Final Project Report

Dog Breed Identification using Transfer Learning

1. Introduction

1.1. Project Overview

The Dog Breed Classification project aims to leverage machine learning and advanced transfer learning techniques to accurately identify the breed of a dog from an image. By utilizing a Kaggle dataset containing thousands of labeled dog images, the project will train and evaluate models to ensure robust breed identification. The ultimate goal is to deploy the model as a user-friendly web application, making it accessible for veterinarians, rescue organizations, and pet owners.

1.2. Objectives

The primary objective of the Dog Breed Classification project is to develop a machine learning model capable of accurately identifying the breed of a dog from an image using advanced transfer learning techniques.

2.

Milestone 1: Project Initialization and Planning Phase

Activity 1: Define Problem Statement

With the increasing popularity of pet ownership, accurately identifying dog breeds can assist veterinarians, rescue organizations, and pet owners. Manual identification can be error-prone and time-consuming, especially with mixed breeds or less common breeds.

Activity 2: Project Proposal (Proposed Solution)

The project employs transfer learning with pretrained models on a Kaggle dataset of 10,222 dog images. Data preprocessing includes standardization and augmentation. Model performance is evaluated using metrics like accuracy, aiming for robust breed identification. Deployment as a user-friendly web app enhances accessibility and usability.

- Use of multiple pre-trained models for robust feature extraction.

- Web-based deployment for user-friendly interaction.

Activity 3: Initial Project Planning

Sprit	Functional Requirement (Epic)	User Story Number	User Story / Task	Story Points	Priority	Team Members
Sprint-1	Data Collection	DBI-4	Collection of Data	2	High	Diya
Sprint-1	Data Collection	DBI-5	Loading the Data	4	Low	Diya
Sprint-2	Data Preprocessing	DBI-7	Understanding the data	3	Medium	Diya
Sprint-2	Data Preprocessing	DBI-8	Classifying the data	5	Medium	Diya
Sprint-3	Model Building	DBI-10	Importing the Model Building Libraries	2	High	Akshay
Sprint-3	Model Building	DBI-11	Importing the Models	3	High	Akshay
Sprint-3	Model Building	DBI-12	Initialization the Models	3	High	Tanmay
Sprint-3	Model Building	DBI-13	Adding Fully Connecting Layers	5	Medium	Tanmay
Sprint-3	Model Building	DBI-14	Configure the Learning Process	5	Medium	Tanmay
Sprint-3	Model Building	DBI-15	Train the Models	8	High	Swarit, Tanmay
Sprint-3	Model Building	DBI-16	Save the Models	2	Medium	Swarit
Sprint-3	Model Building	DBI-17	Test the Models	5	High	Swarit, Tanmay
Sprint-4	Application Building	DBI-19	Create HTML Pages	3	Low	Akshay
Sprint-4	Application Building	DBI-20	Build Python Code	5	High	Diya
Sprint-4	Application Building	DBI-21	Importing Libraries	2	High	Akshay
Sprint-4	Application Building	DBI-22	Creating Our Flask Application and Loading Our Model by Using Load_model Method	8	High	Swarit

Sprit	Functional Requirement (Epic)	User Story Number	User Story / Task	Story Points	Priority	Team Members
Sprint-4	Application Building	DBI-23	Routing to the Html Page	3	Medium	Swarit
Sprint-4	Application Building	DBI-24	Run the Application	2	Medium	Swarit
Sprint-5	Documentation	DBI-26	Project Documentation	3	Medium	Diya

3.

Milestone 2: Data Collection and Preprocessing Phase

Activity 1: Data Collection Plan and Raw Data Sources Identified

Data for this project will be sourced primarily from publicly available datasets. The main dataset will be obtained from the Kaggle competition "Dog Breed Identification," which provides a large collection of labeled dog images. This dataset is ideal for transfer learning as it contains a diverse set of images across various dog breeds.

