‵Waste Classification Model using CNN & Transfer Learning’

Submitted in partial fulfilment of the requirements of the degree in

BACHELOR OF ENGINEERING IN COMPUTER SCIENCE AND ENGINEERING (IOTCSBC)

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CERTIFICATE

This is to certify that the Mini Project entitled '**Waste Classification Model using CNN & Transfer Learning'** is a bonafide work of **Shaikh Saaiem Salaar** Submitted to the University of Mumbai in partial fulfillment of the requirement for the award of the degree of **"Bachelor of Engineering"** in **"Computer Science and Engineering (IOTCSBC)" .**

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Project Report Approval

This Project report entitled

'Waste Classification Model using CNN & Transfer Learning'

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is approved for the degree of **Bachelor of Engineering** in **Computer Science and Engineering (IOTCSBC).**

Examiners

1..

(Internal Examiner Name & Sign)

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(External Examiner name & Sign)

Date:

Place:

Declaration

We declare that this written submission represents our ideas in our own words and where others' ideas or words have been included, we have adequately cited and referenced the original sources. We also declare that we have adhered to all academic honesty and integrity principles and have not misrepresented, fabricated, or falsified any idea/data/fact/source in my submission. We understand that any violation of the above will be cause for disciplinary action by the Institute and can also evoke penal action from the sources which have thus not been properly cited or from whom proper permission has not been taken when needed.

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ABSTRACT

The rapid increase in urban waste has created a pressing need for efficient and sustainable waste management solutions. Traditional manual methods of waste segregation are time-consuming, error-prone, and labor-intensive. To address this challenge, this project presents an **Waste Classification Model using CNN & Transfer Learning**. The model is developed with transfer learning based on EfficientNet, enabling accurate classification of waste into six categories: cardboard, glass, metal, paper, plastic, and trash. A dataset of labeled waste images is preprocessed and augmented to improve generalization, while the model is trained and fine-tuned for robust performance. The system achieves reliable accuracy in identifying different waste types and is integrated with a simple web interface for real-time classification. By automating the segregation process, this approach reduces human effort, enhances efficiency, and contributes to smarter and more sustainable waste management practices.

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Chapter - I

1.1 Introduction to Machine Learning

Machine Learning (ML) is a subset of Artificial Intelligence (AI) that focuses on developing algorithms and statistical models that enable computers to perform tasks without explicit programming. Unlike traditional programming, where instructions are manually coded, machine learning systems learn patterns and make decisions from data.

ML algorithms can automatically improve their performance as they are exposed to more data, making them highly suitable for tasks such as image recognition, speech processing, natural language understanding, and predictive analytics.

There are three main types of machine learning:

1. **Supervised Learning** – The algorithm is trained on labeled data, learning to predict outputs from inputs. Examples include classification and regression tasks.
2. **Unsupervised Learning** – The algorithm analyzes unlabeled data to identify patterns or groupings, such as clustering and dimensionality reduction.
3. **Reinforcement Learning** – The system learns by interacting with an environment, receiving feedback in the form of rewards or penalties, and optimizing its strategy over time.

In the context of waste classification, supervised learning is commonly used, where the model is trained on labeled images of waste categories. The model learns to recognize visual patterns in these images, enabling accurate categorization of new, unseen waste items.

1.2 Waste Classification Model Using Machine Learning

Waste classification is the process of categorizing different types of waste materials into predefined classes such as paper, plastic, metal, glass, cardboard, and general trash. Accurate waste classification is crucial for effective recycling, environmental protection, and sustainable resource management.

Machine Learning (ML) provides a robust approach to automate this process by analyzing images of waste and predicting their categories. In a typical ML-based waste classification model,

The following steps are involved:

1. **Data Collection** – A dataset of labeled waste images is collected, representing each category to be classified.
2. **Data Preprocessing** – Images are resized, normalized, and augmented to improve the model's learning and generalization.
3. **Feature Extraction** – The model identifies important visual features such as shapes, textures, and colors that distinguish one class from another.
4. **Model Training** – A supervised learning algorithm, often a Convolutional Neural Network (CNN), is trained on the preprocessed images to learn patterns associated with each class. Transfer learning with pre-trained networks like EfficientNet can accelerate training and improve accuracy.
5. **Evaluation** – The trained model is evaluated using metrics like accuracy, precision, recall, and F1-score, and a confusion matrix is used to visualize performance across all categories.
6. **Deployment** – The model can be integrated into applications with real-time prediction capabilities, allowing users to classify waste using images from cameras or uploads.

In this project, a **hybrid model combining EfficientNetV2B2 with custom CNN layers** was implemented. EfficientNet serves as a feature extractor, capturing intricate patterns from waste images, while the custom CNN layers fine-tune the model for the specific task of waste classification. This hybrid approach ensures high accuracy, fast convergence, and robust performance across all six waste categories.

Chapter 2 : Literature Survey

2.1 Literature Survey on Waste Classification Using Traditional Machine Learning

In the early stages of waste classification research, **traditional machine learning (ML) techniques** were widely used. Algorithms such as **Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), Decision Trees, and Random Forests** were employed to categorize waste items. These methods relied on **handcrafted features** extracted from images, including color histograms, edge detection, texture descriptors, and shape analysis.

Although these approaches could achieve reasonable results on **small, controlled datasets**, they often struggled with real-world scenarios where images contained **varying lighting conditions, cluttered backgrounds, and different object orientations**. Moreover, these models lacked scalability, as manual feature extraction became inefficient when dealing with **large and diverse datasets**. Researchers concluded that while traditional ML laid the groundwork, more advanced techniques were needed for reliable waste classification.

