Project name:cleantech-Transforming Waste Management With Transfer Learning

Team ID: LTVIP2025TMID41993

Garbage Classification with EfficientNetV2B2

Project Description

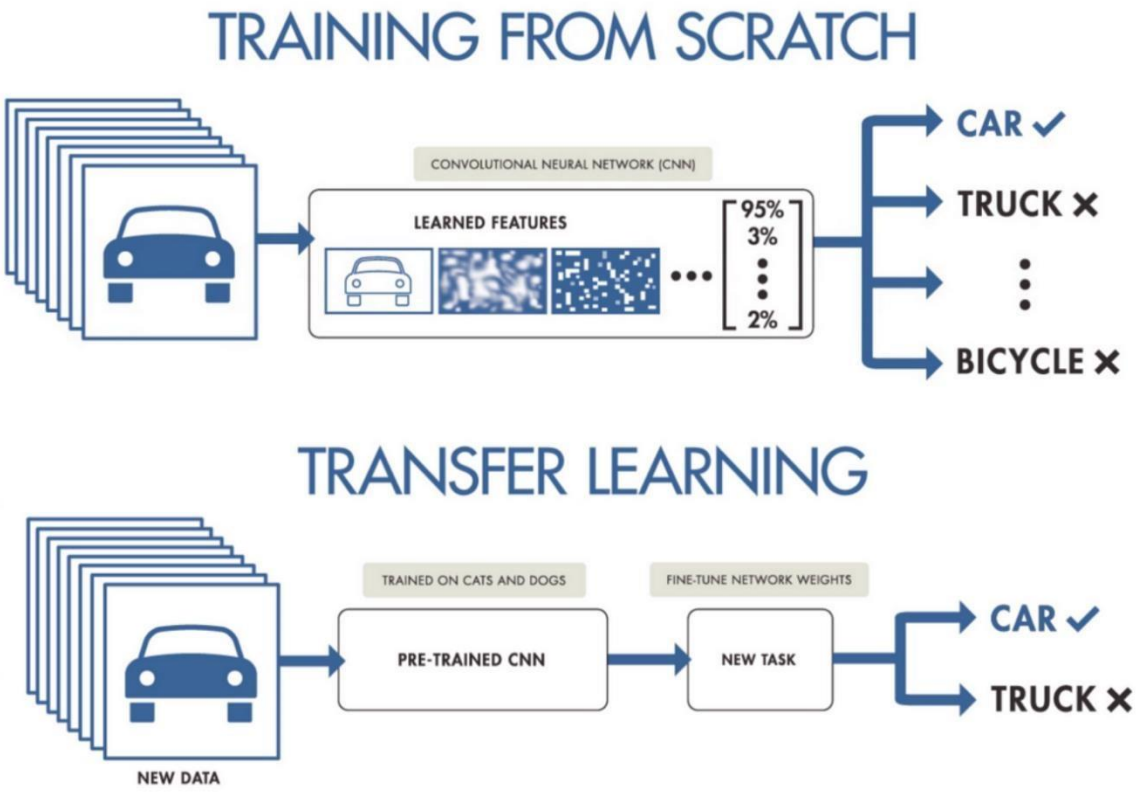
CleanTech leverages the power of transfer learning to revolutionize municipal waste management. By utilizing advanced deep learning models pre-trained on extensive datasets, CleanTech aims to enhance the accuracy and efficiency of waste classification processes. This project involves the development of an intelligent system capable of automatically identifying and categorizing different types of municipal waste from images.

In this project, we aim to develop a sophisticated **garbage classification system** leveraging the **EfficientNetV2B2** architecture. Our primary dataset serves as a foundation for building models that can eventually automate waste segregation, a critical step in optimizing recycling and waste management, ultimately aiding in environmental conservation.

Goal: To develop an accurate and efficient garbage classification model using EfficientNetV2B2 and transfer learning for automated waste sorting.

Challenges and Scope

Key Challenge: A notable challenge encountered is the inherent **class imbalance** within the dataset.



