1413002003 - Computer Vision – Classification Term Project Form

Deadline: 15 / 05 / 2025

Course: Computer Vision

Project Type: Image Classification

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Project Title: Car Brand Classification

Advisor Approval: [ ] Received

1. Project Objective

The goal of this project is to develop a vehicle brand classification model using Convolutional Neural Networks (CNN) and Transfer Learning techniques to accurately classify vehicle images based on their brands and achieve high accuracy and generalization performance using deep learning methods. Using both scratch-built CNN models and Transfer Learning approaches, we aim to evaluate the performance improvement of pre-trained models compared to custom-built CNN architectures. This project will help to understand the effectiveness of these techniques on vehicle classification tasks with a dataset containing various vehicle makes with different number of instances. Additionally, this project has potential applications in the automotive industry, traffic monitoring systems, parking management, and insurance and accident analysis.

2. Dataset Information

Dataset Name: Car Images Dataset

Source link (e.g., Kaggle, OpenCV, custom):cars-image-dataset

Number of Images: 4165

Number of Classes: 7

Class Labels (e.g., 'masked', 'unmasked'):'Audi', 'Hyundai Creta', Mahindra Scorpio', 'Rolls Royce', 'Swift', 'Tata Safari', 'Toyota Innova'.

3. Labeling Process

Is the dataset pre-labeled? [X] Yes [ ] No

Were the labels created manually? [ ] Yes [X] No

Which labeling software or platform was used?: Folder-based labeling (Directory structure used as class labels)

Explanation:

The dataset used in this project is pre-labeled and organized into class-labeled folders. Each folder represents a car brand category (e.g., "Rolls Royce", "Audi", "Toyota"), and these folder names are automatically used as class labels during model training. The labeling is performed through the directory structure and integrated with Keras' flow_from_directory() function for image loading and label assignment. Therefore, no manual labeling process or external software was required.

4. Method Used

Classification algorithm/model used (e.g., CNN, ResNet, SVM + HOG, Transfer Learning – YOLO etc.):

1. **Convolutional Neural Network (CNN):**

   In this project, we designed a Convolutional Neural Network (CNN) model from scratch to classify vehicle brands. The model consists of multiple convolutional layers followed by max-pooling layers, a flatten layer, and dense layers with ReLU activations. Finally, a softmax layer was used for multi-class classification.

2. **Transfer Learning using VGG16:**

   For the Transfer Learning approach, we used the **VGG16** model, which is well-known for its deep and complex architecture, making it highly effective for image classification tasks. VGG16 was pre-trained on the ImageNet dataset, and we fine-tuned the model on our vehicle brand classification data. This approach allowed us to leverage the model's powerful feature extraction capabilities, improving classification accuracy and performance, especially in scenarios with limited data.

3. **Handling Data Imbalance:**

   To handle the imbalance in the dataset, we calculated class weights using the compute_class_weight function from the sklearn library. This ensured that the model did not overlook minority classes during training, which improved the overall performance.

Libraries/Frameworks used:

1. **TensorFlow:** Main framework for building and training the CNN and Transfer Learning models.
2. **Keras:** Used for model creation, compiling, and training with high-level API support.
3. **Scikit-learn (sklearn):** Used for calculating class weights and evaluating metrics like accuracy and F1-score.
4. **Matplotlib:** Visualization of training accuracy, loss curves, and confusion matrix.
5. **Numpy:** Efficient handling of numerical data and array operations.
6. **Pandas:** Structuring and presenting model summary and evaluation results.

5. Preprocessing Techniques

Please mark the techniques you applied:

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[X] Resizing
[X] Normalization
[X] Data Augmentation

Resizing: Images were resized to (224, 224) to match the input requirements of the CNN and Transfer Learning models.

Normalization: Pixel values were scaled to the range [0, 1] for consistent data representation.

Data Augmentation: Using **Roboflow**, we applied augmentation techniques such as **blur**, **rotation**, and **zooming** to increase the diversity of training data. These transformations helped improve the model's ability to generalize by simulating real-world variations.

6. Training - Testing Process

Training set size: 5178

Test set size: 514

Did you apply validation? [X] Yes [ ] No

The validation set size is **1215 images**. Validation data was used to monitor the model's generalization ability and to tune hyperparameters.

7. Results and Evaluation

Summarize your results and comment on performance.

Model accuracy: Cnn: 58.17%, Trasnfer learning: 61.48%

F1: Cnn: 57.19%, Trasnfer learning: 61.79%

Recall: Cnn: 58.17%, Trasnfer learning: 61.48%

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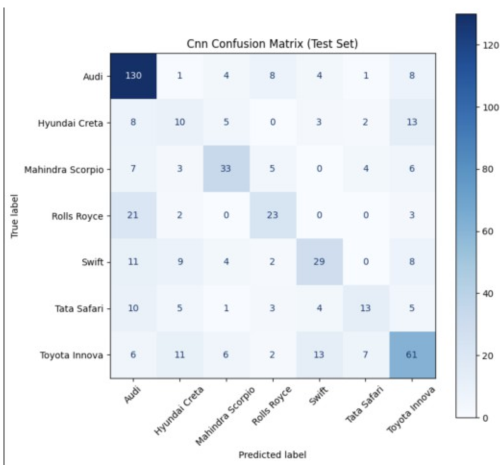
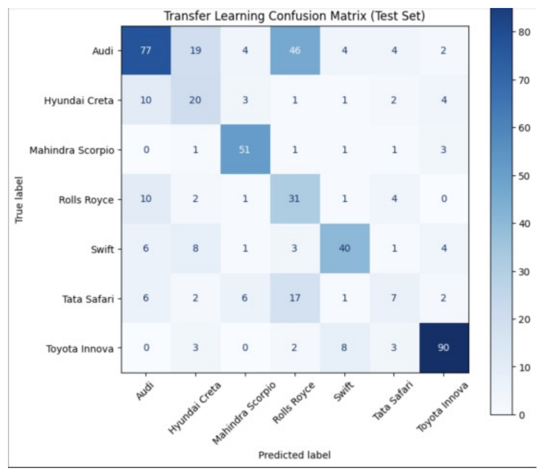
Precission: Cnn: 57.16%, Trasnfer learning: 64.96%

Confusion Matrix: *** add confusion matrix visually***





Strengths of your model:

High Accuracy for Specific Classes: The Transfer Learning model (VGG16) achieved higher accuracy (61.48%) compared to the CNN model (58.17%), demonstrating better generalization capabilities. This indicates that using pre-trained weights from VGG16 helps to better capture the complex features of vehicle images.

