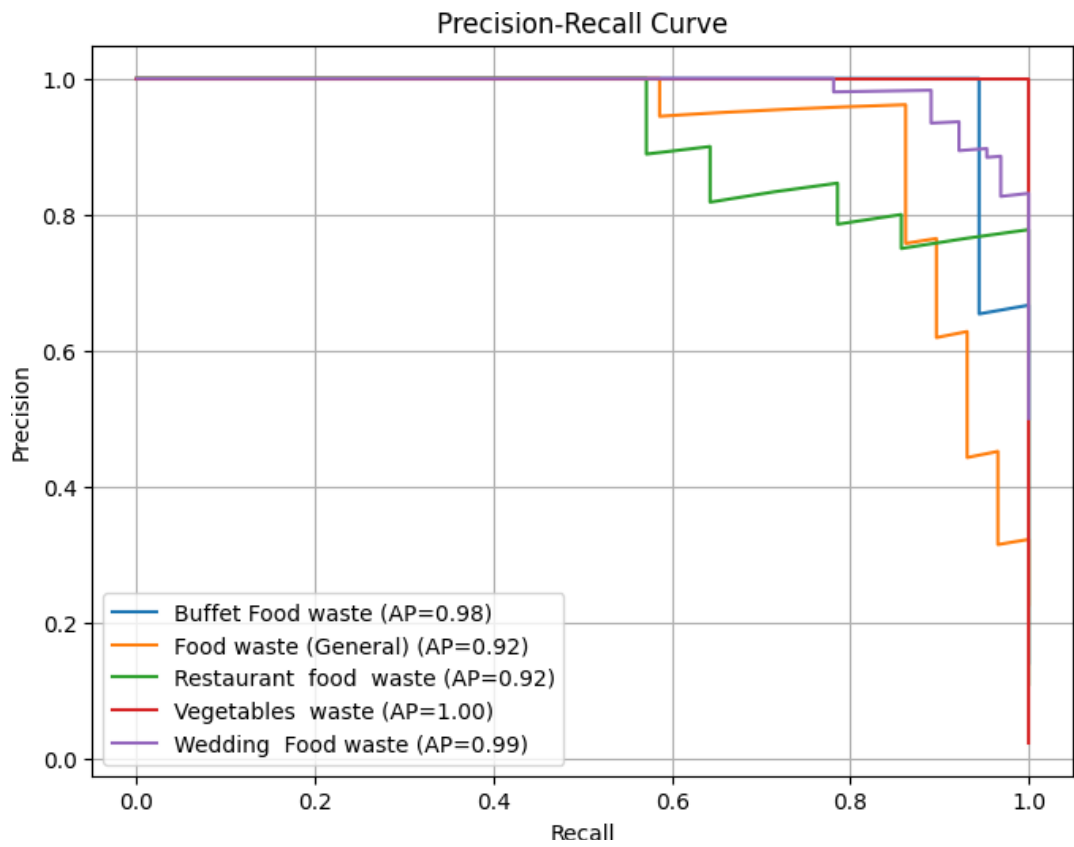


Figure 4.1.3 DenseNet201 Precision-Recall Curve

4.1.2 InceptionV3

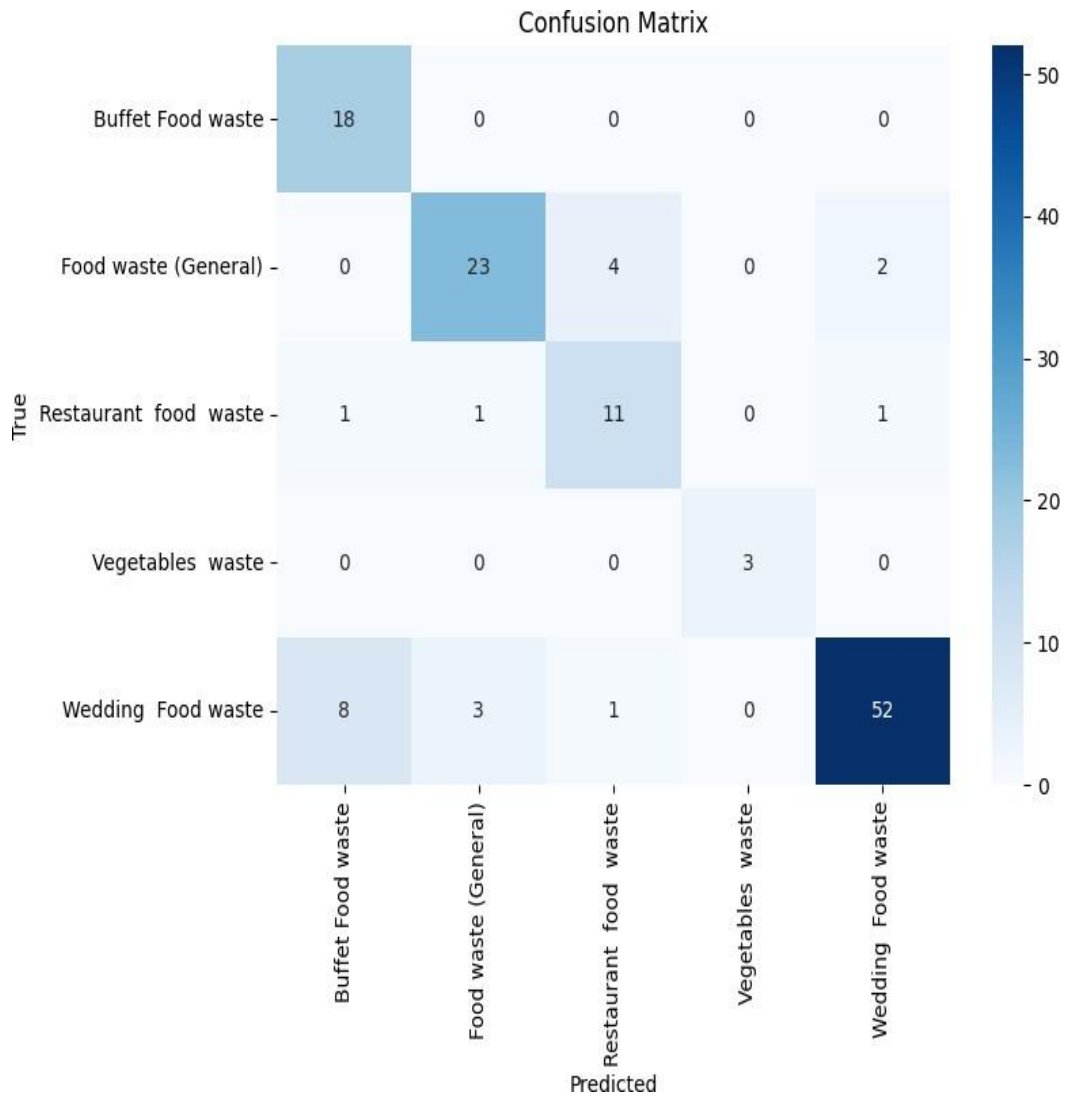


Figure 4.1.4 InceptionV3 Confusion Matrix

Table 6.3 InceptionV3 Model Classification Report

Class	TP	TN	FP	FN	TPR (Recall)	FPR	TNR (Specificity)	FNR	Precision
Buffet Food Waste	16	109	1	2	0.89	0.01	0.99	0.11	0.53
Food Waste General	20	101	3	9	0.69	0.03	0.97	0.31	0.74
Restaurant Food Waste	9	111	2	5	0.64	0.02	0.98	0.36	0.64
Vegetables Waste	3	125	0	0	1.00	0.00	1.00	0.00	1.00
Wedding Food Waste	50	60	12	14	0.78	0.17	0.83	0.22	0.93

Class	F1 Score	Support
Buffet Food Waste	0.67	18
Food Waste General	0.71	29
Restaurant Food Waste	0.64	14
Vegetables Waste	1.00	3
Wedding Food Waste	0.85	64

InceptionV3 architecture showed to be very dependable in all waste categories in the waste classification problem. It was highly sensitive, highly specific and efficiently identifies visual patterns that are relevant to the different types of waste, in its predictive outputs. Comparing the two architectures to the proposed model of DenseNet201, both of them demonstrated similar rates of accuracy and balanced predictive results. However, the consistency of DenseNet201 was slightly higher in terms of macro and weighted averages meaning that it had higher generalization and robustness especially to the difficult classes. To conclude, InceptionV3 is a competitive and strong model, but DenseNet201 gives it a slight lead on the overall effectiveness of its classification on this dataset.