Transfer Learning is a machine learning technique where a pre-trained model developed for a specific task is reused as the starting point for a model on a different but related task. It also allows us to build accurate models in a time-saving way by starting from patterns learned when solving a different problem. This approach is beneficial when there is limited data for the new task, as the pre-trained model already has learned features that can be adapted. Transfer learning can significantly improve

models' performance and efficiency in domains like computer vision and natural language processing.

Benefits

- **Reduces training time** — you don't start from scratch.
- **Leverages learned features** from large datasets (like ImageNet).
- **Improves performance**, especially with limited data.

How Does It Work?

1. Load a pretrained model (e.g., ResNet, EfficientNet).
2. **Freeze** the pretrained layers (optional).
3. Add new layers for your custom task.
4. Train on your new dataset (can also fine-tune).

EfficientNetV2B2: Transfer Learning Backbone

EfficientNetV2B2 is a mid-sized model from the EfficientNetV2 family developed by **Google**, balancing performance and efficiency.

Key Features:

- **Fused MBConv blocks** — enhance both training stability and speed.
- **Progressive learning** — enables better generalization with less computation.
- **Improved architecture** — achieves higher accuracy with optimized FLOPs.

Why Use EfficientNetV2B2?

Feature	**Description**
Balanced Performance	Great trade-off between speed and accuracy
Scalable	Suitable for moderately complex datasets
Pretrained on ImageNet	Solid backbone for transfer learning tasks
Efficient	Faster convergence with fewer resources needed

Core Libraries

- **tensorflow:** For deep learning model building and training.
- **numpy:** For numerical operations and array manipulation.
- **matplotlib.pyplot:** For plotting training curves and results.

1. Explore and Understand the Data

- Load image dataset using tools like image_dataset_from_directory.
- Visualize sample images from each class.
- Check the number of images per class to ensure balance.
- Understand image dimensions, color channels, and class labels.

Load image dataset using tools like image_dataset_from_directory.

Split data into training, validation, and testing sets.

tf.keras.utils.image_dataset_from_directory(...)
Used to load images from a directory where each subfolder represents a class.

path
Root directory path containing one subdirectory per class.

shuffle=True
Randomly shuffles the image data. Useful during training to prevent the model from learning the order of the data.

image_size=(128, 128)
Resizes all loaded images to this target size (width, height). This must match the input size expected by the model.

batch_size=32
Number of images per batch during training.
This affects memory usage and the frequency of model updates.

validation_split=False
If set to a float (e.g., 0.2), splits a portion of the data for validation. If False, no split is applied.

Visualize sample images from each class

- Check the number of images per class to ensur balance
- Understand image properties like Image dimensions and class labels.