2.2 Deep Learning-Based Waste Classification

The introduction of **deep learning**, especially **Convolutional Neural Networks (CNNs)**, transformed waste classification. Unlike traditional ML, CNNs automatically learn hierarchical features from raw images without the need for manual feature extraction. Studies employing architectures such as **VGG16, ResNet, MobileNet, and Inception** demonstrated significant improvements in accuracy and robustness.

Deep learning models can handle **complex image variations**, such as different lighting conditions, overlapping objects, and irregular shapes. For example, a study on multi-class waste classification reported accuracies above 92% using CNNs, significantly outperforming traditional ML methods. Deep learning also allows for **end-to-end model training**, making it easier to integrate classification systems into automated pipelines for recycling and waste management.

Chapter 3 : Existing System

3.1 Brief Explanation of existing system

Traditional waste management relies on **manual sorting**, which is labor-intensive, time-consuming, and prone to errors. Some systems use **automated mechanical sorting** with conveyor belts, magnets, and air jets. Earlier computational approaches employed **traditional machine learning** with handcrafted features (color, texture, shape) and classifiers like SVM, Random Forest, and k-NN. These systems handled basic sorting but struggled with **mixed waste, overlapping items, and varying lighting**, limiting their overall accuracy and efficiency.

3.2 Disadvantages of existing system

The existing waste classification systems, both manual and machine learning-based, have several notable drawbacks:

1. **Low Accuracy in Complex Scenarios** – Traditional ML models rely on handcrafted features and struggle with images that have **variations in background, lighting, and object orientation**.
2. **Labor Intensive and Costly –** Manual sorting requires significant human resources, making it **expensive and inefficient** for large-scale waste management.
3. **Limited Scalability –** Early ML systems cannot easily scale to **large datasets or real-time applications** due to computational constraints and lack of robust feature extraction.
4. **Delayed Processing –** Mechanical or semi-automated sorting systems often operate at **slower speeds**, limiting real-time waste management capabilities.
5. **Poor Generalization** – Systems trained on specific datasets may **fail when exposed to new or unseen waste items**, resulting in misclassification and contamination of recyclable streams.

These disadvantages highlight the need for **advanced, intelligent, and automated waste classification systems**, such as those using deep learning and hybrid models, to improve accuracy, scalability, and efficiency in modern waste management operations.

Chapter 4 : Proposed System

4.1 Brief explanation of proposed system

The proposed system is an **intelligent waste classification model** that combines **EfficientNetV2B2 with custom CNN layers** to classify waste into six categories: Cardboard, Glass, Metal, Paper, Plastic, and Trash. Unlike traditional systems, this model leverages **deep learning and transfer learning** to automatically extract features from images, improving accuracy and robustness.

The system supports **real-time predictions** through a web-based interface using **Gradio**, allowing users to classify waste via image upload or live webcam input. This approach enhances efficiency, reduces human error, and enables **scalable and automated waste management** suitable for modern recycling operations.

4.2 Advantages of Proposed System

The proposed hybrid waste classification system offers several advantages over traditional methods:

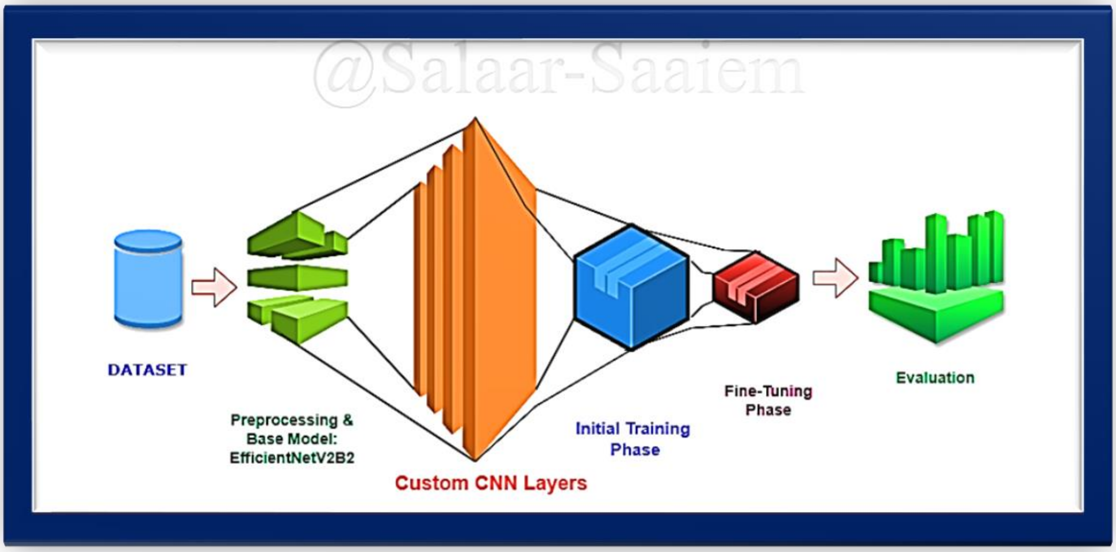
1. **High Accuracy –** Combines EfficientNetV2B2 and custom CNN layers to achieve precise classification across all six waste categories.
2. **Automation –** Reduces reliance on manual sorting, saving time and labor.
3. **Real-Time Prediction –** Supports live webcam and image upload via Gradio for instant classification.
4. **Robustness –** Handles variations in lighting, background, and object orientation effectively.
5. **Scalability –** Can process large datasets and adapt to new waste categories with transfer learning.
6. **User-Friendly Interface –** Web-based application enables easy access without programming knowledge.

