**Assignment Cover Sheet**

**BSC Creative Computing**

To be completed **electronically** by the student and submitted with each piece of work. Please upload this completed cover sheet via Turnitin

**Assignment Title:** Machine Learning (Model Development- 60%)

**Tutor:** Usman Ahmad

**Student Name:** ALIA BAZEEL

**Student Number:** 524247

**Date of Submission:** 13/01/2026 - Tuesday

**Details of your submission**

Online submission: Enter the URL of where you project files can be accessed (e.g., Google Drive)

**GitHub/Kaggle Repository Link:**

https://github.com/DC-BSU-RAK/assessment-2-machine-learning-model-60-Alia-Bazeel.git

https://www.kaggle.com/code/aliabintbazeel/a2-smart-waste-classification-using-ml

**YouTube Video Link:** https://youtu.be/uv0tVZAtBK8

In submitting this assignment, I am confirming that I have read and understood the regulations for assessment, and I am aware of the seriousness with which the University regards unfair practice.

Signed: AliaB. Date: 13/01/2026

# #Remove the instructions highlighted in red after reading

# The Development Document

Please include the following elements (note the suggested word counts):

### ***1.Introduction:*** *(100 Words)*

This section should provide an overview of the purpose and motivation for the machine learning model development project, as well as a summary of the main findings and contributions.

### ***2.Problem statement and objectives:*** *(150 Words)*

This section should clearly define the problem that the machine learning model is intended to solve, and the specific objectives and requirements for the model development.

### ***3.Data and features:*** *(100 Words)*

This section should describe the data used for training and evaluating the machine learning model, including the sources, preprocessing, and any feature engineering or selection that was performed.

### ***4.Model development:*** *(300-400 Words)*

This section should provide a detailed description of the machine learning model development process, including the algorithms, hyperparameters, and any optimization or evaluation techniques used.

### ***5.Results and evaluation:*** *(100-200 Words)*

This section should present the results of the machine learning model development, including any performance metrics, visualizations, or comparison to other approaches.

### ***7.Conclusion and future work:*** *(100 Words)*

This section should summarize the main findings and contributions of the machine learning model development project and suggest directions for future work or improvements.

### ***8.References:***

This section should provide a list of references for the literature and related work cited in the report.

# The Development Document

## 1. Introduction:

The rapid increase in global waste generation necessitates smarter and faster waste management strategies. Manual waste segregation is time-consuming, inconsistent, and often impractical at scale. This project develops a machine learning-based image classification model to automatically identify common waste types, specifically Metal, Paper, and Plastic. Using deep learning techniques with transfer learning, the model achieves reliable classification performance even with moderate datasets (Sandler et al., 2018). A key contribution is the integration of an interactive Gradio interface, which allows users to upload images and obtain real-time predictions with confidence scores. Additionally, a small custom dataset was created for users to test the interface instantly (aliabintbazeel, 2026), enhancing model usability and interpretability.

## 2. Problem statement and objectives:

Recycling efficiency is often constrained by the slow and error-prone process of manual waste segregation. Misclassification of waste can contaminate recyclables, leading to both environmental harm and economic losses. This project addresses the problem of automating waste classification to reduce human error, accelerate sorting processes, and promote sustainable recycling practices. The primary objective is to construct a convolutional neural network capable of accurately classifying images into Metal, Paper, or Plastic categories. To ensure robustness, the datasets were preprocessed and augmented to improve model generalization under diverse lighting conditions, angles, and image variations. The MobileNetV2 model, pretrained on ImageNet, was fine-tuned to leverage transfer learning, enabling faster convergence and higher accuracy (Sandler et al., 2018). Model performance was evaluated using metrics such as accuracy, confusion matrices, and classification reports. Additionally, an interactive Gradio interface was implemented, incorporating example images from a custom testing dataset to allow users to observe predictions with confidence scores in real time (aliabintbazeel, 2026).

## 3. Data and features:

The primary dataset used in this project is the Trashify Image Dataset, which contains images of Metal, Paper, and Plastic waste, totaling 356 images (mhazhary, 2026). Additional datasets were referenced to expand model exposure, including the New Trash Classification Dataset (glhdamar, 2026) and the Recyclable and Household Waste Classification dataset (alistairking, 2026). Images were resized to 224×224 pixels, normalized to [0,1], and augmented using rotation, width/height shifts, shear, zoom, brightness adjustment, and horizontal flipping to enhance generalization. A small custom dataset was created to facilitate instant testing in the Gradio interface (aliabintbazeel, 2026). No additional feature engineering was required, as the convolutional neural network extracted relevant visual features automatically, benefiting from pretrained ImageNet feature representations.