glass

plastic

glass

metal

plastic

metal

cardboard

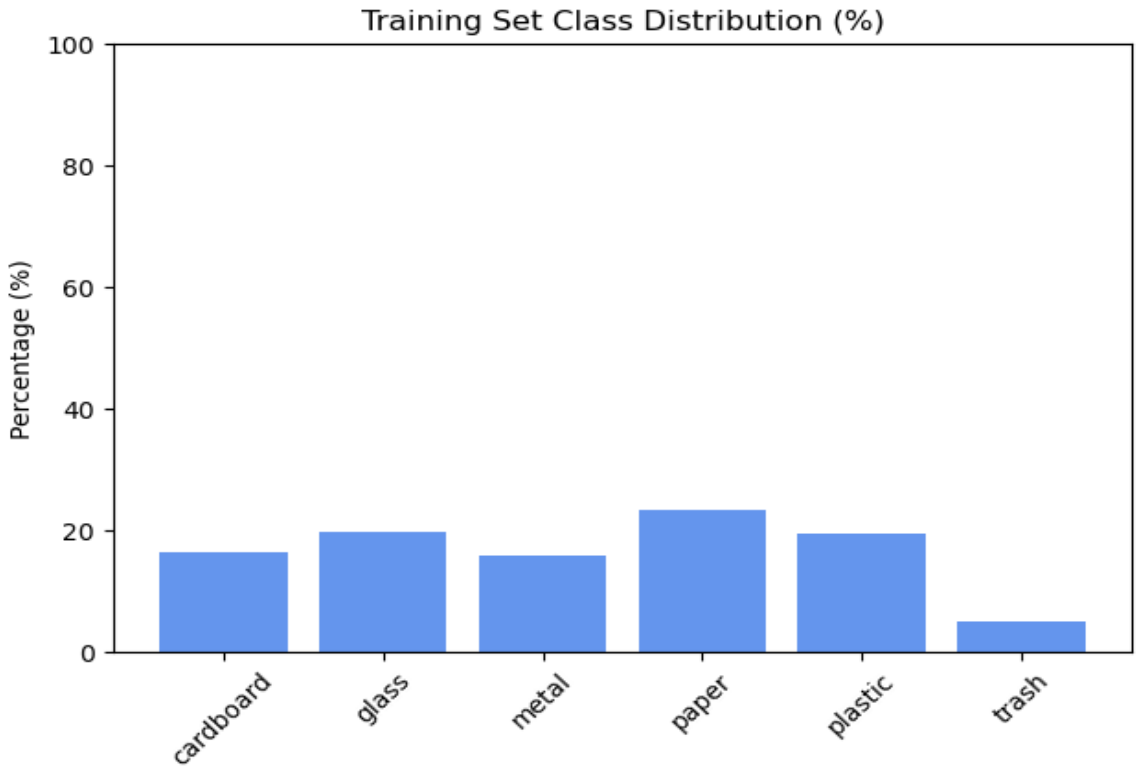
plastic

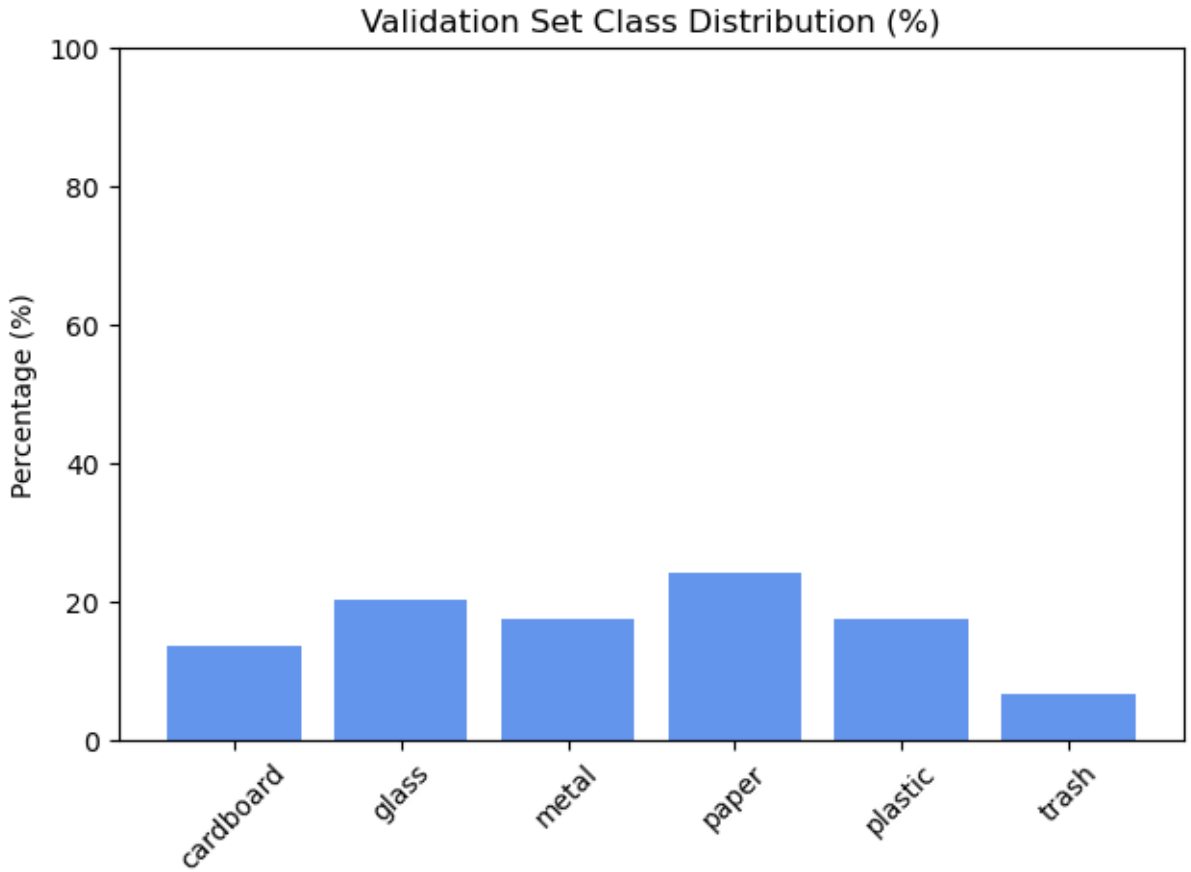
plastic