Effective Use of Transfer Learning: The Transfer Learning model utilized VGG16's pre-trained feature extraction capabilities, which led to a more robust classification performance, particularly on vehicle brands with fewer samples.

Balanced Performance Metrics: Both models have balanced Precision, Recall, and F1-Score, indicating consistent performance across different classes.

Robustness to Data Imbalance: Both models use class weighting to mitigate data imbalance issues, but the Transfer Learning model demonstrated more consistent performance across different classes.

Data Augmentation for Generalization: Applying data augmentation techniques like rotation, flipping, and zooming increased the model's ability to generalize to new and unseen data, which was more effective in the Transfer Learning model.

Challenges faced:

Data Imbalance : The dataset contained an uneven distribution of vehicle brands, with some classes having significantly more images than others. This led to the model favoring majority classes during prediction. Despite using class weighting to mitigate this issue, achieving balanced performance across all classes remained challenging.

Limited Dataset Diversity: Despite using augmentation techniques, the diversity of the dataset was limited, making it challenging for the model to generalize to unseen data. Transfer Learning helped improve generalization compared to the CNN model, but the challenge persisted.

Overfitting on Training Data: The CNN model, when trained for too many epochs, tended to overfit, especially on classes with higher representation. Early stopping was used to mitigate this issue.

Computational Limitations: Training deep models like CNNs and Transfer Learning on large image datasets required substantial computational power, which at times led to slower training, especially for the VGG16-based Transfer Learning model.

Fine-Tuning Pre-Trained Models: Integrating and fine-tuning the transfer learning model required careful adjustment of the learning rate and optimizer to prevent loss divergence, which was more challenging compared to the scratch-built CNN model.

Confusion Between Similar Classes: Some vehicle brands had visually similar features, which caused the model to confuse them (e.g., Swift and Tata Safari).

8. Improvement Suggestions

If you had more time or resources, how would you improve this project?

Increase Dataset Diversity: Collecting a more diverse and balanced dataset, including more images from underrepresented vehicle brands, can improve model generalization. Addressing class imbalance would help the model perform better on minority classes.

Use Advanced Data Augmentation: Implementing advanced augmentation techniques such as random cropping, color jitter, adaptive noise addition, and geometric transformations can make the model more robust against variations and noise in real-world scenarios.

Experiment with More Architectures: Exploring additional deep learning architectures such as ResNet, EfficientNet, Inception, and other pre-trained models like VGG19 can help identify the most effective model. Comparing multiple architectures ensures that the model's performance is not limited.

Fine-Tune Hyperparameters: Optimizing hyperparameters using techniques like Grid Search or Bayesian Optimization helps find the best combination for learning rate, batch size, and dropout rate. This approach can prevent overfitting and enhance generalization.

Conduct Error Analysis: Performing a detailed error analysis helps identify which classes are frequently misclassified. Understanding the specific visual similarities that lead to errors can guide improvements in feature representation.

Real-Time Deployment: Deploying the model as a web service or mobile application can assess its performance in real-world scenarios, including accuracy and responsiveness under varying conditions.

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Summary of Project:

This project aimed to accurately classify vehicle brands based on their images, which is crucial for applications in the automotive industry, traffic monitoring systems, parking management, and insurance analysis. To achieve this, Convolutional Neural Networks (CNN) and Transfer Learning techniques were employed. The CNN model was built from scratch to learn image features and classify vehicle brands, while Transfer Learning utilized the pre-trained VGG16 model to speed up training and enhance generalization. Transfer Learning proved to be particularly effective for classes with fewer samples, while the CNN model demonstrated better accuracy for specific brands. Overall, the Transfer Learning approach improved model performance by leveraging powerful feature extraction capabilities, leading to better generalization across diverse vehicle classes.

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

from google.colab import drive: Imports the drive module from Google Colab.
drive.mount('/content/drive'): Mounts Google Drive to the specified directory.

```
!ls /content/drive/MyDrive/carbrand
```

```
README.dataset.txt  README.roboflow.txt  test  train  valid
```

!ls: Allows us to use shell commands within Colab.
'/content/drive/MyDrive/carbrand': Specifies the car brand folder on Google Drive.

```
from tensorflow.keras.preprocessing.image import ImageDataGenerator

#1
train_datagen = ImageDataGenerator(rescale=1./255)
valid_datagen = ImageDataGenerator(rescale=1./255)
test_datagen  = ImageDataGenerator(rescale=1./255)

#2
train_generator = train_datagen.flow_from_directory(
    '/content/drive/MyDrive/carbrand/train',
    target_size=(224, 224),
    batch_size=32,
    class_mode='sparse'
)

#3

validation_generator = valid_datagen.flow_from_directory(
    '/content/drive/MyDrive/carbrand/valid',
    target_size=(224, 224),
    batch_size=32,
    class_mode='sparse'
)

#4

test_generator = test_datagen.flow_from_directory(
    '/content/drive/MyDrive/carbrand/test',
    target_size=(224, 224),
    batch_size=32,
    class_mode='sparse',
    shuffle=False
)
```

```
Found 5178 images belonging to 7 classes.
Found 1215 images belonging to 7 classes.
Found 514 images belonging to 7 classes.
```

1-) ImageDataGenerator: A Keras class used for processing and scaling image data.
rescale=1./255: Transforms pixel values from the range 0-255 to 0-1.

2-)Load training data,
-flow_from_directory: Fetches data from the specified folder.

- target_size=(224, 224): Adjusts the images to the input size of the model.
- batch_size=32: Sets the number of images processed simultaneously.
- class_mode='sparse': Provides classification labels as indices (e.g., 0, 1, 2).
  This structure ensures that the model receives data in a continuous flow.