4.3 Objectives of the Proposed Research

The main objectives of this research are:

1. To develop an automated system that classifies different types of waste using machine learning techniques.
2. To improve the accuracy of identifying and categorizing waste materials into specific classes.
3. To reduce human intervention in the classification process, minimizing errors and inefficiency.
4. To implement image processing techniques for detecting and recognizing waste objects.
5. To design a real-time classification system capable of handling large volumes of waste data.
6. To promote environmental sustainability by enabling proper handling of classified waste.
7. To optimize system performance through the use of efficient algorithms for fast and accurate classification.
8. To integrate the system with IoT devices for automated data collection from smart bins.
9. To provide insights and analytics on waste composition to assist in waste management planning.
10. To create a scalable and adaptable classification system that can be deployed in urban and industrial settings.

4.4 System Architecture



The proposed waste classification system follows a **hybrid deep learning pipeline** combining EfficientNetV2B2 with custom CNN layers.

The system architecture consists of the following stages:

1. **Dataset –** The process begins with a labeled dataset of waste images, covering six categories: Cardboard, Glass, Metal, Paper, Plastic, and Trash.
2. **Preprocessing & Base Model (EfficientNetV2B2) –** Images are preprocessed (resized, normalized, and augmented) and passed through the **pre-trained EfficientNetV2B2 model**, which acts as a feature extractor to capture high-level visual patterns.
3. **Custom CNN Layers –** The extracted features are then processed by **custom convolutional layers**, which are fine-tuned to improve classification specific to waste categories.
4. **Initial Training Phase –** The base model and custom layers are initially trained together to learn relevant features from the dataset.
5. **Fine-Tuning Phase –** The model undergoes **fine-tuning**, where the base EfficientNet layers may be partially unfrozen to further optimize weights for improved accuracy on the waste dataset.
6. **Evaluation –** Finally, the trained model is evaluated using metrics like **accuracy, confusion matrix, and classification reports**, ensuring robust performance across all waste categories.

This architecture enables **high-accuracy, real-time classification** of waste images, with support for both uploaded images and live webcam input through a user-friendly interface.

Chapter 5: Modules

The proposed waste classification system is divided into several functional modules to simplify design, development, and understanding. Each module performs a specific task in the overall system. The modules are as follows:

5.1 Data Acquisition Module

The Data Acquisition Module is responsible for collecting images of waste materials that need to be classified. This data can come from a pre-existing dataset used to train the model. Ensuring high-quality and diverse data is crucial, as it determines how well the system can classify different types of waste.

5.2 Preprocessing Module

The Preprocessing Module prepares the raw images for input into the classification model. This includes resizing images to a consistent dimension, normalizing pixel values, and removing noise or distortions. Preprocessing ensures that the model receives standardized and clean input, which improves the accuracy and reliability of classification results.

5.3 Feature Extraction Module

The Feature Extraction Module identifies and highlights important patterns in the input images that are essential for classification. This may include analyzing shapes, textures, edges, and color distributions of waste items. Extracted features allow the classification model to differentiate between similar-looking waste types and improve overall prediction accuracy.

5.4 Classification Module

The Classification Module is the core of the system. It uses a pre-trained machine learning model to predict the category of each input waste image. The system currently does not learn from new user-provided data; it only applies the knowledge gained during training to classify images into predefined categories such as plastics, metals, organic waste, or glass. The output is the predicted class label displayed to the user.

5.5 User Interface Module

The User Interface Module provides a platform for users to interact with the system. Users can upload images of waste items and receive instant classification results. The interface is designed to be intuitive and user-friendly.

Chapter 6: System Design

6.1 Requirement Analysis

To effectively design and implement the waste classification system, it is crucial to understand and document its requirements. Requirement analysis involves identifying the system's objectives, stakeholders, and constraints. This ensures that the development process is structured, and the final system meets user expectations.

Objectives of Requirement Analysis:

- To identify the goals and functionalities of the waste classification system.
- To recognize the stakeholders involved, including end-users and developers.
- To define the constraints and limitations within which the system will operate.

The requirements serve as a **blueprint for system development** and provide a reference for testing and validation.