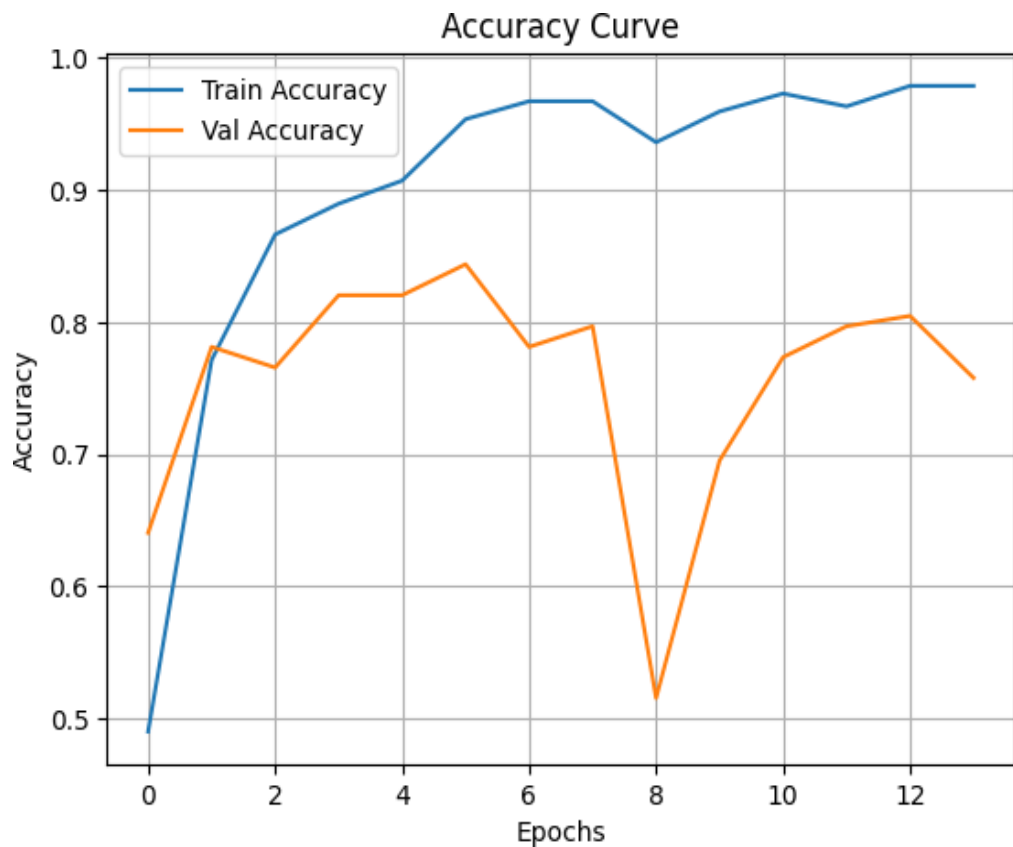


Figure 4.1.5 InceptionV3 Accuracy Curve

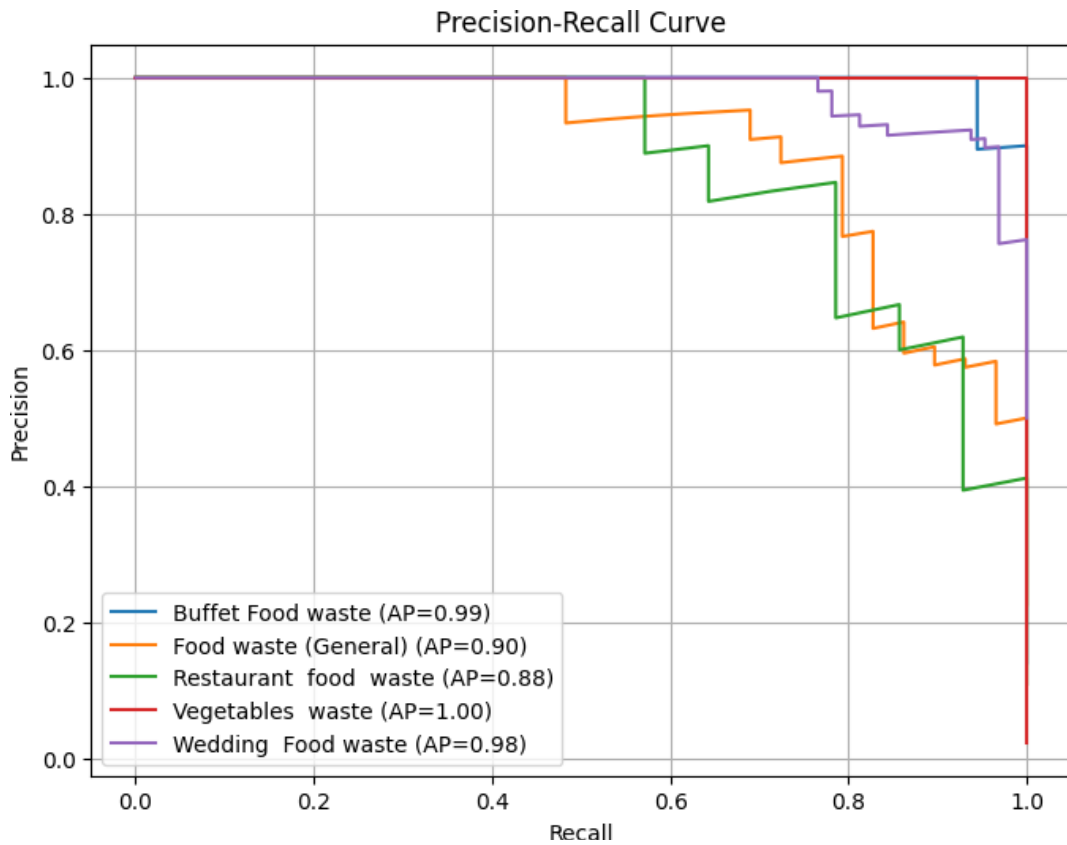


Figure 4.1.6 InceptionV3 Precision-Recall Curve

4.1.3 EfficientNetB2