3-)Load validation data,
Validation data helps evaluate the model's generalization capability during training.The structure is the same as the training data loader but specifically for validation.

4-)Load test data, -shuffle=False: Loads test data without shuffling to maintain the correct order.
-Unlike training and validation data, it is specifically used for independent accuracy measurement.

```
from tensorflow.keras import Input
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense, Dropout
import pandas as pd
```

```
from io import StringIO
import sys

#2
# Create Model
model = Sequential([
    Input(shape=(224, 224, 3)),
    Conv2D(32, (3,3), activation='relu', name='Conv2D_1'),
    MaxPooling2D(2,2, name='MaxPool_1'),

    Conv2D(64, (3,3), activation='relu', name='Conv2D_2'),
    MaxPooling2D(2,2, name='MaxPool_2'),

    Conv2D(128, (3,3), activation='relu', name='Conv2D_3'),
    MaxPooling2D(2,2, name='MaxPool_3'),

    Flatten(name='Flatten'),
    Dense(128, activation='relu', name='Dense_1'),
    Dropout(0.6, name='Dropout'),
    Dense(7, activation='softmax', name='Output')
])

#3

stream = StringIO()
sys.stdout = stream
model.summary()
sys.stdout = sys.__stdout__

summary_str = stream.getvalue()

summary_lines = summary_str.split('\n')

layer_info = []
for line in summary_lines[2:-4]:
    parts = line.split()
    if len(parts) >= 4:
        layer_name = parts[0]
        layer_type = parts[1]
        output_shape = ' '.join(parts[2:-1])
        num_params = parts[-1]
        layer_info.append([layer_name, layer_type, output_shape, num_params])

model_df = pd.DataFrame(layer_info, columns=['Layer Name', 'Layer Type', 'Output Shape', 'Param #'])
print("CNN Model Yapısı:")
print(model_df)
```

Model: "sequential_1"

Layer (type)	Output Shape	Param #
Conv2D_1 (Conv2D)	(None, 222, 222, 32)	896
MaxPool_1 (MaxPooling2D)	(None, 111, 111, 32)	0
Conv2D_2 (Conv2D)	(None, 109, 109, 64)	18,496
MaxPool_2 (MaxPooling2D)	(None, 54, 54, 64)	0
Conv2D_3 (Conv2D)	(None, 52, 52, 128)	73,856
MaxPool_3 (MaxPooling2D)	(None, 26, 26, 128)	0
Flatten (Flatten)	(None, 86528)	0
Dense_1 (Dense)	(None, 128)	11,075,712
Dropout (Dropout)	(None, 128)	0
Output (Dense)	(None, 7)	903

Total params: 11,169,863 (42.61 MB)
Trainable params: 11,169,863 (42.61 MB)
Non-trainable params: 0 (0.00 B)

1-) This code block imports the necessary libraries for model building and result formatting.

2-)-Sequential: Used to stack layers sequentially.
-Input: Defines the input shape (224x224x3). -Conv2D: Adds convolutional layers., First layer has 32 filters, second has 64, third has 128.
-MaxPooling2D:Reduces dimensionality (2x2 pooling).
-Flatten: Converts multi-dimensional data to a single dimension.
-Dense: Fully connected layer with 128 neurons.

-Dropout: Reduces overfitting by randomly dropping 60% of neurons.

-Output: Final layer with softmax activation (7 classes).

3-)This code block formats the model summary as a table.

-StringIO: Captures the model summary as text.

-sys.stdout: Redirects standard output to capture.

-Table creation: Displays each layer as a table row.

```
cnn_model.compile(
    optimizer='adam',
    loss='sparse_categorical_crossentropy',
    metrics=['accuracy']
)
#compile cnn
```

This code block compiles the CNN model to make it ready for training.

-optimizer='adam': Speeds up the learning process. ,Provides more stable and faster convergence.

-Sparse Categorical Crossentropy:Ideal when the class labels are represented as integers.

-Accuracy Metric:Provides a straightforward evaluation of classification performance.

```
history = cnn_model.fit(
    train_generator,
    epochs=10,
    validation_data=validation_generator
)
```

```
/usr/local/lib/python3.11/dist-packages/keras/src/trainers/data_adapters/py_dataset_adapter.py:121: UserWarning: Your `P
  self._warn_if_super_not_called()
Epoch 1/10
162/162 ━━━━━━━━━━━━━━━━━━━━ 1919s 12s/step - accuracy: 0.2590 - loss: 2.0087 - val_accuracy: 0.2979 - val_loss: 1.7390
Epoch 2/10
162/162 ━━━━━━━━━━━━━━━━━━━━ 631s 4s/step - accuracy: 0.3595 - loss: 1.6992 - val_accuracy: 0.3951 - val_loss: 1.5767
Epoch 3/10
162/162 ━━━━━━━━━━━━━━━━━━━━ 634s 4s/step - accuracy: 0.4474 - loss: 1.4350 - val_accuracy: 0.4601 - val_loss: 1.4801
Epoch 4/10
162/162 ━━━━━━━━━━━━━━━━━━━━ 660s 4s/step - accuracy: 0.5803 - loss: 1.1226 - val_accuracy: 0.5111 - val_loss: 1.5709
Epoch 5/10
162/162 ━━━━━━━━━━━━━━━━━━━━ 685s 4s/step - accuracy: 0.7047 - loss: 0.8147 - val_accuracy: 0.5621 - val_loss: 1.4522
Epoch 6/10
162/162 ━━━━━━━━━━━━━━━━━━━━ 650s 4s/step - accuracy: 0.7791 - loss: 0.5836 - val_accuracy: 0.5712 - val_loss: 1.4441
Epoch 7/10
162/162 ━━━━━━━━━━━━━━━━━━━━ 653s 4s/step - accuracy: 0.8298 - loss: 0.4469 - val_accuracy: 0.5770 - val_loss: 1.5870
Epoch 8/10
162/162 ━━━━━━━━━━━━━━━━━━━━ 666s 4s/step - accuracy: 0.8719 - loss: 0.3457 - val_accuracy: 0.6049 - val_loss: 1.6557
Epoch 9/10
162/162 ━━━━━━━━━━━━━━━━━━━━ 657s 4s/step - accuracy: 0.8922 - loss: 0.2767 - val_accuracy: 0.5827 - val_loss: 1.6968
Epoch 10/10
162/162 ━━━━━━━━━━━━━━━━━━━━ 687s 4s/step - accuracy: 0.9079 - loss: 0.2497 - val_accuracy: 0.5737 - val_loss: 2.0463
```

This code block is used to train the CNN model.