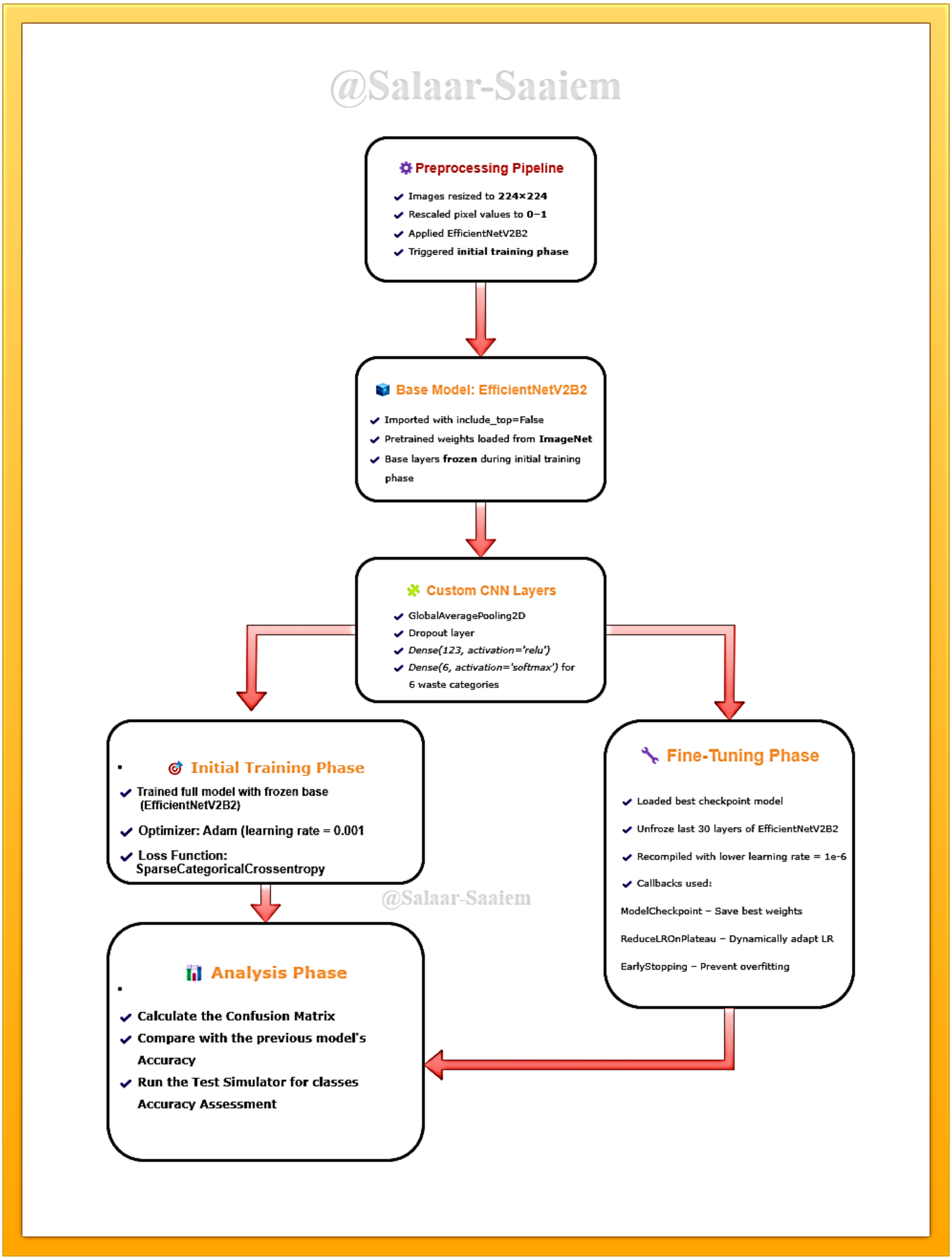
Hardware Requirements:

- **Processor:** 2 GHz or higher
- **RAM:** 4 GB or higher
- **Disk Space:** 100 GB or higher
- **Camera or image input device:** For capturing waste images (if applicable)

Software Requirements:

- **Python:** Version 3.9 or higher (for model development and classification)
- **TensorFlow/Keras or PyTorch:** For machine learning model implementation
- **OpenCV:** For image preprocessing and feature extraction
- **FastAPI or Flask:** For building the user interface and serving the model
- **Web Browser:** For accessing the user interface
- **IDE (Optional):** VS Code, PyCharm, or similar