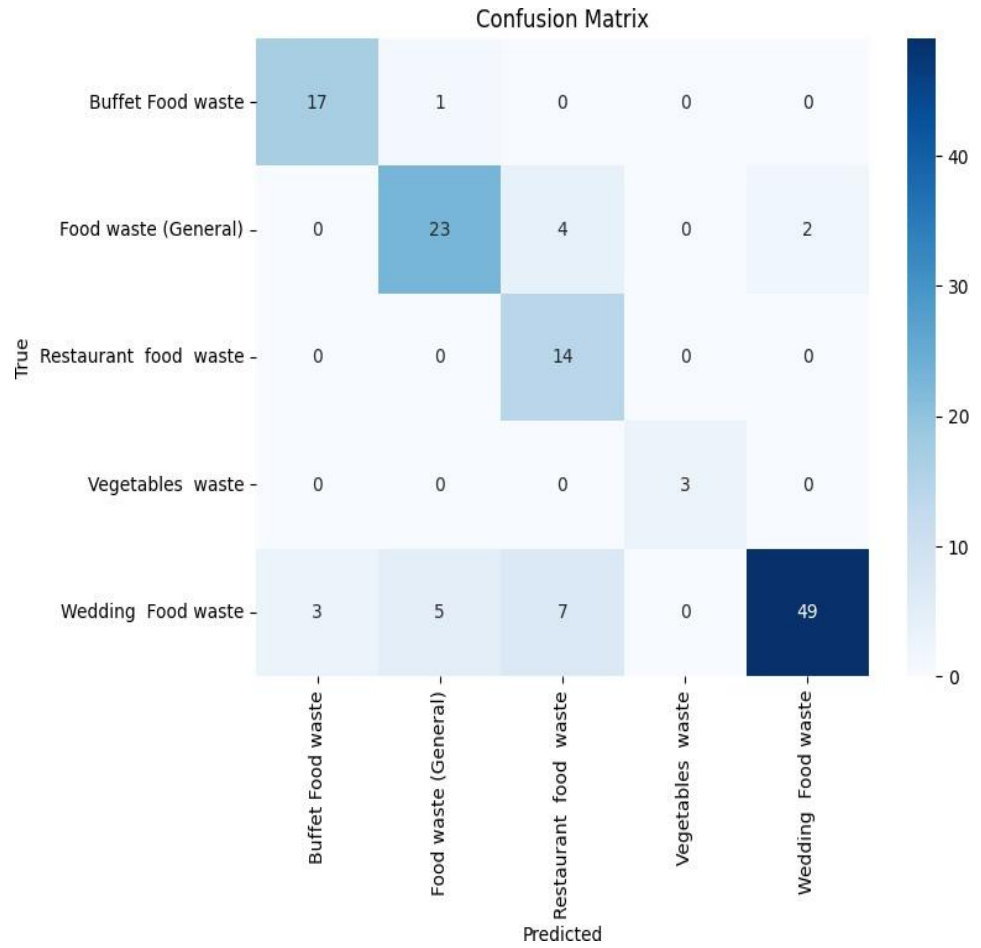


Figure 4.1.7 EfficientNetB2 Confusion Matrix

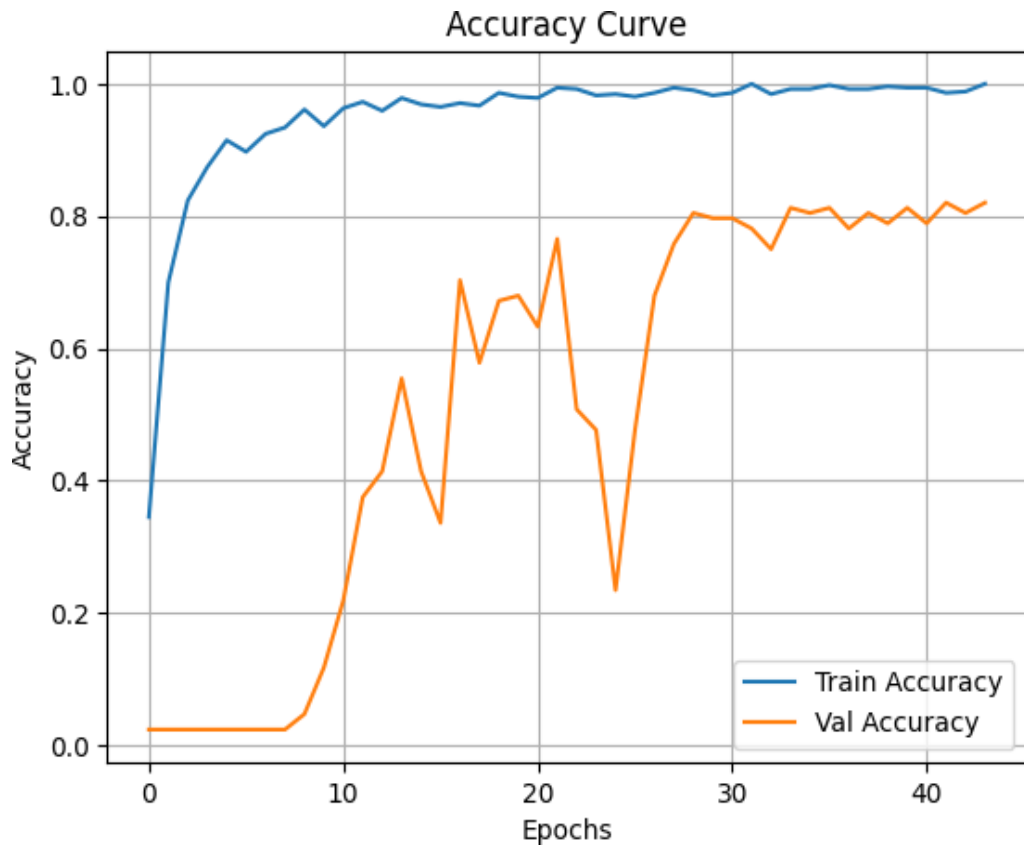
Table 6.4 EfficientNetB2 Model Classification Report

