





Garbage Classification with EfficientNetV2B2

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Learning Objectives:

- Understand image classification in waste management
- Apply EfficientNetV2B2 for classification tasks
- Preprocess and augment datasets
- Evaluate model performance
- Deploy trained models in real-world scenarios





Tools and Technology used:

- Python
- TensorFlow / Keras
- EfficientNetV2B2
- Garbage Classification Dataset (Kaggle)
- Jupyter Notebook / Google Colab
- NumPy, Pandas, Matplotlib, OpenCV



Problem Statement:

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



Solution:

1. <u>Leveraging Pre-trained EfficientNetV2B2</u>

- •Utilize **EfficientNetV2B2**, a state-of-the-art CNN architecture pre-trained on ImageNet.
- ·Benefits:
 - High accuracy with fewer parameters.
 - Faster training and inference.
 - Scales well for various datasets.

2. Transfer Learning Approach

- •Freeze initial layers of EfficientNetV2B2 to retain learned features.
- •Customize final classification layers (Dense + Softmax) for garbage categories (e.g., Plastic, Metal, Organic, etc.).
- •Fine-tune on a garbage image dataset for higher accuracy.

3. Garbage Image Dataset

- •Train on a labeled dataset of waste images:
 - •Categories: Cardboard, Glass, Metal, Paper, Plastic, Trash.
 - •Data Augmentation: Rotation, Zoom, Flip to handle variability.

4. Model Training and Evaluation

- •Use Adam optimizer, categorical crossentropy loss, and early stopping for stable training.
- •Evaluate using accuracy, precision, recall, and F1-score.
- Achieved accuracy

5. Deployment Readiness

- •Export trained model to TensorFlow Lite or ONNX format for edge deployment (e.g., on mobile or smart bins).
- •Integrate with a camera-based detection system for real-time classification and sorting.



Methodology:

- 1. Dataset Collection
- 2. Data Preprocessing (resize, normalize, augment)
- 3. Model Building (EfficientNetV2B2 + custom layers)
- 4. Training (Adam optimizer, categorical loss)
- 5. Evaluation (accuracy, confusion matrix)



Model Architecture (Diagram):

- EfficientNetV2B2 (base)
- Global Average Pooling
- Dense (ReLU)
- Dropout
- Dense Softmax (Output Classes)



CODE SCREENSHOT:

```
In [2]:
         import numpy as np # Importing NumPy for numerical operations and array manipulations
         import matplotlib.pyplot as plt # Importing Matplotlib for plotting graphs and visualizations
         import seaborn as sns # Importing Seaborn for statistical data visualization, built on top of Matplotlib
         import tensorflow as tf # Importing TensorFlow for building and training machine learning models
         from tensorflow import keras # Importing Keras, a high-level API for TensorFlow, to simplify model building
         from tensorflow.keras import Layer # Importing Layer class for creating custom layers in Keras
         from tensorflow.keras.models import Sequential # Importing Sequential model for building neural networks layer-by-layer
         from tensorflow.keras.layers import Rescaling , GlobalAveragePooling2D
         from tensorflow.keras import layers, optimizers, callbacks # Importing various modules for layers, optimizers, and callback
         from sklearn.utils.class weight import compute class weight # Importing function to compute class weights for imbalanced de
         from tensorflow.keras.applications import EfficientNetV2B2 # Importing EfficientNetV2S model for transfer learning
         from sklearn.metrics import confusion matrix, classification report # Importing functions to evaluate model performance
         import gradio as gr # Importing Gradio for creating interactive web interfaces for machine learning models
In [3]:
         dataset dir= r"C:\Users\adity\Downloads\TrashType Image Dataset"
         image size = (124, 124)
         batch size = 32
         seed = 42
In [4]:
         train ds = tf.keras.utils.image dataset from directory(
             dataset dir,
             validation split=0.2,
             subset="training",
             seed=seed.
             shuffle = True,
             image size=image size,
             batch size=batch size
```

Found 2527 files belonging to 6 classes. Using 2022 files for training.