-train_generator:Data generator that supplies the training data., Feeds data to the model in the required format and initiates training.

-epochs=10:Specifies how many iterations over the entire dataset the model will perform.

-validation_data=validation_generator:Provides validation data to assess model performance during training. , The model's generalization ability is measured after each epoch.

```
from sklearn.metrics import classification_report, accuracy_score, precision_score, recall_score, f1_score
```

classification_report: Generates a detailed performance report.

accuracy_score: Calculates the accuracy of predictions.

precision_score: Measures how many selected items are relevant.

recall_score: Measures how many relevant items are selected.

f1_score: Combines precision and recall into one metric.

```
# get predict
import numpy as np
test_pred = cnn_model.predict(test_generator)
test_pred_labels = np.argmax(test_pred, axis=1)

# Real label
true_labels = test_generator.classes
```

```
17/17 ━━━━━━━━━━━━━━━━━━━━ 24s 1s/step
```

model.predict(test_generator): Uses the trained model to predict labels for the test dataset.

np.argmax(test_pred, axis=1): Converts the probability output of the model to class labels by selecting the index with the highest value.

true_labels = test_generator.classes: Retrieves the actual labels from the test data generator.

```
# Accuracy
accuracy = accuracy_score(true_labels, test_pred_labels)

# Precision, Recall, F1-Score

precision = precision_score(true_labels, test_pred_labels, average='weighted')
recall = recall_score(true_labels, test_pred_labels, average='weighted')
f1 = f1_score(true_labels, test_pred_labels, average='weighted')
# Detaylı Rapor

report = classification_report(true_labels, test_pred_labels, target_names=test_generator.class_indices.keys())

print("\nClassification Report:\n", report)
```

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

             Audi       0.65      0.88      0.75       156
    Hyundai Creta       0.62      0.44      0.51        41
 Mahindra Scorpio       0.62      0.48      0.54        58
      Rolls Royce       0.50      0.49      0.49        49
            Swift       0.63      0.52      0.57        63
      Tata Safari       0.54      0.46      0.50        41
   Toyota Innova       0.71      0.62      0.66       106

         accuracy                           0.63       514
        macro avg       0.61      0.56      0.58       514
     weighted avg       0.63      0.63      0.62       514
```

Accuracy: 58.17%

Precision: 57.16%

Recall: 58.17%

F1-Score: 57.19%

accuracy = accuracy_score(true_labels, test_pred_labels): Calculates the model accuracy by comparing the true labels with the predicted labels.

average='weighted': Calculates metrics for each label and finds their average, weighted by support.

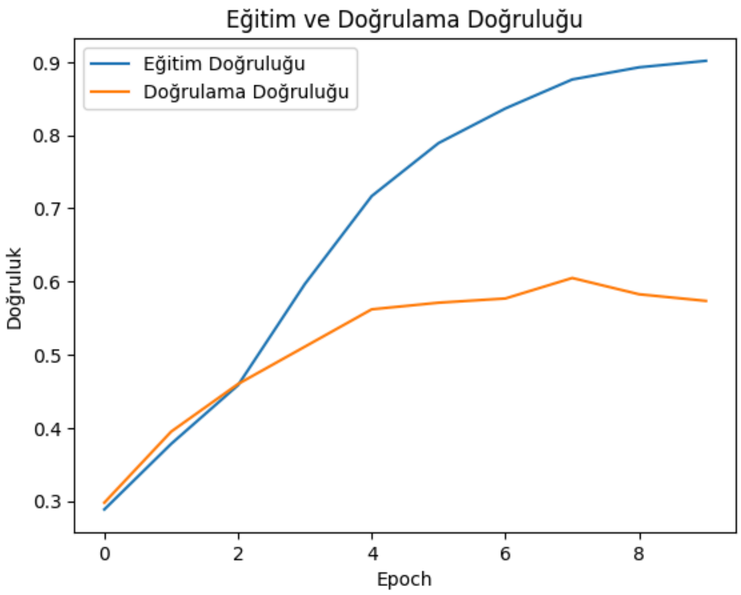
Precision: How many of the predicted positive cases are correct.

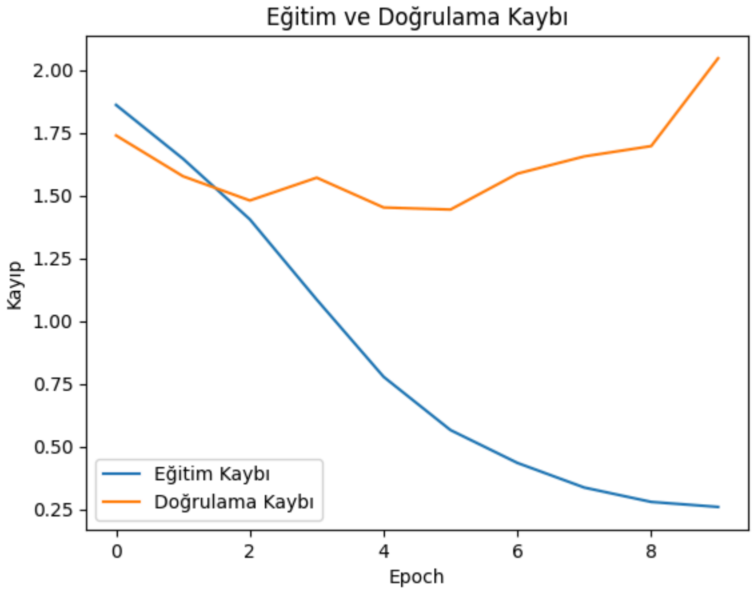
Recall: How many of the actual positive cases are captured.

F1-Score: Harmonic mean of precision and recall.

report = classification_report(true_labels, test_pred_labels, target_names=test_generator.class_indices.keys()): Creates a classification report that includes precision, recall, F1-score, and support for each class.