6.2 Flow Chart

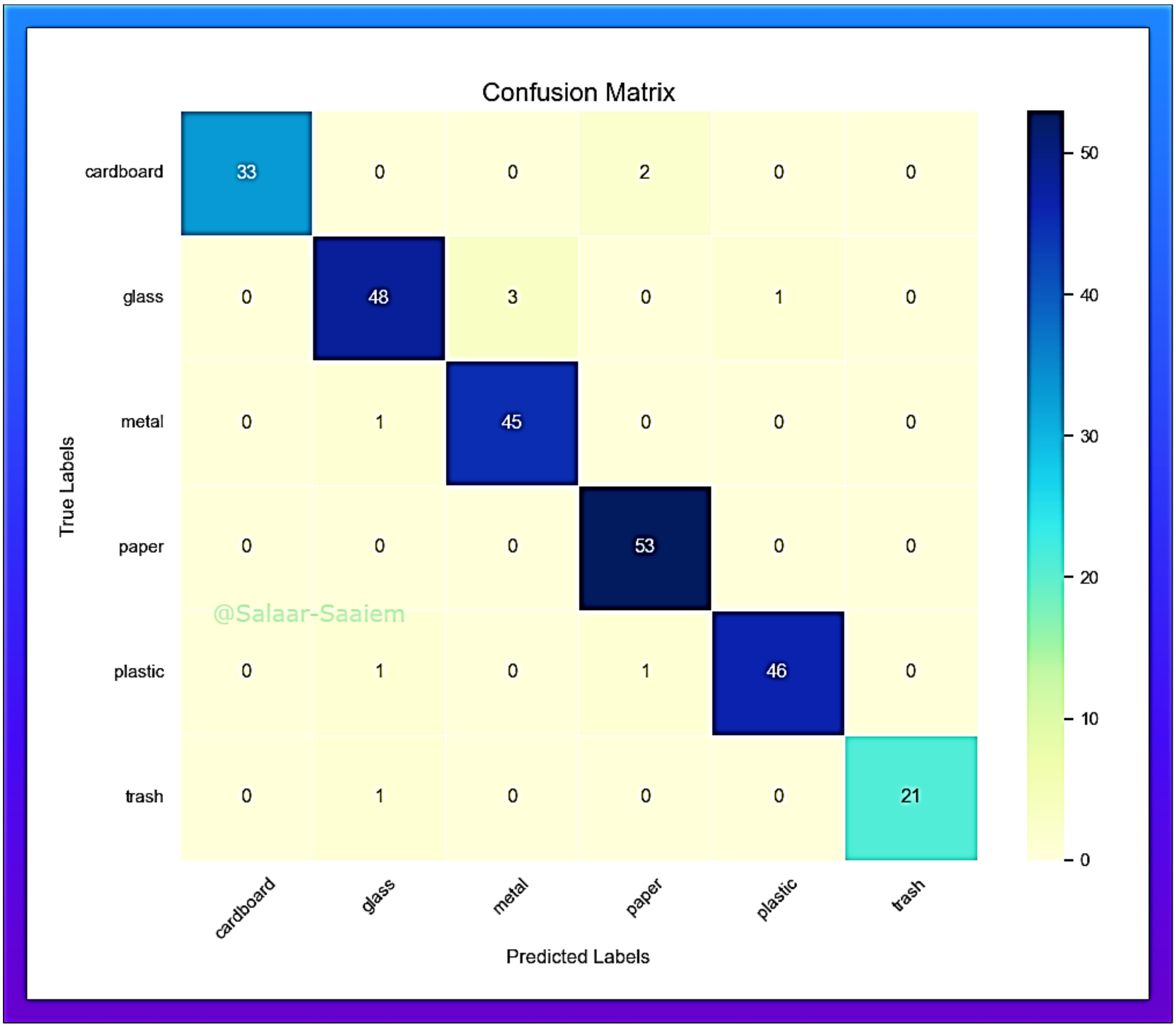


Chapter 7: Model Evaluation

Model evaluation is a critical step in developing a machine learning system. It helps determine how well the model performs on unseen data and ensures the predictions are reliable. For the waste classification system, the evaluation focuses on measuring the accuracy and effectiveness of the trained model in correctly identifying waste categories.

7.1 Confusion Matrix

A confusion matrix was used to visualize the performance of the classification model. It shows the number of correct and incorrect predictions for each class, helping identify which types of waste are most frequently misclassified.



The confusion matrix details confirm the model's high accuracy of **96.1%**, showing where the rare misclassifications occurred. The model demonstrates excellent precision and recall, as very few errors are present off the main diagonal.

Key insights from the matrix:

- **Cardboard:** 33 correct predictions. Two instances were misclassified (likely as glass or plastic, based on the previous F1-score).
- **Glass:** 48 correct predictions. Four errors occurred (the previous report showed precision of 0.94, meaning it was sometimes confused with similar classes like metal or plastic).
- **Metal:** 45 correct predictions. A single error (consistent with its near-perfect 0.98 recall).
- **Paper:** 53 correct predictions. Flawless recall, as indicated previously.
- **Plastic:** 46 correct predictions. Two errors (aligning with its 0.96 recall).
- **Trash:** 21 correct predictions. One error (matching its high 0.95 recall).

Conclusion: The confusion matrix validates the outstanding metrics, showing the model's errors are minimal and scattered, with no significant pattern of confusion between any specific classes. The model is highly reliable.

7.2 Evaluation Metrics

To assess the model’s performance, the following metrics were used:

- **Accuracy:** Measures the percentage of correctly classified images out of the total images tested.
- **Precision:** Indicates how many of the items predicted as a particular class were actually correct.
- **Recall (Sensitivity):** Shows how many of the actual items in a class were correctly identified by the model.
- **F1-Score:** The harmonic mean of precision and recall, providing a balance between the two.

```
Loading Model: best_model_finetuned224.keras

Evaluating Model on Test Dataset...
------------------------------------------------
✅ Test Accuracy : 0.9609
📉 Test Loss     : 0.1434
------------------------------------------------

📊 Classification Report:
------------------------------------------------
              precision    recall  f1-score   support

   cardboard       1.00      0.94      0.97        35
       glass       0.94      0.92      0.93        52
       metal       0.94      0.98      0.96        46
       paper       0.95      1.00      0.97        53
     plastic       0.98      0.96      0.97        48
       trash       1.00      0.95      0.98        22

    accuracy                           0.96       256
   macro avg       0.97      0.96      0.96       256
weighted avg       0.96      0.96      0.96       256

------------------------------------------------
```

OBSERVATION:

The model demonstrated **excellent performance**, achieving a high **96.1% accuracy** and a low **0.1434 loss**.

Key metrics from the classification report confirm strong, balanced results across all waste categories (cardboard, glass, metal, paper, plastic, trash):