Raw Data Sources Identified

This dataset consists of images of dogs labeled with their corresponding breeds. The dataset includes a training set with labeled images and a test set with unlabeled images. The training set will be used to train the model, while the test set will be used to evaluate its performance.

- Contents:

  - train/: A folder containing training images.

  - test/: A folder containing test images.

  - labels.csv: A CSV file containing image IDs and their corresponding breed labels.

Activity 2: Data Quality Report

The Kaggle Dog Breed Identification dataset, used for this project, presents several data quality issues that need to be addressed. Firstly, the dataset may have missing labels, which is a moderate severity issue. To resolve this, we will verify the integrity of the dataset by checking for any missing or null values in the labels file. Using pandas, we can identify and handle missing labels by either removing the corresponding images or imputing the missing values if applicable.

Secondly, there is variability in image sizes, which is a low severity issue. To ensure uniform input dimensions for the neural network, we will resize all images to a consistent size of 224x224 pixels using the `ImageDataGenerator`.

Thirdly, the dataset shows variability in image quality, a moderate severity issue. To address this, we will apply image preprocessing techniques such as normalization to scale pixel values and possibly use denoising filters to improve image quality.

Fourthly, the high dimensionality of the images poses a high severity issue. We will use feature extraction from pre-trained models such as VGG19, EfficientNetB7, and MobileNetV2 to reduce the dimensionality of the images and focus on the most informative features.

Lastly, the dataset is imbalanced, which is the least severe issue. To counter this, we will use data augmentation techniques such as rotation, shifting, zooming, and flipping to artificially increase the number of images for underrepresented classes. This will help in creating a more balanced dataset for training the model.

Activity 3: Data Preprocessing

The dataset used in this project comprises images of dogs labeled with their corresponding breeds. The primary dataset is sourced from the Kaggle Dog Breed Identification competition. It includes a diverse collection of dog images spanning multiple breeds, which will be used for training and evaluating the dog breed identification model.

- Dimension:
  - Training Set: 10,222 images
  - Test Set: 10,357 images
  - Number of Classes: 120 dog breeds
  - Feature Dimension: Images resized to 224x224 pixels with 3 color channels (RGB)

4.

Milestone 3: Model Development Phase

Activity 1: Model Selection Report

Model 1: MobileNetV2

MobileNetV2 is a deep convolutional neural network architecture designed for mobile and embedded vision applications. It emphasizes efficiency and small model size while maintaining good accuracy in various computer vision tasks like image classification and object detection.

Model 2: VGG19

VGG-19 is a deep convolutional neural network architecture known for its simplicity and effectiveness. It consists of 19 layers (16 convolutional and 3 fully connected layers) and has been

widely used as a benchmark in image classification tasks due to its strong performance and straightforward architecture.

Model 3: EfficientNetB7

EfficientNet-B7 is part of the EfficientNet family of neural network architectures, which are designed to achieve state-of-the-art accuracy with increased efficiency. EfficientNet-B7 specifically is one of the largest models in the family, capable of achieving high accuracy while being computationally efficient, making it suitable for a wide range of tasks including image classification and object detection.

Activity 2: Initial Model Training Code, Model Validation and Evaluation Report

Initial Model Training Code (5 marks):

```
[ ] train_datagen = ImageDataGenerator(rescale=1./255, shear_range=0.2, zoom_range=0.2, horizontal_flip=True)

[ ] selected_classes = []
    for breed in labels.breed.unique():
        selected_classes.append(breed)

    datagen = ImageDataGenerator()

    generator = datagen.flow_from_directory(
        'subset/train',
        target_size=(224, 224),
        batch_size=32,
        class_mode='categorical',
        shuffle=False,
        classes=selected_classes
    )

    Found 10222 images belonging to 120 classes.

[ ] test_datagen = ImageDataGenerator(rescale=1./255)
```

```
[ ] Image_size=[224,224]
    sol=MobileNetV2(input_shape=Image_size + [3], weights='imagenet', include_top = False)
    for i in sol.layers:
        i.trainable = False
    y=Flatten()(sol.output)
```

```
Downloading data from https://storage.googleapis.com/tensorflow/keras-applications/mobilenet_v2/
9406464/9406464 [==============================] - 1s 0us/step
```

```
[ ] final = Dense(120, activation='softmax')(y)
```

```
model = Model(inputs=sol.input, outputs=final)
```