CODE SCREENSHOT:

```
import matplotlib.pyplot as plt
plt.figure(figsize=(10, 10))
for images, labels in train_ds.take(1):
 for i in range(12):
    ax = plt.subplot(4, 3, i + 1)
    plt.imshow(images[i].numpy().astype("uint8"))
    plt.title(train_ds.class_names[labels[i]])
    plt.axis("off")
```

glass



metal



cardboard

plastic



plastic



plastic



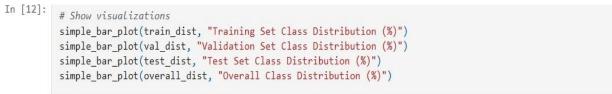
glass

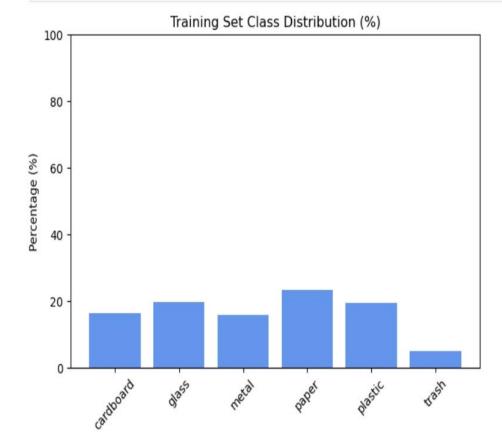


metal



plastic







CODE SCREENSHOT:

```
epochs = 15 # Number of times the model will go through the entire dataset
  # Train the model using the fit function
  history = model.fit(
      train_ds,
                               # Training dataset used to adjust model weights
      validation data=val ds, # Validation dataset to monitor performance on unseen data
                               # Number of training cycles, referencing the variable set earlier
      epochs=epochs,
      class_weight=class_weights, # Handles class imbalances by assigning appropriate weights
      batch_size=32,
                               # Number of samples processed in each training step
      callbacks=[early]
                               # Implements early stopping to prevent unnecessary training
Epoch 1/15
64/64 -
                           70s 476ms/step - accuracy: 0.3224 - loss: 1.6997 - val accuracy: 0.6673 - val loss: 1.1279
Epoch 2/15
                           27s 414ms/step - accuracy: 0.6878 - loss: 1.0827 - val_accuracy: 0.7980 - val_loss: 0.7614
64/64 -
Epoch 3/15
                          27s 415ms/step - accuracy: 0.7973 - loss: 0.7131 - val_accuracy: 0.8475 - val_loss: 0.5521
64/64 -
Epoch 4/15
64/64
                          27s 423ms/step - accuracy: 0.8308 - loss: 0.5213 - val accuracy: 0.8535 - val loss: 0.4630
Epoch 5/15
64/64 -
                          28s 435ms/step - accuracy: 0.8860 - loss: 0.3735 - val_accuracy: 0.8673 - val_loss: 0.3865
Epoch 6/15
                          28s 438ms/step - accuracy: 0.9076 - loss: 0.2947 - val_accuracy: 0.8733 - val_loss: 0.3565
64/64 -
Epoch 7/15
64/64
                           28s 443ms/step - accuracy: 0.9247 - loss: 0.2286 - val_accuracy: 0.8733 - val_loss: 0.3481
Epoch 8/15
64/64 -
                          29s 450ms/step - accuracy: 0.9332 - loss: 0.1895 - val_accuracy: 0.8911 - val_loss: 0.3133
Epoch 9/15
64/64
                          29s 446ms/step - accuracy: 0.9470 - loss: 0.1918 - val_accuracy: 0.8812 - val_loss: 0.3146
Epoch 10/15
64/64 -
                          31s 476ms/step - accuracy: 0.9588 - loss: 0.1269 - val accuracy: 0.8891 - val loss: 0.3071
Epoch 11/15
64/64
                           30s 469ms/step - accuracy: 0.9566 - loss: 0.1175 - val accuracy: 0.8871 - val loss: 0.2984
Epoch 12/15
64/64
                           30s 465ms/step - accuracy: 0.9697 - loss: 0.1059 - val accuracy: 0.8911 - val loss: 0.2781
Fnoch 13/15
```

```
#  Summary (optional but useful)
model.summary()
```