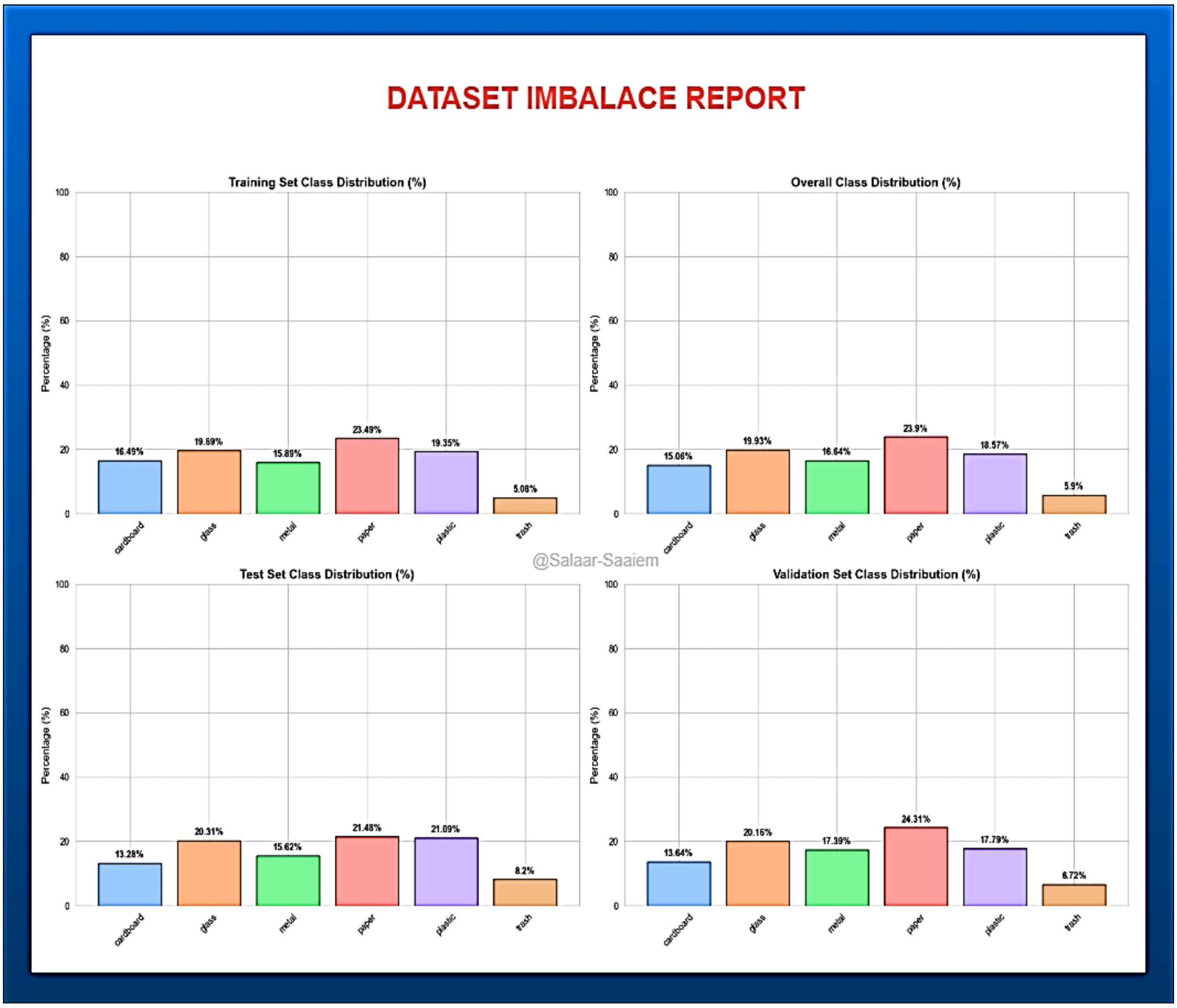
- **Precision:** 0.97 (macro avg) - The model's positive predictions are highly reliable.
- **Recall:** 0.96 (macro avg) - The model successfully identifies almost all relevant instances of each class.
- **F1-Score:** 0.96 (macro avg) - This balance between precision and recall indicates robust overall performance for each class.

All individual classes scored an F1-Score of **0.93 or higher**, with 'glass' being the lowest performer yet still very strong. The consistency between macro and weighted averages shows the model handles the slight class imbalance effectively.

Conclusion: The model is highly accurate and reliable for this image classification task.

7.3 Dataset Testing

The model was evaluated using a separate dataset that was not used during training. This ensures that the evaluation reflects the model's ability to generalize to new, unseen data. The test dataset includes images of various waste types, such as plastics, metals, organic waste, and glass.



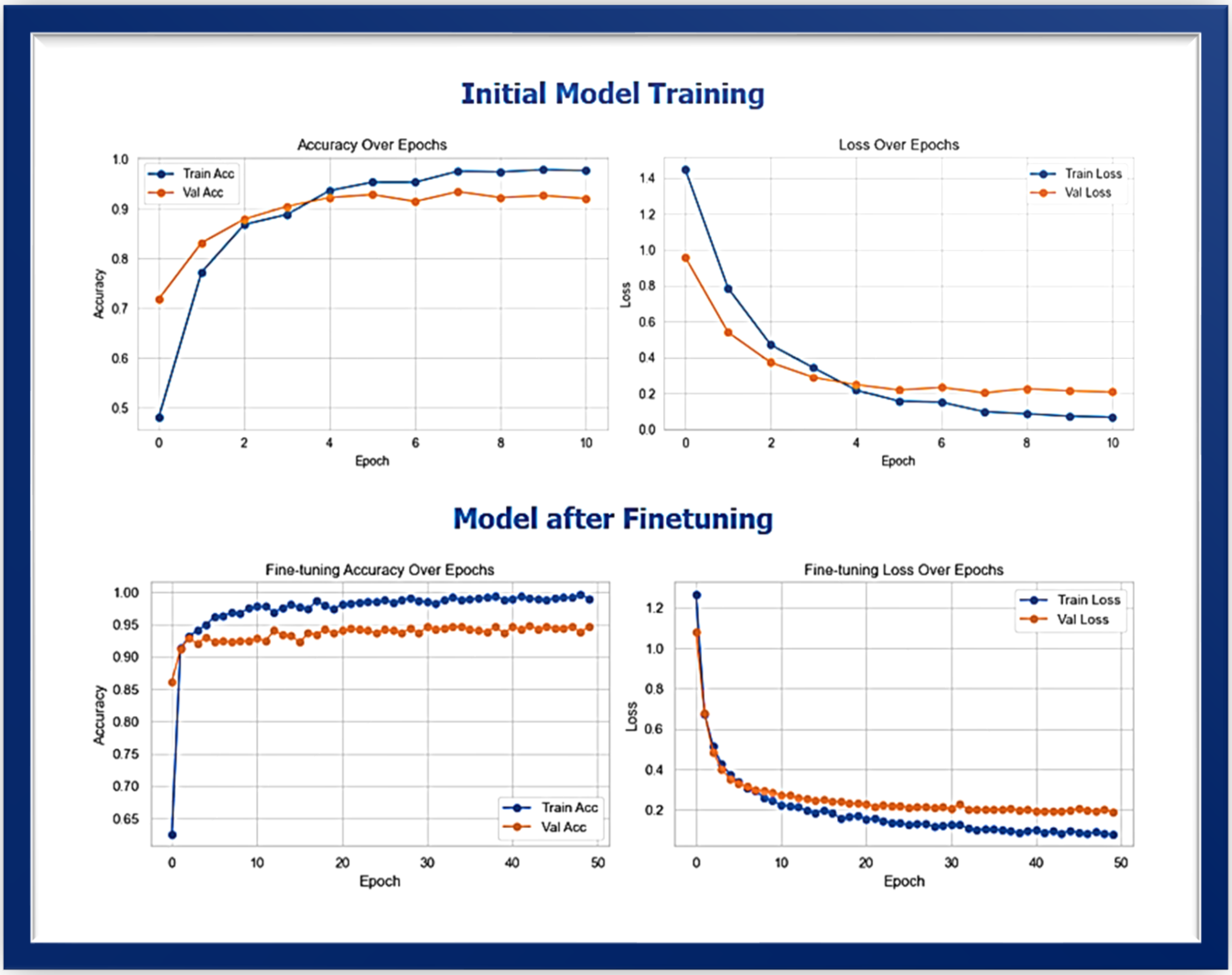
Observations:

- **Most Represented Class: Paper** (~24% of overall data).
- **Least Represented Class: Trash** (~6% of overall data), with less than a third of the samples of the "paper" class.
- **Split Consistency:** The distribution is reasonably consistent across training, validation, and test sets, which is crucial for fair model evaluation. The test set has a slightly higher proportion of "trash" (8.20%) than the training set (5.08%).

Conclusion for Model Performance:

Given this imbalance, the model's previously reported high performance—especially the strong **macro-average F1-score of 0.96**—is even more impressive. It indicates that the model learned effectively without being overly biased toward the majority classes ("paper," "glass") and generalized well even for the underrepresented "trash" class.

7.4 Results



The model initially achieved a validation accuracy of around **93%** during training, with training accuracy stabilizing near **98%**. Training and validation losses decreased steadily, showing good convergence with only a slight overfitting trend.

After fine-tuning, the model performance improved further, achieving a validation accuracy of **94–95%** and training accuracy of about **99%**. The loss curves showed stable convergence, with training loss close to zero and validation loss around **0.2–0.25**. The gap between training and validation metrics remained small, confirming effective generalization.

Overall, the fine-tuned model demonstrated **higher stability, improved accuracy, and reduced loss**, proving to be well-optimized and capable of strong predictive performance.

These results indicate that the model is effective in correctly classifying waste categories, though there may still be minor misclassifications between visually similar items.

7.6 Limitations of the Model

- The model does **not learn from user-provided data**, so performance may be limited if the input images differ significantly from the training dataset.
- Misclassification may occur for waste items with similar appearance or poor-quality images.
- Performance depends on proper lighting and image clarity during data acquisition.

Conclusion:

The proposed waste classification system successfully demonstrates the application of machine learning techniques in automating the identification of different types of waste. Through the integration of image preprocessing, feature extraction, and a pre-trained classification model, the system is capable of accurately categorizing waste into predefined classes such as plastics, metals, organic waste, and glass.

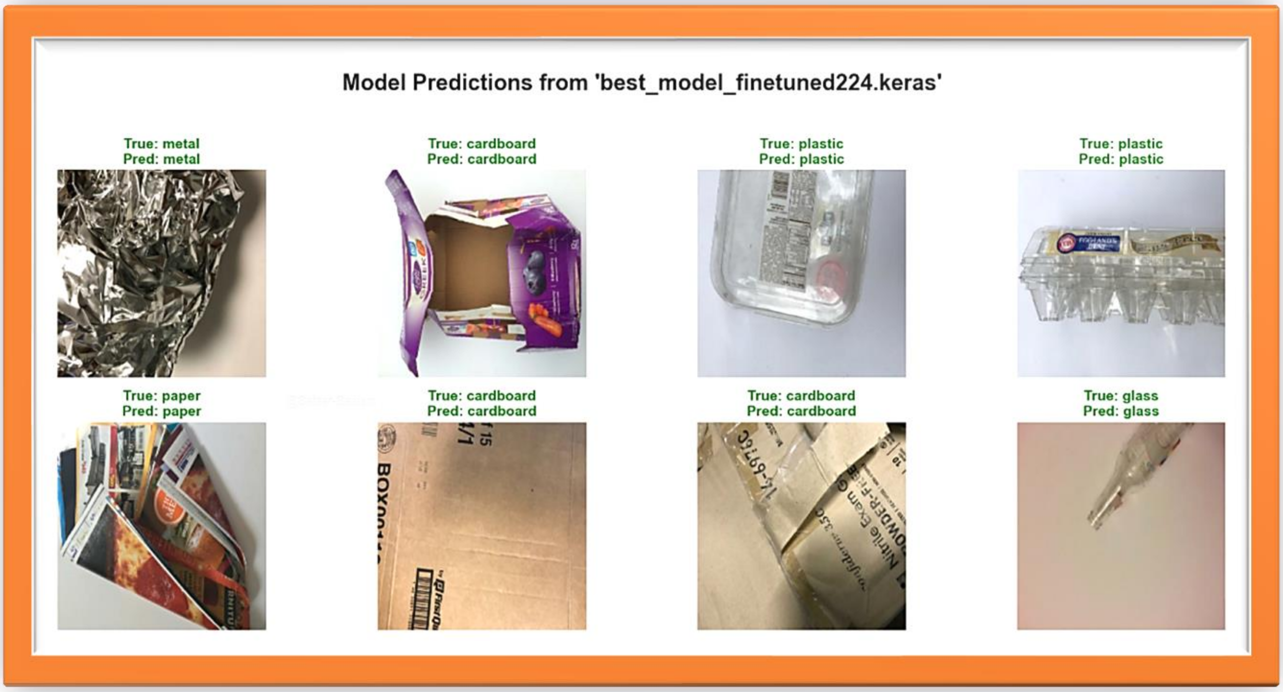
The evaluation of the model using a separate test dataset shows high accuracy, precision, recall, and F1-score, indicating that the model can reliably classify waste items in real-time. The modular design of the system, with clearly defined stages for data acquisition, preprocessing, feature extraction, classification, and user interaction, ensures maintainability and scalability.