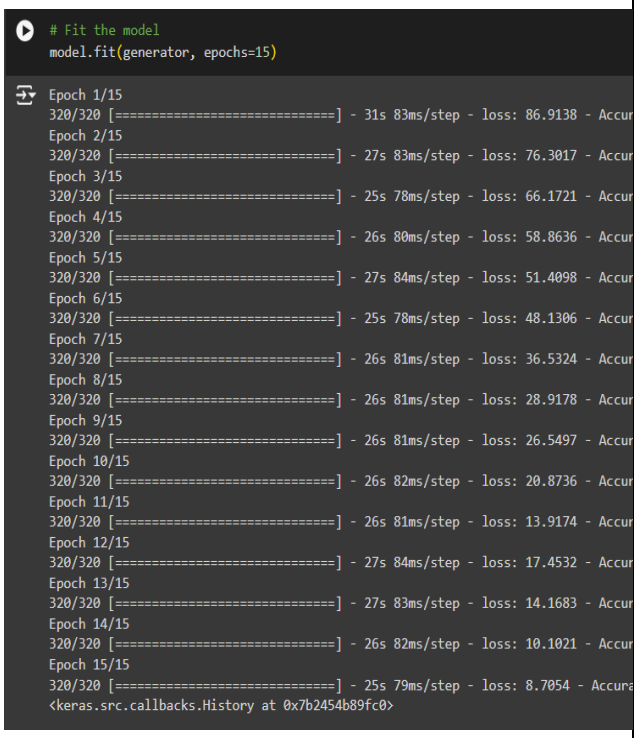
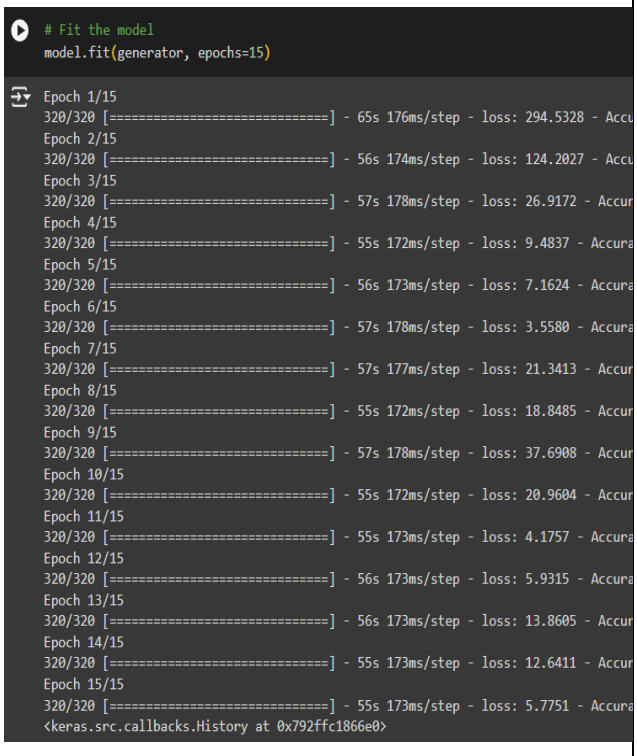
```
[ ] model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['Accuracy'])
```

```
[ ] for data, labels in generator:
        print('Data shape:', data.shape)
        print('Labels shape:', labels.shape)
        break  # Only need to check one batch
```

```
Data shape: (32, 224, 224, 3)
Labels shape: (32, 120)
```

```
[ ] # Fit the model
    model.fit(generator, epochs=15)
```

Model Validation and Evaluation Report (5 marks):

Model	Summary	Training and Validation Performance Metrics
Model 1 MobileNetV2		
Model 2 VGG19		