Class	TP	TN	FP	FN	TPR (Recall)	FPR	TNR (Specificity)	FNR	Precision
Buffet Food Waste	16	109	1	2	0.89	0.01	0.99	0.11	0.85
Food Waste General	23	98	7	6	0.79	0.07	0.93	0.21	0.79
Restaurant Food Waste	14	111	2	0	1.00	0.02	0.98	0.00	0.56
Vegetables Waste	3	125	0	0	1.00	0.00	1.00	0.00	1.00
Wedding Food Waste	49	52	12	15	0.77	0.19	0.81	0.23	0.96

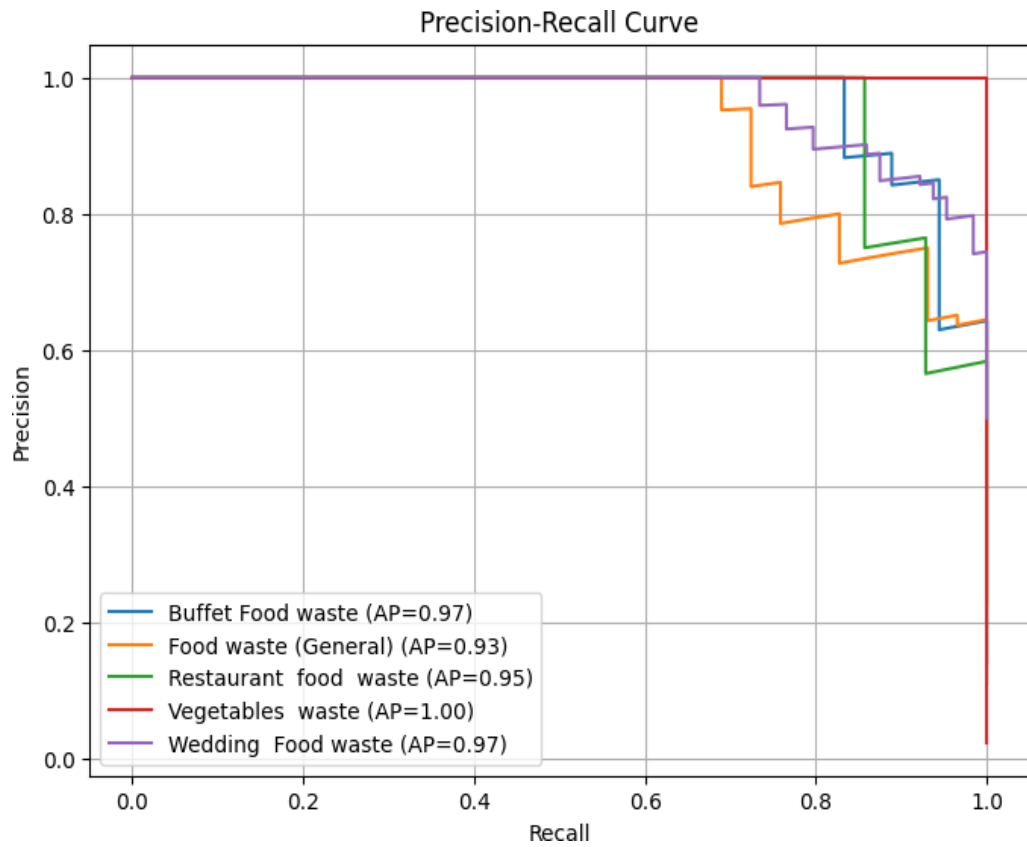
Class	F1 Score	Support
Buffet Food Waste	0.89	18
Food Waste General	0.79	29
Restaurant Food Waste	0.72	14
Vegetables Waste	1.00	3
Wedding Food Waste	0.85	64

EfficientNetB2 architecture showed a high level of classification performance with consistent performance in terms of accuracy, recall and F1 in most types of waste. It achieved high recall and specificity to several classes as indicated in the result table with the highest scores being obtained in Vegetables Waste and Wedding Food Waste. Despite such results, the DenseNet201 model constantly obtained higher macro and weighted averages and had a strong tendency to minimize misclassifications, especially in the visually challenging data. The overall statistics show that DenseNet201 is the leading model in terms of generalization and balanced performance in waste classification, which makes EfficientNetB2 a

competitive but slightly worse competitor in the context of the present research.