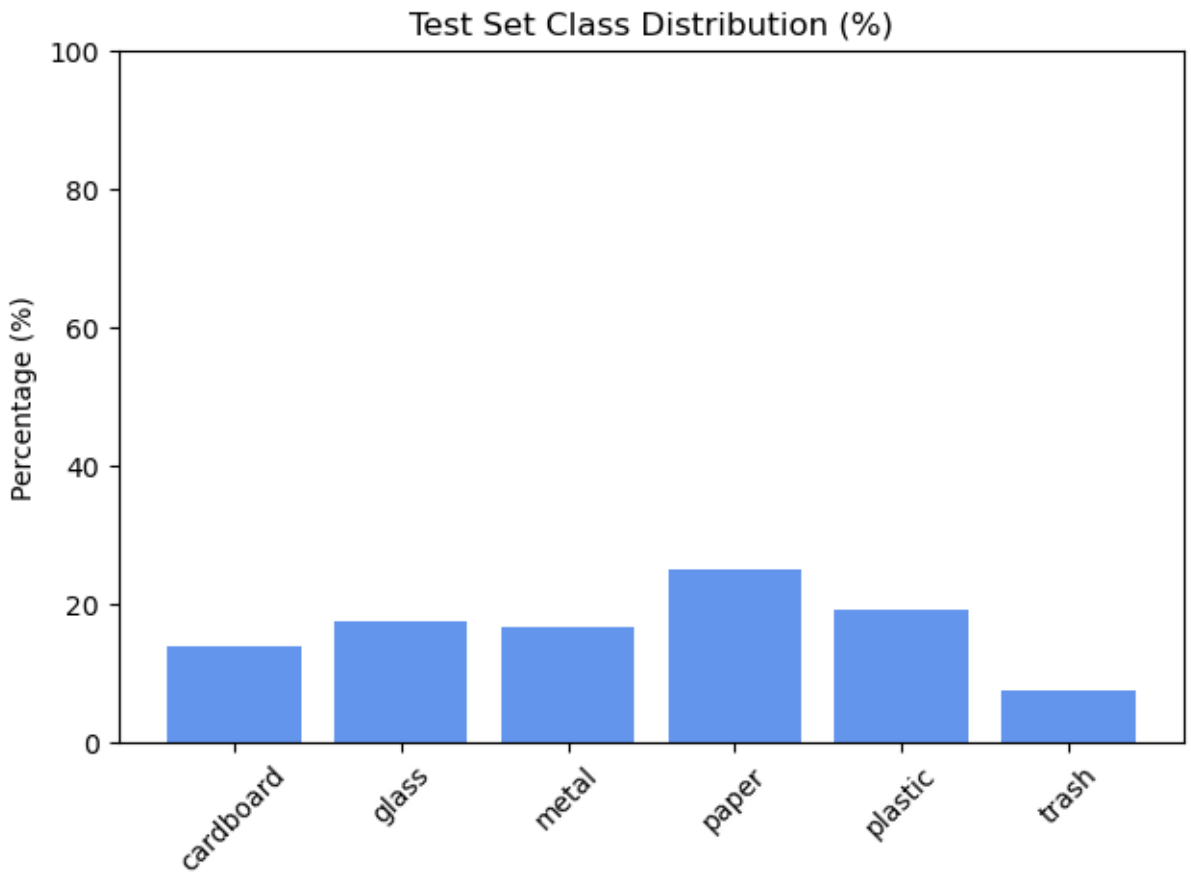
paper

metal

paper


Training Set Class Distribution (%)
Percentage (%)
100
80
60
40
20
0
cardboard
glass
metal
paper
plastic
trash