```
import matplotlib.pyplot as plt

#1

# Accuracy grafiği
plt.plot(history.history['accuracy'], label='Eğitim Doğruluğu')
plt.plot(history.history['val_accuracy'], label='Doğrulama Doğruluğu')
plt.xlabel('Epoch')
plt.ylabel('Doğruluk')
plt.legend()
plt.title('Eğitim ve Doğrulama Doğruluğu')
plt.show()

#2

# Loss grafiği
plt.plot(history.history['loss'], label='Eğitim Kaybı')
plt.plot(history.history['val_loss'], label='Doğrulama Kaybı')
plt.xlabel('Epoch')
plt.ylabel('Kayıp')
plt.legend()
plt.title('Eğitim ve Doğrulama Kaybı')
plt.show()
```





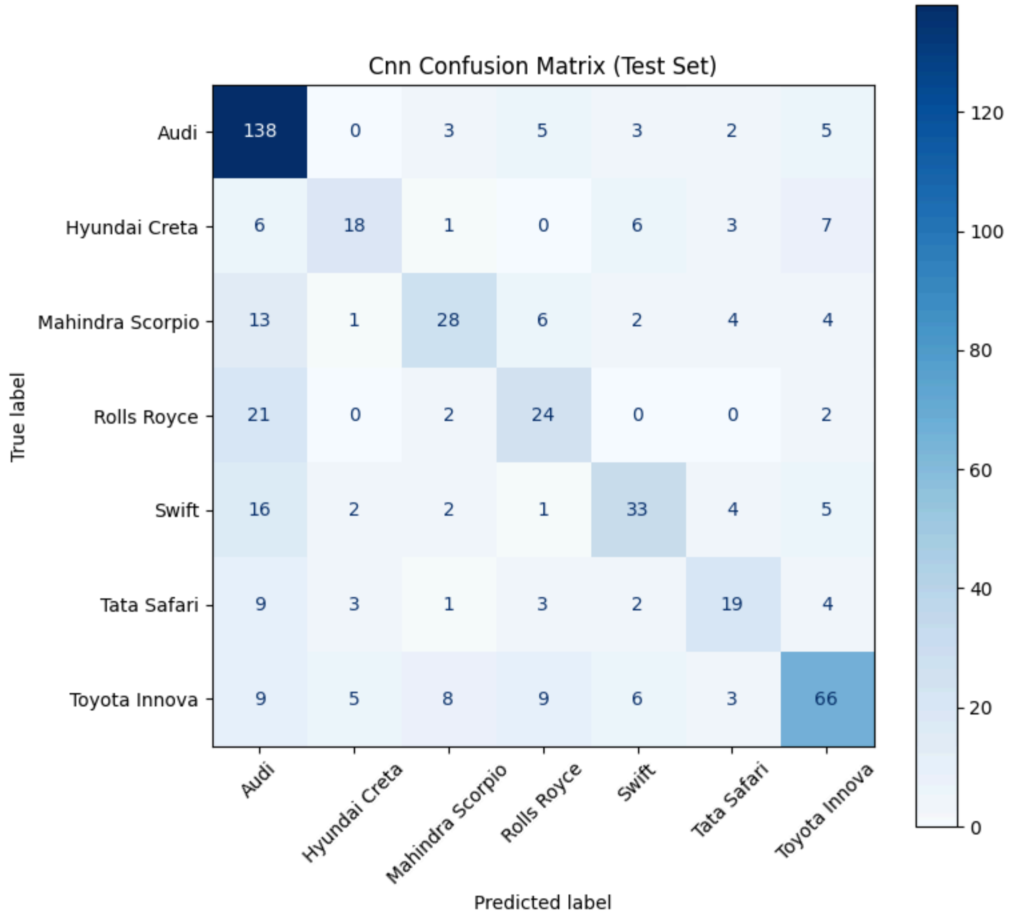
1-)This part is used to plot the training and validation accuracy. -plt.plot(): Used to create a plot., history.history['accuracy']: Gets training accuracy values., history.history['val_accuracy']: Gets validation accuracy values.
-plt.xlabel(): Sets the label for the X-axis (Epoch).
-plt.ylabel(): Sets the label for the Y-axis (Accuracy).
-plt.legend(): Adds labels to the plot lines.
-plt.title(): Sets the title of the graph.
-plt.show(): Displays the graph.

2-)This part is used to plot the training and validation loss. -plt.plot(): Plots the training and validation loss on the same graph.,history.history['loss']: Retrieves training loss values.,history.history['val_loss']: Retrieves validation loss values. -plt.xlabel(): Sets the label for the X-axis (Epoch).
-plt.ylabel(): Sets the label for the Y-axis (Loss).
-plt.legend(): Adds labels to the plot lines.
-plt.title(): Sets the title of the graph. -plt.show(): Displays the graph.

```
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
import matplotlib.pyplot as plt
import numpy as np

#1

# Predict over the test set
test_pred = cnn_model.predict(test_generator)
test_pred_labels = np.argmax(test_pred, axis=1)

#2

# Real labels
```

```
true_labels = test_generator.classes

#3

# Create Confusion Matrix
cm = confusion_matrix(true_labels, test_pred_labels)

#4

# Visualization
fig, ax = plt.subplots(figsize=(8, 8))
disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=list(test_generator.class_indices.keys()))
disp.plot(cmap='Blues', ax=ax, xticks_rotation=45)  # xticks_rotation=45
plt.title("Cnn Confusion Matrix (Test Set)")
plt.show()
```

```
17/17 ━━━━━━━━━━━━━━━━━━━━ 27s 2s/step
```



1-) In this step, we obtain the model predictions on the test data.
-model.predict(test_generator):Makes predictions on the test dataset., The predicted values are returned as probabilities.
-np.argmax(test_pred, axis=1):Selects the maximum probability as the predicted class., axis=1: Finds the maximum value in each row (sample).

2-)test_generator.classes:Returns the true class labels from the test data. , Used to compare with the model predictions.

3-)confusion_matrix(true_labels, test_pred_labels):Rows represent the actual labels, columns represent the predicted labels., Clearly shows correct and incorrect classifications.

4-)Used to visually plot the Confusion Matrix. -ConfusionMatrixDisplay:Takes the matrix data and displays it visually., cmap='Blues': Creates a graph with blue shades. -plt.title:Adds a title to the graph.
-plt.show(): Displays the plot on the screen.