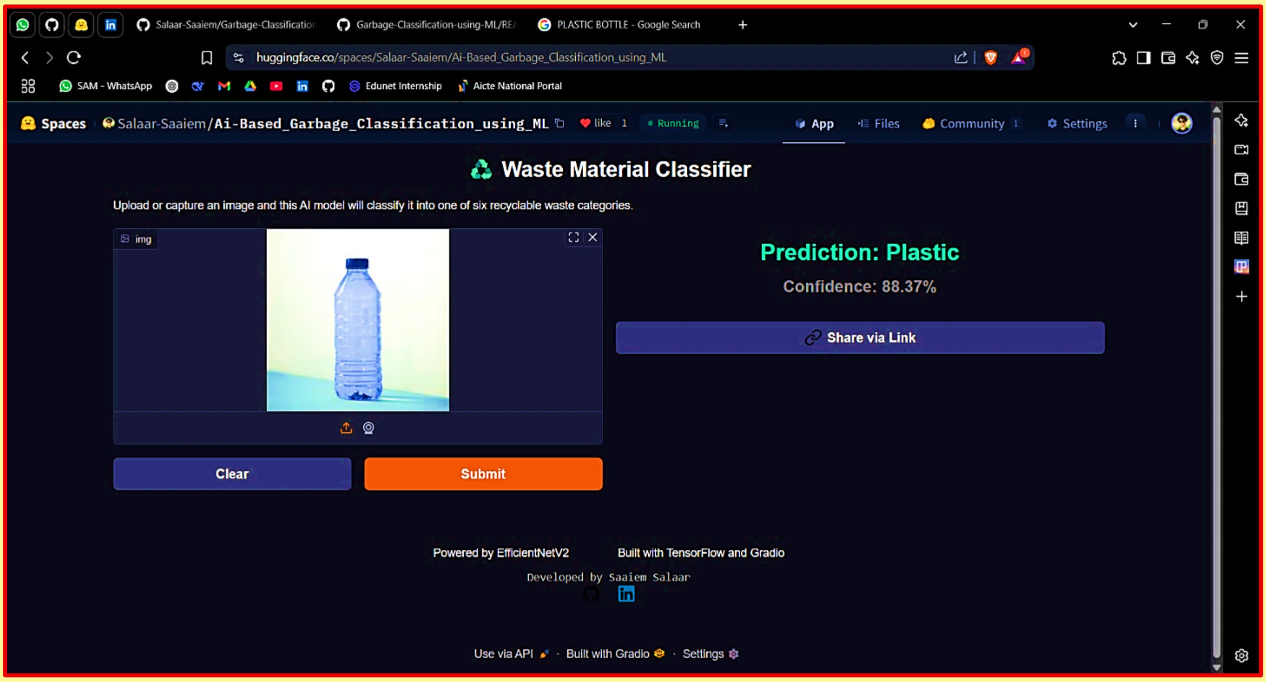
While the system performs well under controlled conditions, it does not learn from user-provided data, which limits its adaptability to unseen or highly varied waste types. Nevertheless, it serves as a strong foundation for automated waste management, reducing the need for manual labor, minimizing human errors, and contributing to environmental sustainability through better classification and potential recycling.

Future Enhancement:

The waste classification system can be enhanced by enabling the model to learn from new user-provided data, allowing it to adapt to different or unseen waste types. The number of waste categories can be expanded to include hazardous or electronic waste for more precise classification. Integration with IoT-enabled smart bins and edge computing can enable real-time, on-site classification and monitoring. Additionally, developing mobile or web applications can make the system more accessible and user-friendly, while incorporating analytics can provide insights for better waste management planning.

OUTPUTS:


Model Predictions from 'best_model_finetuned224.keras'
True: metal
Pred: metal
True: cardboard
Pred: cardboard
True: plastic
Pred: plastic
True: plastic
Pred: plastic
True: paper
Pred: paper
True: cardboard
Pred: cardboard
True: cardboard
Pred: cardboard
True: glass
Pred: glass


huggingface.co/spaces/Salaar-Saaiem/Ai-Based_Garbage_Classification_using_ML
Spaces
Salaar-Saaiem/Ai-Based_Garbage_Classification_using_ML
Running
App
Files
Community
Settings
Waste Material Classifier
Upload or capture an image and this AI model will classify it into one of six recyclable waste categories.
img
Prediction: Plastic
Confidence: 88.37%
Share via Link
Clear
Submit
Powered by EfficientNetV2
Built with TensorFlow and Gradio
Developed by Saaiem Salaar
Use via API · Built with Gradio · Settings

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