Validation Set Class Distribution (%)
Percentage (%)
100
80
60
40
20
0
cardboard
glass
metal
paper
plastic
trash



Inference on Class Imbalance

The **"Garbage Image Dataset"** reveals a noticeable **imbalance** in the distribution of its image categories:

Category	Image Count	Updated Distribution
Cardboard	403	15.09
Glass	501	19.96
Metal	410	16.68
Paper	594	23.82
Plastic	482	18.53
Trash	137	5.91

Analogy:

Imagine teaching a child to identify animals by showing them **95 pictures of cats** and just **5 pictures of dogs**.
They'd probably think **most pets are cats**, right?
Similarly, our model sees a lot of "**paper**" and very little "**trash**", which **biases** its understanding.

Key Problems Caused by Class Imbalance:

1 **Bias**

- The model may **overpredict common classes** like "paper" and **underpredict rare ones** like "trash".

2 **Generalization Issues**

- If the real-world distribution is more balanced, the model may **fail to generalize** and **misclassify rare classes**.

3 **Accuracy Deception**

- The model might appear to have **high overall accuracy** just by **predicting the majority class**, while **failing** on underrepresented ones.

Solution Approaches :

- Use **class weights** to handle imbalanced data in training,
- Apply **data augmentation** to increase training data diversity

---

Conclusion: Always check class distribution. A seemingly "accurate" model might just be **biased** toward the dominant class.

Addressing Imbalance Using Class Weights:

To tackle our imbalanced image dataset, we'll utilize **class weights**. These weights assign more importance to underrepresented classes during training. The weights are computed inversely proportional to class frequencies using utilities like compute_class_weight from **scikit-learn**, based on the distribution of images in each class. The formula is:

These computed weights are then passed to the model.

2. Data Preprocessing / Preparation

- Resize and rescale images.
- Apply data augmentation (e.g., RandomFlip, RandomRotation, RandomZoom) to improve generalization.
- Normalize images (using preprocess_input if using pre-trained models like EfficientNet)

3. Model Selection

- Choose a base model: Custom CNN or Transfer Learning (e.g., EfficientNetV2B2).
- Decide whether to use pre-trained weights (e.g., ImageNet).
- Define whether layers should be trainable or frozen during initial training.

4. Model Training

- Build the model architecture using Sequential or Functional API.
- Compile the model with loss function (sparse_categorical_crossentropy), optimizer (e.g., Adam), and evaluation metrics (accuracy).

5. Model Tuning and Optimization

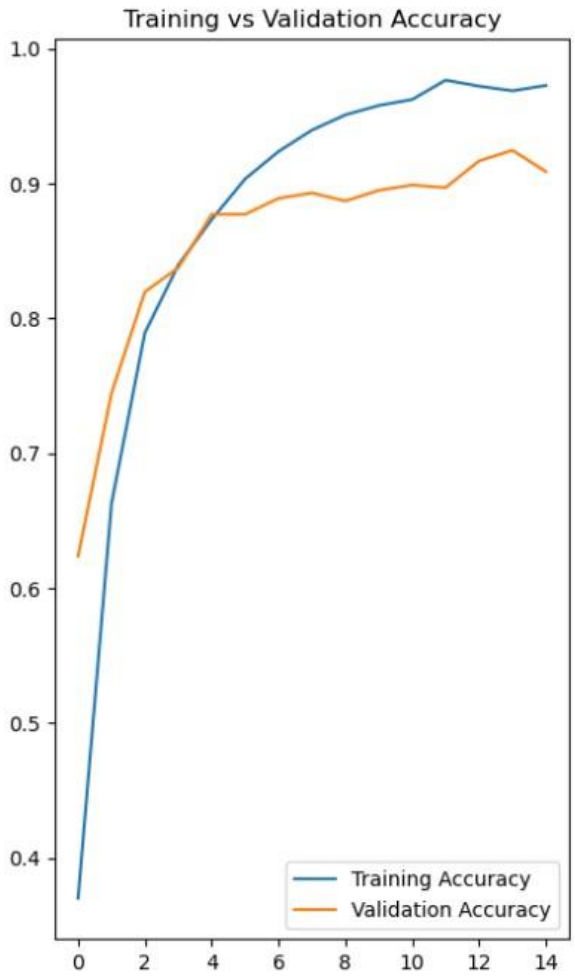
- **Tune hyperparameters**: learning rate, batch size, number of layers, dropout rate. •