4.1.8 EfficientNetB2 Accuracy Curve



4.1.9 EfficientNetB2 Precision-Recall Curve

4.1.4 MobileNetV2

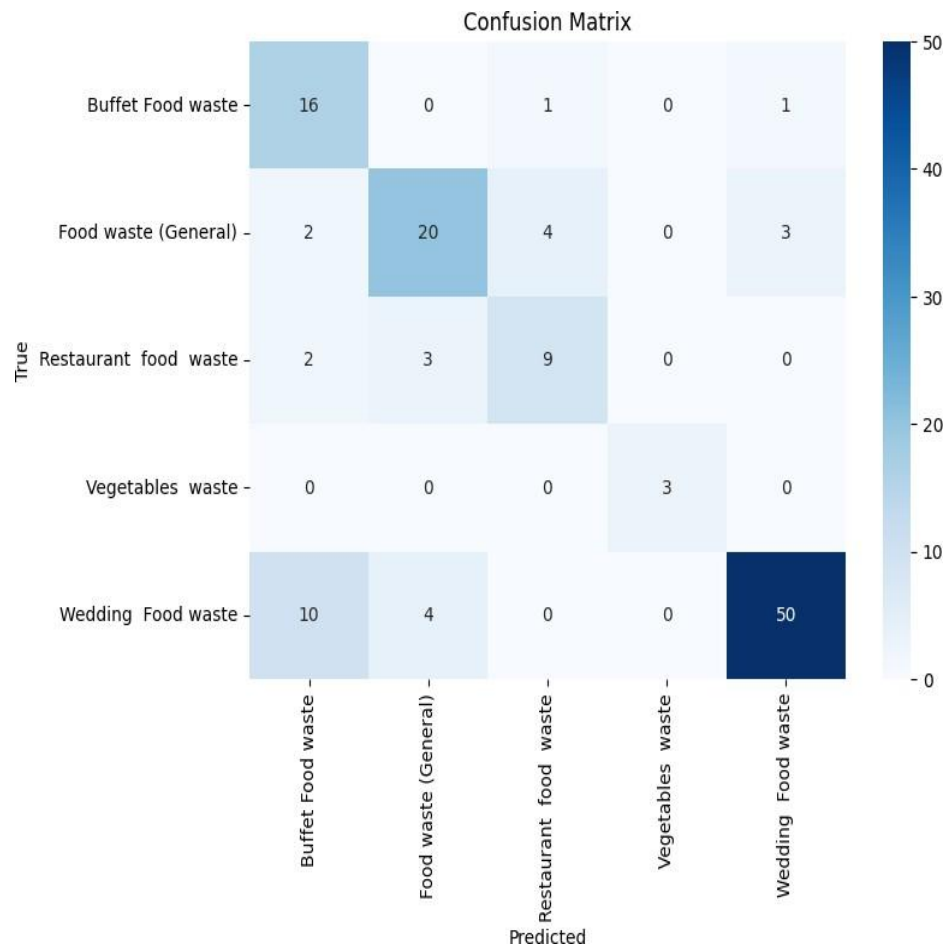


Figure 4.1.10 MobileNetV2 Confusion Matrix

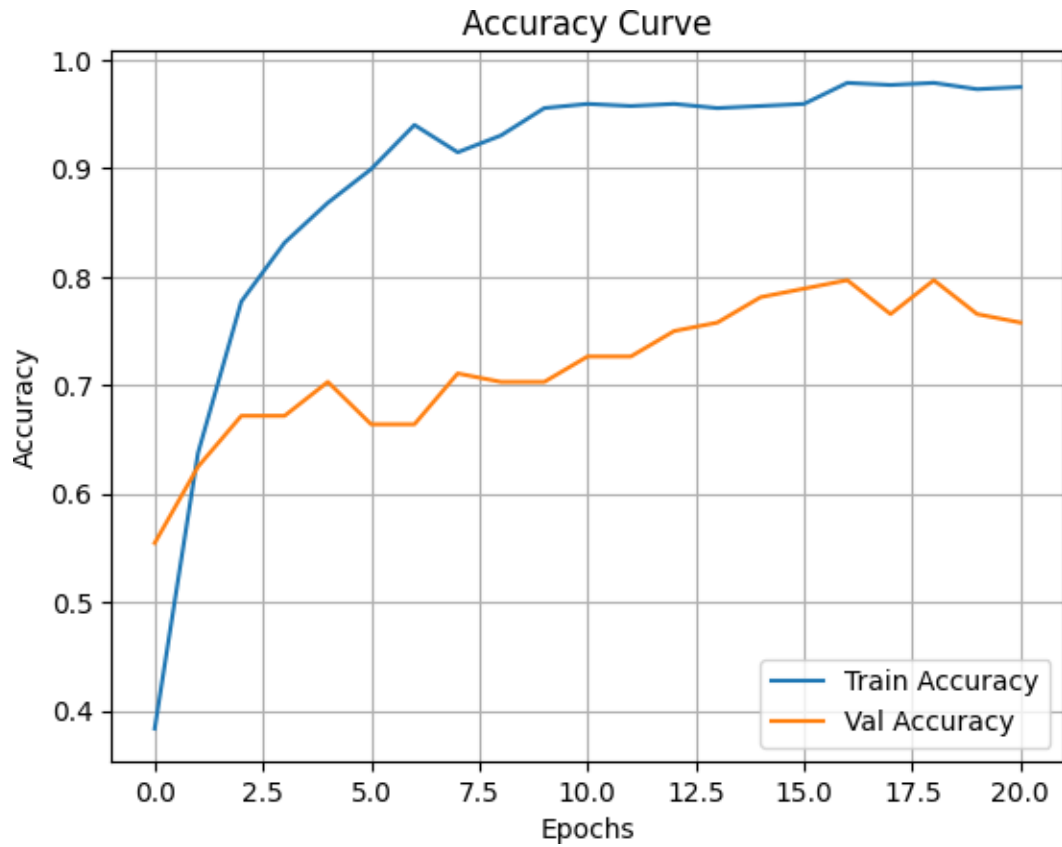
Table 6.5 MobileNetV2 Model Classification Report