```
import os
from collections import Counter

train_dir = '/content/drive/MyDrive/carbrand/train'

labels = []
for folder in os.listdir(train_dir):
    folder_path = os.path.join(train_dir, folder)
    if os.path.isdir(folder_path):
```

```
        count = len(os.listdir(folder_path))
        labels.append((folder, count))

for label, count in sorted(labels, key=lambda x: x[1], reverse=True):
    print(f"{label}: {count} görsel")
```

```
Audi: 1527 görsel
Toyota Innova: 1113 görsel
Rolls Royce: 594 görsel
Swift: 582 görsel
Tata Safari: 510 görsel
Mahindra Scorpio: 453 görsel
Hyundai Creta: 399 görsel
```

This loop finds each class folder within the training directory and counts the number of images inside. -os.listdir(train_dir):Lists all subfolders (classes) within the training directory.

-os.path.join(train_dir, folder):Joins the main directory path with the subfolder name.

-os.path.isdir(folder_path):Selects only folder items (excludes files).

-len(os.listdir(folder_path)):Finds the number of images within the folder.

-labels.append((folder, count)):Adds the folder name and image count as a tuple to the list.

-sorted(labels, key=lambda x: x[1], reverse=True):Sorts the classes by the number of images, in descending order.

-print(f"{label}: {count} images"):Displays the class name and the number of images.

```
from sklearn.utils.class_weight import compute_class_weight
import numpy as np

class_indices = train_generator.classes
weights = compute_class_weight(class_weight='balanced', classes=np.unique(class_indices), y=class_indices)
class_weights = dict(enumerate(weights))

print("Class weights:", class_weights)
```

```
Class weights: {0: np.float64(0.48442323884367106), 1: np.float64(1.853920515574651), 2: np.float64(1.6329233680227058),
```

class_indices = train_generator.classes = This line fetches the class indices from the training data.

-train_generator.classes:Returns class labels from the training data generator.

-compute_class_weight:class_weight='balanced': Balances the weights according to class distribution.

-classes=np.unique(class_indices): Finds unique class labels. -y=class_indices: Uses class labels from the training data generator.

-dict(enumerate(weights)):Converts weight values into a dictionary format., Uses class indices as keys.

```
from tensorflow.keras.applications import VGG16
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Flatten, Dropout
from tensorflow.keras.optimizers import Adam


#1
base_model = VGG16(weights='imagenet', include_top=False, input_shape=(224, 224, 3))

#2
for layer in base_model.layers:
    layer.trainable = False

#3
tl_model = Sequential([
    base_model,
    Flatten(),
    Dense(128, activation='relu'),
    Dropout(0.5),
    Dense(train_generator.num_classes, activation='softmax')
])

#4
tl_model.compile(optimizer=Adam(), loss='sparse_categorical_crossentropy', metrics=['accuracy'])
```

```
Downloading data from https://storage.googleapis.com/tensorflow/keras-applications/vgg16/vgg16_weights_tf_dim_ordering_t
58889256/58889256 ━━━━━━━━━━━━━━━━━━━━ 3s 0us/step
```

1-) Loads the VGG16 model without the top fully connected layers (include_top=False) and with input shape of (224, 224, 3). The model uses weights from ImageNet for transfer learning.

2-)Freezes all layers of the pre-trained VGG16 model to prevent their weights from being updated during training. This ensures that only the new layers are trained. 3-)Flatten(): Converts the feature map into a 1D vector, Dense(128, activation='relu'): Fully connected layer with 128 neurons and ReLU activation, Dropout(0.5): Regularization to prevent overfitting, Dense(train_generator.num_classes, activation='softmax'): Output layer with softmax activation for multi-classclassification.

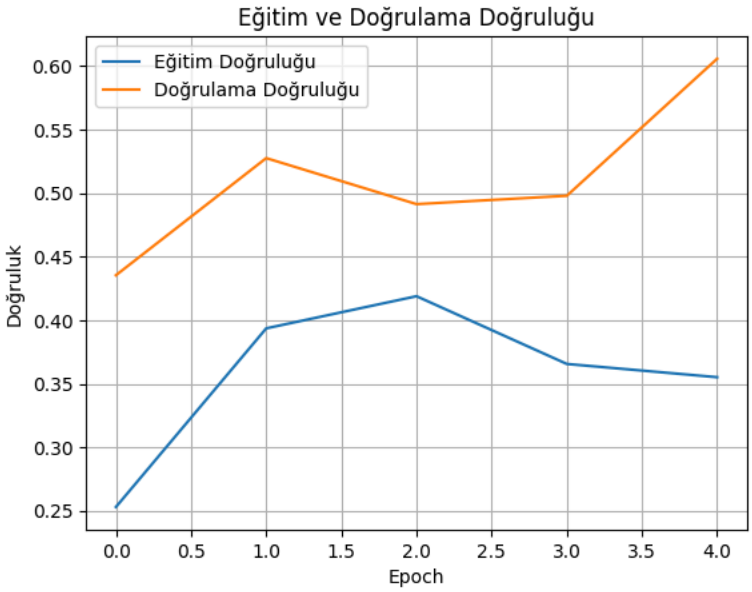
4-)Compiles the model using the Adam optimizer, sparse categorical crossentropy as the loss function, and accuracy as the evaluation metric.

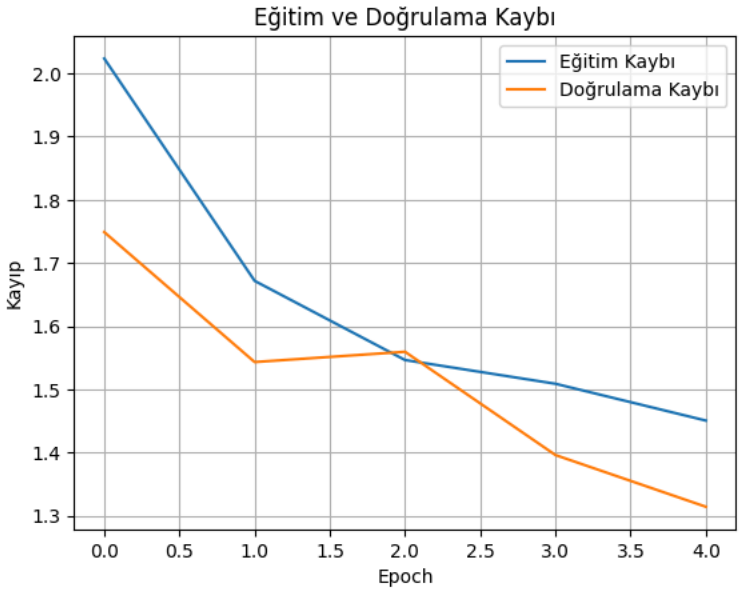
```
history_tl = tl_model.fit(
    train_generator,
    epochs=5,
    validation_data=validation_generator,
    class_weight=class_weights
)
```