Model 3
 	
EfficientNet B7
	`[ ] final = Dense(120, activation='softmax`	`# Fit the model`
		`model.fit(generator, epochs=15)`
		
		Epoch 1/15
		320/320 [==========] - 114s 355ms/step - loss: 22.3111 - Accu
		Epoch 2/15
		320/320 [==========] - 114s 357ms/step - loss: 14.3997 - Accu
		Epoch 3/15
		320/320 [==========] - 114s 356ms/step - loss: 9.5306 - Accur
		Epoch 4/15
		320/320 [==========] - 114s 356ms/step - loss: 12.6607 - Accu
		Epoch 5/15
		320/320 [==========] - 114s 355ms/step - loss: 6.0558 - Accur
		Epoch 6/15
		320/320 [==========] - 114s 356ms/step - loss: 9.5931 - Accur
		Epoch 7/15
		320/320 [==========] - 114s 356ms/step - loss: 7.7925 - Accur
		Epoch 8/15
		320/320 [==========] - 114s 355ms/step - loss: 7.0943 - Accur
		Epoch 9/15
		320/320 [==========] - 114s 356ms/step - loss: 4.9911 - Accur
		Epoch 10/15
		320/320 [==========] - 114s 356ms/step - loss: 5.9198 - Accur
		Epoch 11/15
		320/320 [==========] - 114s 356ms/step - loss: 9.4890 - Accur
		Epoch 12/15
		320/320 [==========] - 114s 356ms/step - loss: 5.3840 - Accur
		Epoch 13/15
		320/320 [==========] - 114s 355ms/step - loss: 4.4254 - Accur
		Epoch 14/15
		320/320 [==========] - 114s 356ms/step - loss: 12.4857 - Accu
		Epoch 15/15
		320/320 [==========] - 114s 356ms/step - loss: 6.6507 - Accur
		<keras.src.callbacks.History at 0x7ac7a0541660>

5.

Milestone 4: Model Optimization and Tuning Phase

Activity 1: Tuning Documentation

Model	Tuned Hyperparameters
EfficientNetB7	1. Rescale: `1./255` o Normalizes the image pixel values to the range [0, 1]. 2. Shear Range: `0.2` o Randomly applies shearing transformations to the images. 3. Zoom Range: `0.2` o Randomly zooms inside images. 4. Horizontal Flip: `True` o Randomly flips half of the images horizontally. 5. Target Size: `(224, 224)` o The size to which all images are resized. 6. Batch Size: `32` o The number of images to be used in each batch for training. 7. Optimizer: `Adam` o Optimizer used to minimize the loss function.

	8. Loss Function: `categorical_crossentropy` o Loss function used for multi-class classification problems. 9. Epochs: `15` o The number of times the entire dataset is passed through the network during training. 10. **Activation**: `softmax` o Activation function used in the output layer for multi-class classification.
vgg19	1. Learning Rate: Defined by the `Adam` optimizer with default settings. 2. Batch Size: 32 (used in `ImageDataGenerator`). 3. Epochs: 15 (defined in the `model.fit` function). 4. Image Size: 224x224 pixels (used in `ImageDataGenerator` and `load_img`). 5. Pre-trained Model: VGG19 (imported and used as base model).

```
[ ] import os

    def make_dir(x):
        if os.path.exists(x) == False:
            os.makedirs(x)
    base_dir = './subset'
    make_dir(base_dir)
```

```
[ ] train_dir = os.path.join(base_dir, 'train')
    make_dir(train_dir)
```

```
    breeds = labels.breed.unique()
    for breed in breeds:
        _ = os.path.join(train_dir, breed)
        make_dir(_)

        images = labels[labels.breed == breed]['id']
        for image in images:
            source = os.path.join(dataset_dir, f'{image}.jpg')
            destination = os.path.join(train_dir, breed, f'{image}.jpg')
            shutil.copyfile(source, destination)
```