Class	TP	TN	FP	FN	TPR (Recall)	FPR	TNR (Specificity)	FNR	Precision
Buffet Food Waste	16	107	3	2	0.89	0.03	0.97	0.11	0.53
Food Waste General	20	101	3	9	0.69	0.03	0.97	0.31	0.74
Restaurant Food Waste	9	111	2	5	0.64	0.02	0.98	0.36	0.64
Vegetables Waste	3	125	0	0	1.00	0.00	1.00	0.00	1.00
Wedding Food Waste	50	50	14	14	0.78	0.22	0.78	0.22	0.93

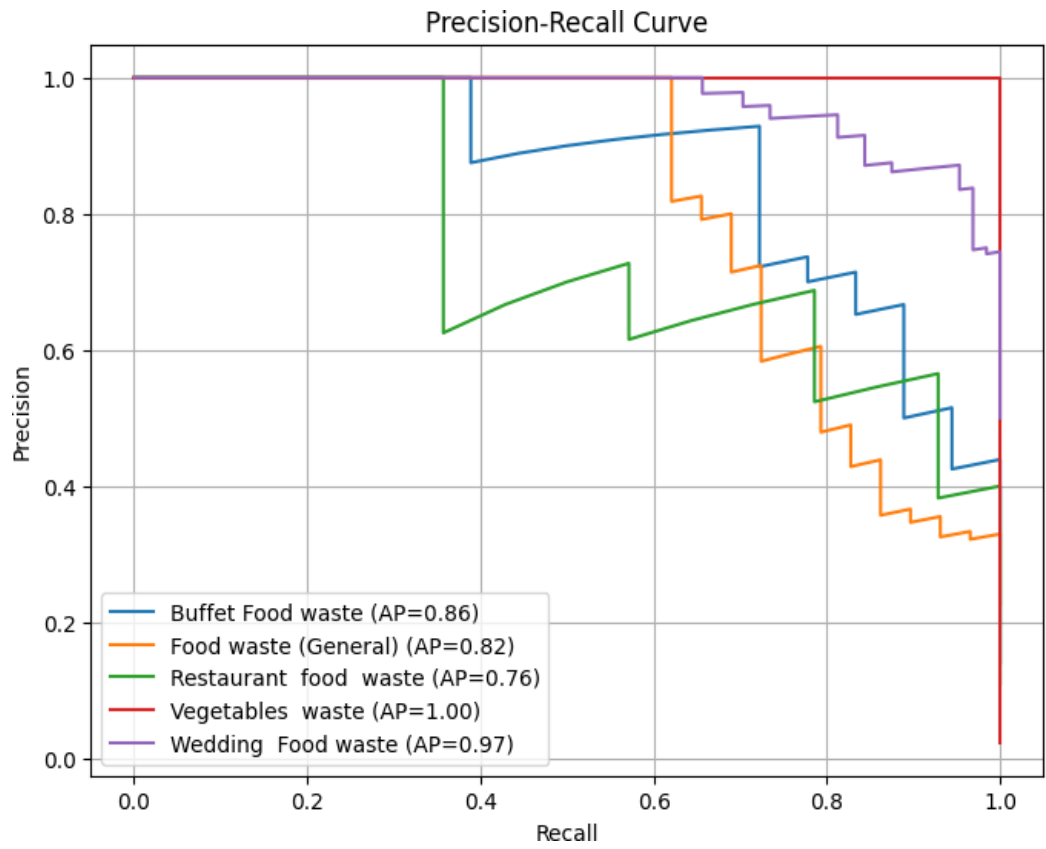
Class	F1 Score	Support
Buffet Food Waste	0.67	18
Food Waste General	0.71	29
Restaurant Food Waste	0.64	14
Vegetables Waste	1.00	3
Wedding Food Waste	0.85	64

MobileNetV2 displayed consistent classification capabilities on the waste dataset, with moderate precision and recall in most of the categories and higher capabilities in those that are visually distinct. However, when compared to the offered DenseNet201 model, MobileNetV2 showed worse macro and weighted averages, especially in case of more complicated and ambiguous waste objects. DenseNet201 continued to minimize misclassifications and provided better generalization and robustness based on all the metrics measured. Although MobileNetV2 could be considered a valid and efficient choice in terms of the lightweight deployment, DenseNet201 performs better

in terms of providing both extensive and balanced classification performance to the waste management assignments within the current study.