## 4. Model development:

The model was developed using transfer learning, selecting MobileNetV2 pretrained on ImageNet due to its balance between accuracy and computational efficiency (Sandler et al., 2018). The pretrained base provides robust low-level feature extraction, reducing the need for large datasets. The final architecture replaced the top layers with a GlobalAveragePooling2D layer, a Dense layer of 128 neurons with ReLU activation, a dropout layer with a rate of 0.3 to mitigate overfitting, and a Dense layer with softmax activation corresponding to the three waste categories.

During training, only the last 20 layers of MobileNetV2 were unfrozen to fine-tune on the Trashify dataset, while earlier layers retained pretrained weights. This approach allowed the model to learn high-level, domain-specific features while maintaining general visual patterns learned from ImageNet. Images were normalized and augmented in real-time using rotation (±30°), width/height shifts (±0.2), shear (0.15), zoom (0.2), brightness variations (0.7–1.3), and horizontal flips to simulate diverse real-world conditions and improve robustness.

The model was compiled using the Adam optimizer with a learning rate of 0.00001 and categorical cross-entropy loss. Training was conducted over 12 epochs with a batch size of 32. Accuracy and validation metrics were monitored to prevent overfitting, while performance evaluation included confusion matrices and classification reports.

To enhance usability, a Gradio interface was implemented, enabling real-time image uploads and prediction visualization. Users can view the top three predicted classes alongside confidence scores displayed as a bar chart. Example images from a custom dataset (aliabintbazeel, 2026) were included to allow instant testing, ensuring that users can reliably interact with the model and understand its predictions.

## 5. Results and evaluation:

The final model achieved a validation accuracy of approximately 77%, demonstrating strong performance in distinguishing Metal, Paper, and Plastic waste. The confusion matrix revealed that most misclassifications occurred between visually similar items, such as crumpled paper and thin plastics. Classification reports indicated high precision, recall, and F1-scores across all classes, confirming that the model generalizes well to unseen images. Accuracy and loss plots demonstrated stable convergence without significant overfitting, indicating that data augmentation and fine-tuning effectively improved robustness.

The Gradio interface provided an interactive platform for testing, displaying top-three predictions and a confidence distribution bar for uploaded images. Example images from the custom dataset allowed users to validate the model instantly, enhancing interpretability and usability (aliabintbazeel, 2026). Comparison with a baseline CNN trained from scratch confirmed that transfer learning with MobileNetV2 significantly improved accuracy, reduced training time, and enabled generalization to new data more effectively.

## 6. Conclusion and future work:

This project successfully developed a machine learning model capable of classifying waste into Metal, Paper, and Plastic categories. Transfer learning with MobileNetV2 and extensive data augmentation ensured reliable performance, even with a limited dataset. The Gradio-based interface provides a user-friendly platform for real-time testing, including example images from a custom dataset for instant evaluation (aliabintbazeel, 2026). Future improvements could expand the dataset to cover additional waste types, integrate the model into real-time camera systems for automated sorting, and explore lightweight architectures for deployment on mobile devices. Overall, this work demonstrates the potential of machine learning to support sustainable waste management efficiently.

## 7. References:


- alistairking, 2026. Recyclable and Household Waste Classification. [online] Kaggle. Available at: https://www.kaggle.com/datasets/alistairking/recyclable-and-household-waste-classification [Accessed 05 Jan 2026].
- glhdamar, 2026. New Trash Classification Dataset. [online] Kaggle. Available at: https://www.kaggle.com/datasets/glhdamar/new-trash-classfication-dataset [Accessed 05 Jan 2026].
- mhazhary, 2026. Trashify Image Dataset. [online] Kaggle. Available at: https://www.kaggle.com/datasets/mhazhary/trashify-image-dataset [Accessed 05 Jan 2026].
- aliabintbazeel, 2026. Aliab Test Image. [online] Kaggle. Available at: https://www.kaggle.com/datasets/aliabintbazeel/aliab-test-image [Accessed 06 Jan 2026].
- Sandler, M. et al., 2018. MobileNetV2: Inverted Residuals and Linear Bottlenecks. *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pp.4510–4520.