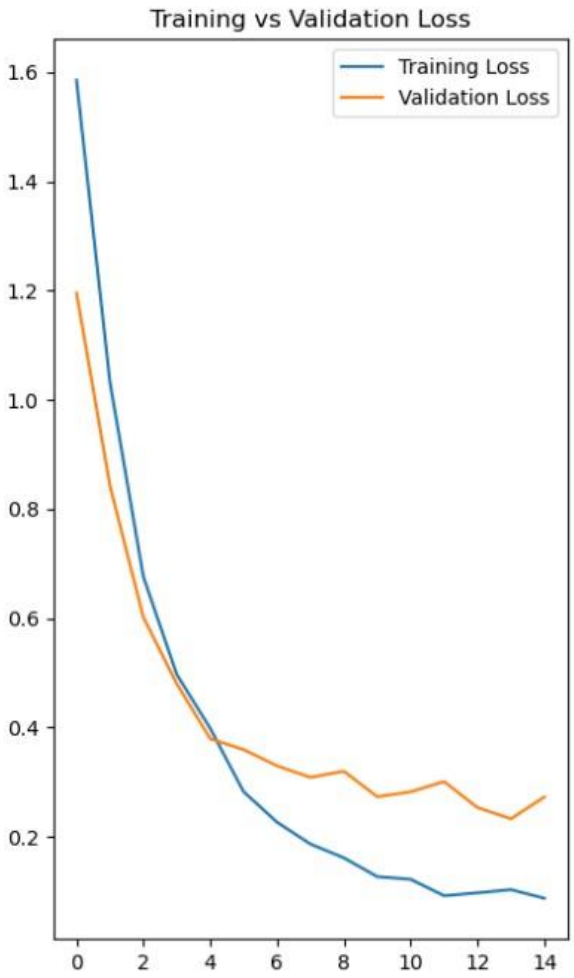
  Use callbacks: EarlyStopping,

- Optionally perform fine-tuning on pre-trained models by unfreezing some layers.