```
/usr/local/lib/python3.11/dist-packages/keras/src/trainers/data_adapters/py_dataset_adapter.py:121: UserWarning: Your `P
  self._warn_if_super_not_called()
Epoch 1/5
162/162 ━━━━━━━━━━━━━━━━━━━━ 4263s 26s/step - accuracy: 0.1845 - loss: 2.5255 - val_accuracy: 0.4354 - val_loss: 1.7489
Epoch 2/5
162/162 ━━━━━━━━━━━━━━━━━━━━ 4159s 26s/step - accuracy: 0.3969 - loss: 1.6980 - val_accuracy: 0.5276 - val_loss: 1.5431
Epoch 3/5
162/162 ━━━━━━━━━━━━━━━━━━━━ 4157s 26s/step - accuracy: 0.4195 - loss: 1.5326 - val_accuracy: 0.4914 - val_loss: 1.5593
Epoch 4/5
162/162 ━━━━━━━━━━━━━━━━━━━━ 4094s 25s/step - accuracy: 0.3904 - loss: 1.5095 - val_accuracy: 0.4979 - val_loss: 1.3959
Epoch 5/5
162/162 ━━━━━━━━━━━━━━━━━━━━ 4157s 26s/step - accuracy: 0.3440 - loss: 1.4746 - val_accuracy: 0.6058 - val_loss: 1.3140
```

This code block is used for training the model.
-train_generator:Data generator that supplies the training data. Feeds data to the model in the required format and initiates training.
-epochs=10:Specifies how many iterations over the entire dataset the model will perform.
-validation_data=validation_generator:Provides validation data to assess model performance during training. , The model's generalization ability is measured after each epoch.
-class_weight=class_weights:Passes class weights to the model to handle class imbalance., Ensures that the model does not ignore minority classes during training.
-callbacks=[early_stop]:Enables the early stopping mechanism during training., Stops training if no improvement in validation loss is observed.

```
import matplotlib.pyplot as plt

# Accuracy graph
plt.plot(history_tl.history['accuracy'], label='Eğitim Doğruluğu')
plt.plot(history_tl.history['val_accuracy'], label='Doğrulama Doğruluğu')
plt.xlabel('Epoch')
plt.ylabel('Doğruluk')
plt.legend()
plt.title('Eğitim ve Doğrulama Doğruluğu')
plt.grid(True)
plt.show()

# Loss graph
plt.plot(history_tl.history['loss'], label='Eğitim Kaybı')
plt.plot(history_tl.history['val_loss'], label='Doğrulama Kaybı')
plt.xlabel('Epoch')
plt.ylabel('Kayıp')
plt.legend()
plt.title('Eğitim ve Doğrulama Kaybı')
plt.grid(True)
plt.show()
```





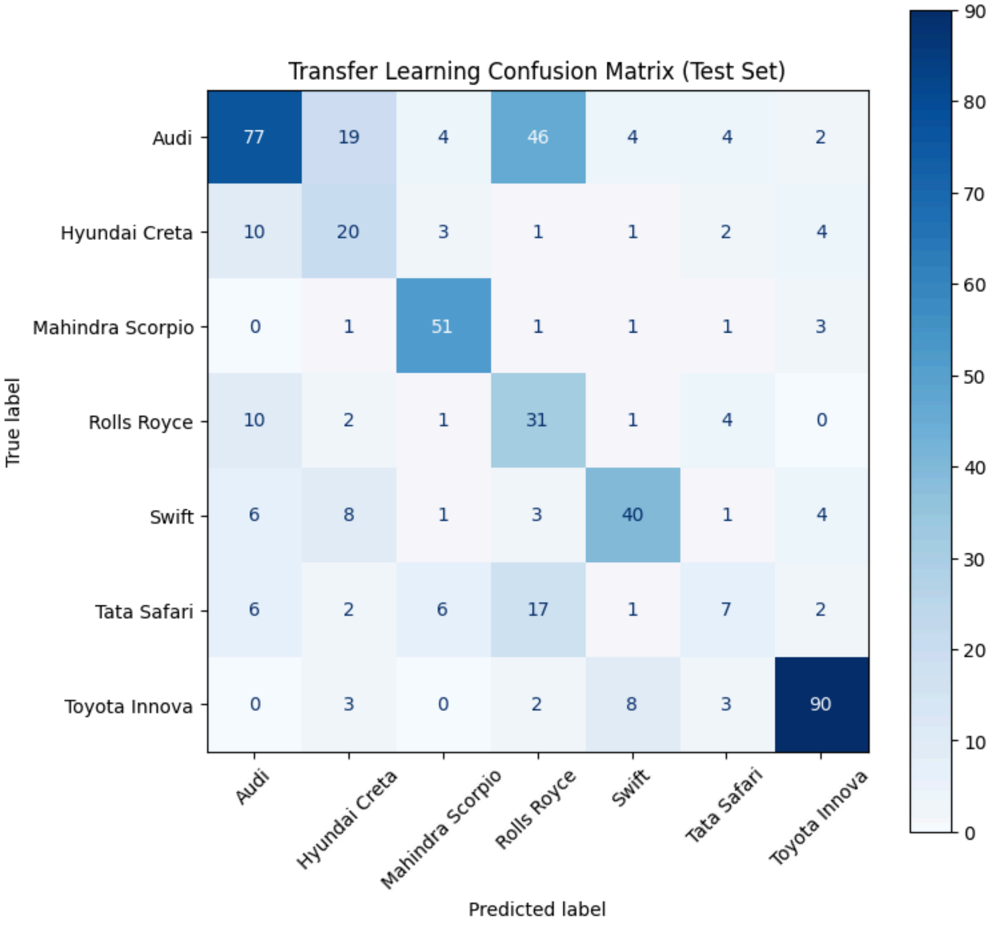
1-)This part is used to plot the training and validation accuracy. -plt.plot(): Used to create a plot., history.history['accuracy']: Gets training accuracy values., history.history['val_accuracy']: Gets validation accuracy values.
-plt.xlabel(): Sets the label for the X-axis (Epoch).
-plt.ylabel(): Sets the label for the Y-axis (Accuracy).
-plt.legend(): Adds labels to the plot lines.
-plt.title(): Sets the title of the graph.
-plt.show(): Displays the graph.

2-)This part is used to plot the training and validation loss. -plt.plot(): Plots the training and validation loss on the same graph.,history.history['loss']: Retrieves training loss values.,history.history['val_loss']: Retrieves validation loss values. -plt.xlabel(): Sets the label for the X-axis (Epoch).
-plt.ylabel(): Sets the label for the Y-axis (Loss).
-plt.legend(): Adds labels to the plot lines.
-plt.title(): Sets the title of the graph. -plt.show(): Displays the graph.