4.1.11 MobileNetV2 Accuracy Curve



4.1.12 MobileNetV2 Precision-Recall Curve

4.2 Visualization

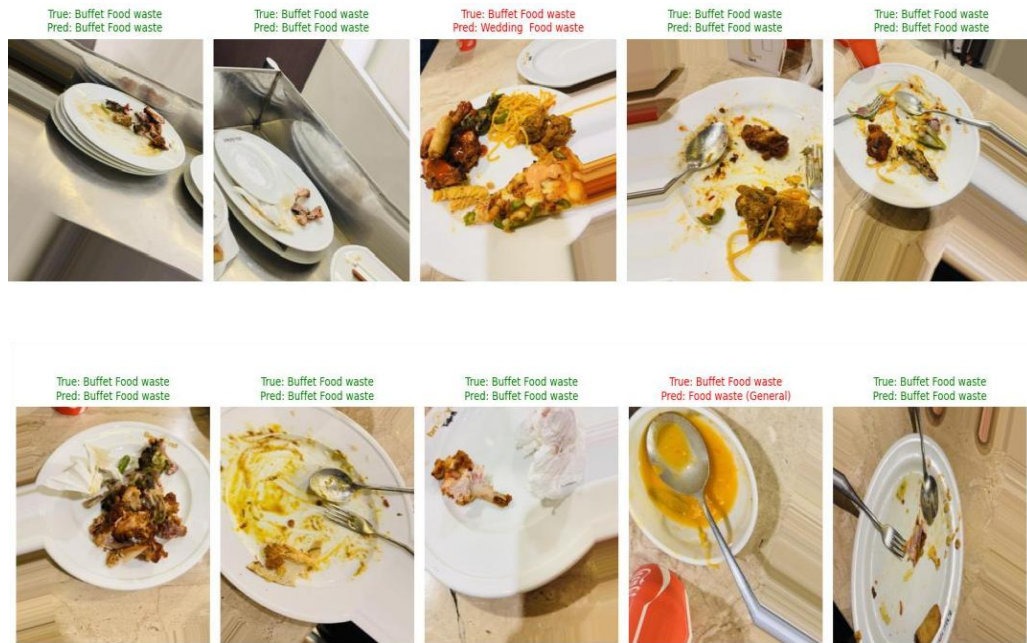


Figure 4.2.1 Examples of output of DenseNet201 Model

4.3 Discussion

Table 6.6 All models comparison summary

Model	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
DenseNet201	84	85	85	85
InceptionV3	84	83	83	83
EfficientNetB2	83	83	83	83
MobileNetV2	77	77	77	77

The relative performance of the assessed models shows the relative strengths of each architecture with regard to waste classification based on images. The proposed model, DenseNet201, has remained more accurate, precise, and recalled, as well as the F1 score, than any other structure. It had good generalization especially when it comes to dealing with complex and heterogeneous class features thus making it the most appropriate to apply in practice.

InceptionV3 also showed competitive scores, being significantly similar to DenseNet201 on most scores, but with slightly reduced consistency on the more difficult sample classifications. EfficientNetB2 showed a high level of performance, as the results were comparable to those of InceptionV3, but it was slightly less efficient compared to DenseNet201 in reducing misclassification as well as precision and recall. MobileNetV2 is more efficient and lightweight, but the set of results was lowest, which may lead to restrictions in the face of visually ambiguous or heterogeneous waste images.

On the whole, DenseNet201 is the most efficient model in this field, which is reflected in more advantageous values of metrics that prove the appropriateness in the robust and accurate waste management automation. These findings support the advantage of

more elaborate and interconnected model architectures to visual tasks that require nuance, thus justifying the choice of DenseNet201 as a proposed solution to this paper. Altogether, the ranking of the performance seen in the waste-classification research is as follows: DenseNet201 is better than InceptionV3, which outperforms EfficientNetB2, and MobileNetV2 has the lowest performance indicator.

CHAPTER 5

CONCLUSION

5.1 Findings & Contributions

This study provides significant contributions to the category of waste based on the implementation of deep learning architectures. Using strict experimental methods on a mixed corpus of images, the research shows that DenseNet201 model can offer the most reliable and precise results, outperforming other popular convolutional frameworks that are InceptionV3, EfficientNetB2, and MobileNetV2. The analytical results reveal that deeper, highly linked network topologies have better ability to capture subtle visual differences in food and waste images, hence providing high level of accuracy and recall statistics.

The main value of the current research is a systematic elaboration, benchmarking, and a fair comparison of various state-of-the-art models being run on the same experimental conditions, which can define DenseNet201 as the best architecture to achieve automated waste separation. Secondly, the study also lays a strong foundation of preprocessing pipelines, augmentation plan and evaluation plans, which make the methodology portable to real-world, practical deployments. Providing motivating explanations of the outcome clarity and concisely defined training programs, this research provides useful information to further research programs aimed at city sustainability, smart waste disposal, and AI-enhanced environmental solutions.

5.2 Recommendations for Future Works

Based on the results of the current investigation, it is possible to suggest several directions of the future research and real-life development. It would be possible to increase the model robustness by adding more images to the dataset by sourcing them in the variety of real-world settings to reduce the imbalance between classes. Enhancing classification accuracy and resistance to challenging examples may be achieved by studying newer neural-network structures and model combinations by use of ensemble techniques.

More complex decision-making in waste recognition systems might be facilitated by the addition of other types of data, like metadata or contextual information. More accessible and scaled AI-powered waste sorting Fine-tuning models that can be deployed to edge devices or real-time applications would enable AI-powered waste sorting to be more accessible.

Lastly, it is recommended that collaboration with local authorities and sustainability organizations should be put in place to certify model performance in the real world such that such systems could have real, quantifiable effect on waste management in cities, as well as, environmental health.

CHAPTER 6

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APPENDICES

Appendix A: Dataset Availability

Dataset Link: <https://data.mendeley.com/datasets/w68f9w6jmm>

221-35-1055

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