Model Architecture and Layer Utilities

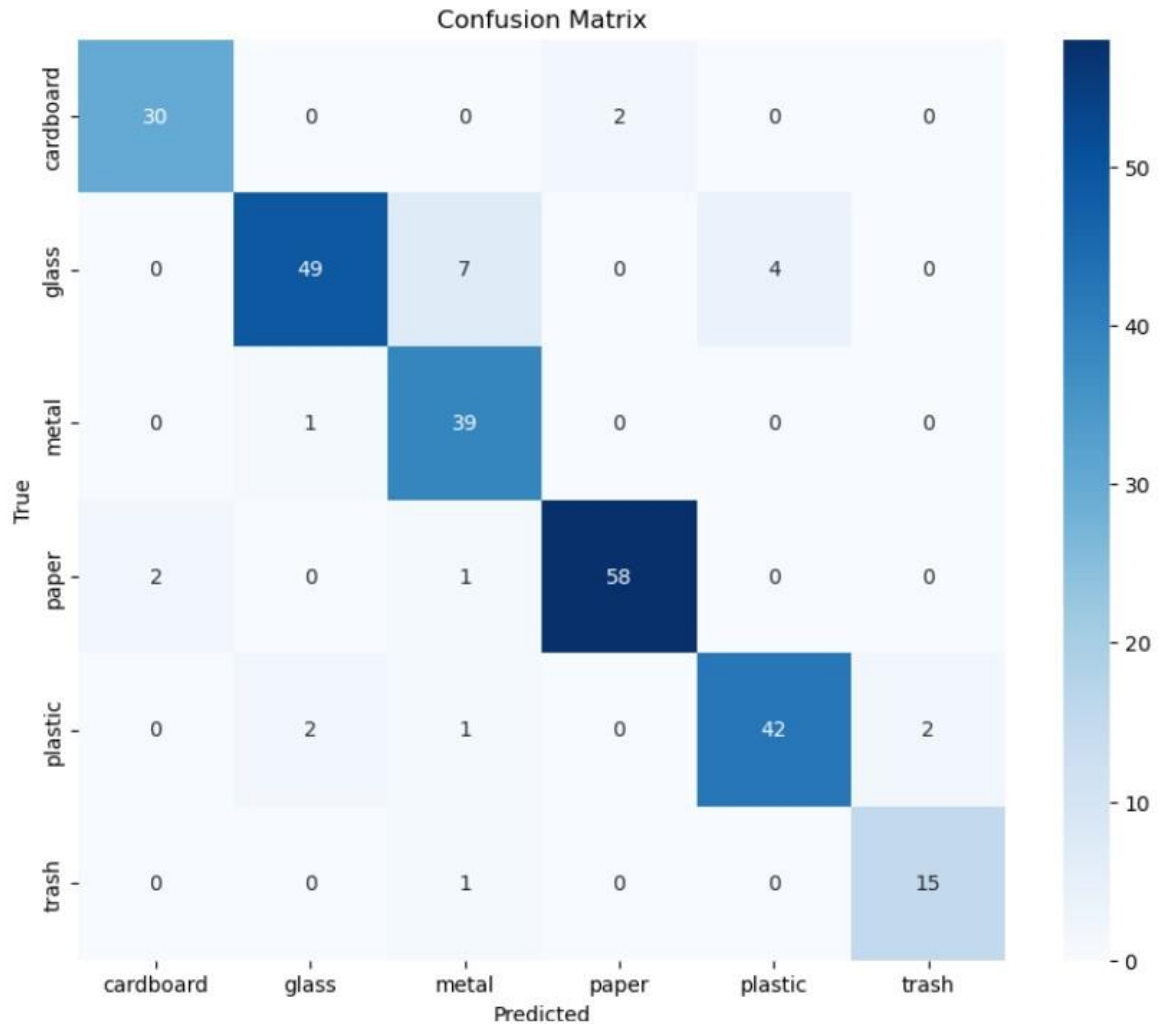
- **Sequential**: A simple way to build models by stacking layers one after the other in a linear fashion.
- **RandomFlip**: A data augmentation layer that flips input images horizontally or vertically at random, helping the model generalize better.
- **RandomRotation**: Randomly rotates images by a specified angle range during training to make the model invariant to orientation.
- **RandomZoom**: Applies random zoom-in or zoom-out to training images, helping the model recognize objects at various scales.
- **Dropout**: A regularization method that randomly "drops" (sets to zero) a fraction of input units during training to prevent overfitting.
- **GlobalAveragePooling2D**: Reduces each feature map to a single number by taking the average, reducing model parameters and helping prevent overfitting.
- **Dense**: A fully connected neural network layer used to learn complex features and typically found at the end of the model for classification.
- **Input**: Specifies the input shape and data type for the model; acts as the starting point of the model architecture.
- **EfficientNetV2B2**: A pre-trained convolutional neural network from the EfficientNetV2 family, known for being lightweight and high-performing, commonly used for transfer learning





6. Model Evaluation

- Plot training and validation accuracy/loss curves.
- Evaluate model performance on validation or test set.
- Use metrics like:
  - **Confusion Matrix**
  - **Classification Report** (Precision, Recall, F1-score)
  - confusion_matrix, classification_report: To evaluate the model's classification performance.



7. Final Testing and Save the Model

- Evaluate the final model on the unseen **test dataset**

True: glass, Pred: glass

True: paper, Pred: paper

True: cardboard, Pred: cardboard

True: glass, Pred: glass

True: metal, Pred: metal

True: paper, Pred: paper

8. Model Deployment (Optional)

- Create a web interface using **Gradio**.
- Load the saved model and preprocess input images before prediction.

Gradio Interface and Preprocessing

- gr: To build a web interface for the model.
- PIL.Image: For handling image input in Gradio.
- preprocess_input: Preprocessing method for EfficientNet.
- load_model: For loading a saved model for inference.

Conclusion

The image classification model demonstrates strong accuracy in identifying objects, leveraging deep learning to refine predictions effectively. Its robust performance ensures reliable classification, making it a valuable tool for various applications