Model: "sequential_1"

Layer (type)	Output Shape	Param #
sequential (Sequential)	(None, 124, 124, 3)	0
efficientnetv2-b2 (Functional)	(None, 4, 4, 1408)	8,769,374
global_average_pooling2d (GlobalAveragePooling2D)	(None, 1408)	0
dropout (Dropout)	(None, 1408)	0
dense (Dense)	(None, 6)	8,454

Total params: 24,727,114 (94.33 MB)

Trainable params: 7,974,642 (30.42 MB)

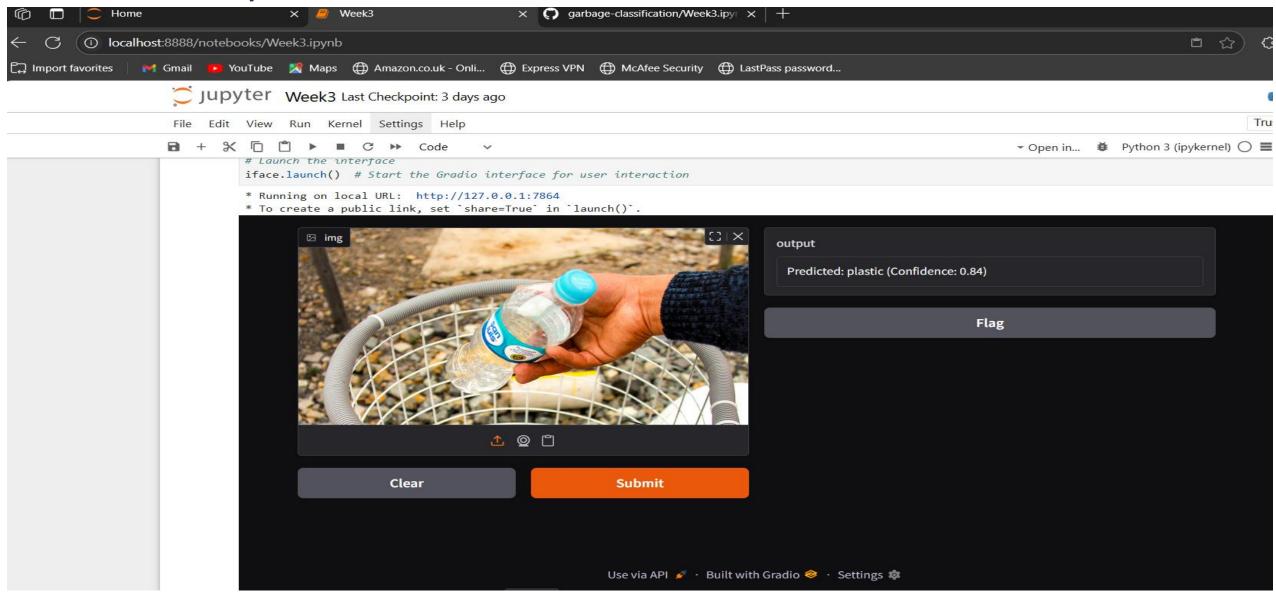
Non-trainable params: 803,186 (3.06 MB)

Optimizer params: 15,949,286 (60.84 MB)

FOR FULL CODE VISIT MY GITHUB LINK: https://github.com/AdityaSharma-12/garbage-classification.git



Screenshot of Output:





Conclusion:

- Waste classification can be automated
- EfficientNetV2B2 is accurate and scalable
- Integrates into smart waste management systems



Future Scope:

- Real-time detection on edge/mobile devices
- Classify sub-types of recyclables
- Field testing with local authorities