```
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
import matplotlib.pyplot as plt
import numpy as np

# Predict over the test set
test_pred = tl_model.predict(test_generator)
test_pred_labels = np.argmax(test_pred, axis=1)

# Real labels
true_labels = test_generator.classes

# Create Confusion Matrix
cm = confusion_matrix(true_labels, test_pred_labels)
```

```
# Visualization
fig, ax = plt.subplots(figsize=(8, 8))
disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=list(test_generator.class_indices.keys()))
disp.plot(cmap='Blues', ax=ax, xticks_rotation=45)
plt.title("Transfer Learning Confusion Matrix (Test Set)")
plt.show()
```

```
17/17 ━━━━━━━━━━━━━━━━━━━━ 352s 21s/step
```



1-) In this step, we obtain the model predictions on the test data.
-model.predict(test_generator):Makes predictions on the test dataset., The predicted values are returned as probabilities.
-np.argmax(test_pred, axis=1):Selects the maximum probability as the predicted class., axis=1: Finds the maximum value in each row (sample).

2-)test_generator.classes:Returns the true class labels from the test data. , Used to compare with the model predictions.

3-)confusion_matrix(true_labels, test_pred_labels):Rows represent the actual labels, columns represent the predicted labels., Clearly shows correct and incorrect classifications.

4-)Used to visually plot the Confusion Matrix. -ConfusionMatrixDisplay:Takes the matrix data and displays it visually., cmap='Blues': Creates a graph with blue shades. -plt.title:Adds a title to the graph.
-plt.show(): Displays the plot on the screen.

```
from sklearn.metrics import classification_report, accuracy_score, precision_score, recall_score, f1_score
```

classification_report: Generates a detailed performance report.
accuracy_score: Calculates the accuracy of predictions.
precision_score: Measures how many selected items are relevant.
recall_score: Measures how many relevant items are selected.
f1_score: Combines precision and recall into one metric.

```
# Tahminleri al
test_pred = tl_model.predict(test_generator)
test_pred_labels = np.argmax(test_pred, axis=1)

# Gerçek etiketler
```

```
true_labels = test_generator.classes
```

```
17/17 ━━━━━━━━━━━━━━━━━━━━ 328s 19s/step
```

model.predict(test_generator): Uses the trained model to predict labels for the test dataset.

np.argmax(test_pred, axis=1): Converts the probability output of the model to class labels by selecting the index with the highest value.

true_labels = test_generator.classes: Retrieves the actual labels from the test data generator.

```
# Accuracy
accuracy = accuracy_score(true_labels, test_pred_labels)

# Precision, Recall, F1-Score
precision = precision_score(true_labels, test_pred_labels, average='weighted')
recall = recall_score(true_labels, test_pred_labels, average='weighted')
f1 = f1_score(true_labels, test_pred_labels, average='weighted')

# Detaylı Rapor
report = classification_report(true_labels, test_pred_labels, target_names=test_generator.class_indices.keys())

print("Accuracy: {:.2f}%".format(accuracy * 100))
print("Precision: {:.2f}%".format(precision * 100))
print("Recall: {:.2f}%".format(recall * 100))
print("F1-Score: {:.2f}%".format(f1 * 100))
print("\nClassification Report:\n", report)
```

```
Accuracy: 61.48%
Precision: 64.96%
Recall: 61.48%
F1-Score: 61.79%

Classification Report:
                   precision    recall  f1-score   support

            Audi       0.71      0.49      0.58       156
   Hyundai Creta       0.36      0.49      0.42        41
Mahindra Scorpio       0.77      0.88      0.82        58
     Rolls Royce       0.31      0.63      0.41        49
           Swift       0.71      0.63      0.67        63
     Tata Safari       0.32      0.17      0.22        41
   Toyota Innova       0.86      0.85      0.85       106

        accuracy                           0.61       514
       macro avg       0.58      0.59      0.57       514
    weighted avg       0.65      0.61      0.62       514
```

accuracy = accuracy_score(true_labels, test_pred_labels): Calculates the model accuracy by comparing the true labels with the predicted labels.

average='weighted': Calculates metrics for each label and finds their average, weighted by support.

Precision: How many of the predicted positive cases are correct.

Recall: How many of the actual positive cases are captured.

F1-Score: Harmonic mean of precision and recall.

report = classification_report(true_labels, test_pred_labels, target_names=test_generator.class_indices.keys()): Creates a classification report