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

```
[ ] train_datagen = ImageDataGenerator(rescale=1./255, shear_range=0.2, zoom_range=0.2, horizontal_flip=True)
```

```
[ ] selected_classes = []
    for breed in labels.breed.unique():
        selected_classes.append(breed)
```

```
[ ] datagen = ImageDataGenerator()

    generator = datagen.flow_from_directory(
        'subset/train',
        target_size=(224, 224),
        batch_size=32,
        class_mode='categorical',
        shuffle=False,
        classes=selected_classes
    )
```

```
    Found 10222 images belonging to 120 classes.
```

```
[ ] test_datagen = ImageDataGenerator(rescale=1./255)
```

MobileNet	1. Image Size: The target size of the input images used for the VGG19 model. 2. Pre-trained Weights: Specifies that the model uses pre-trained weights from ImageNet. 3. Trainable Layers: Sets all layers of MobileNet to be non-trainable to use the pre-trained features. 4. Output Layer Activation: The activation function used in the final output layer, set to 'softmax' for multi-class classification

Activity 2: Final Model Selection Justification

Final Model	Reasoning
EfficientNetB7	• EfficientNetB7 is known for its superior performance on a variety of image classification benchmarks. It achieves high accuracy with relatively fewer parameters compared to other models. • The EfficientNet architecture scales efficiently in terms of depth, width, and resolution, allowing it to perform well on large datasets while maintaining computational efficiency. • EfficientNetB7 comes pre-trained on ImageNet, providing a strong feature extraction capability which is beneficial for fine-tuning on the dog breed identification dataset. • Despite being a deep model, EfficientNetB7 is optimized for both speed and memory usage, making it practical for real-world applications where computational resources might be limited. • **We chose the model because for specific images nearly every prediction was correct for this model which was not much accurate in other models.**

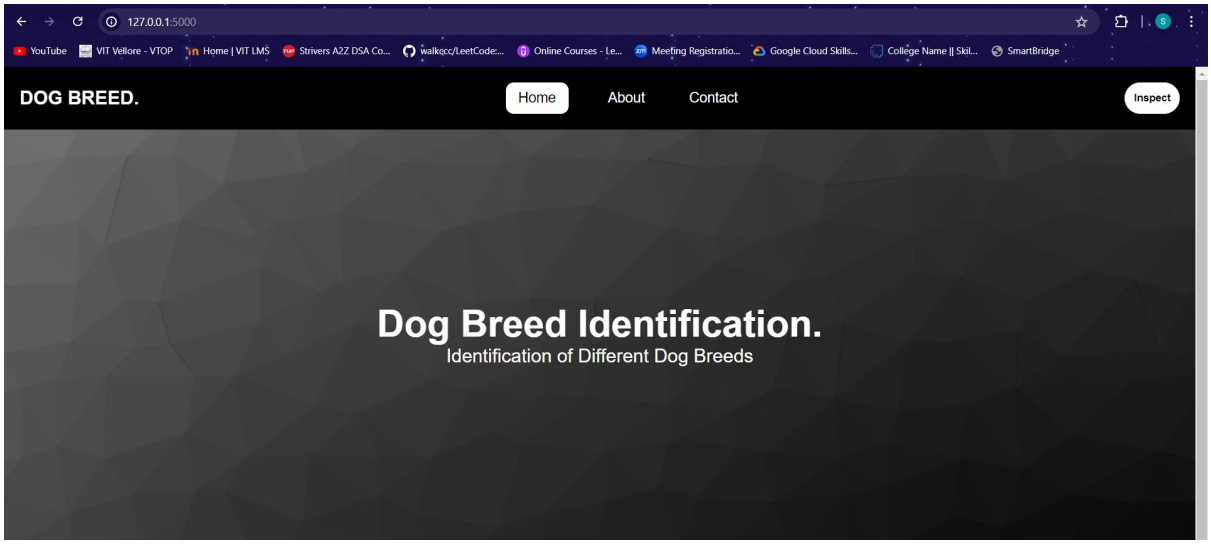
6.

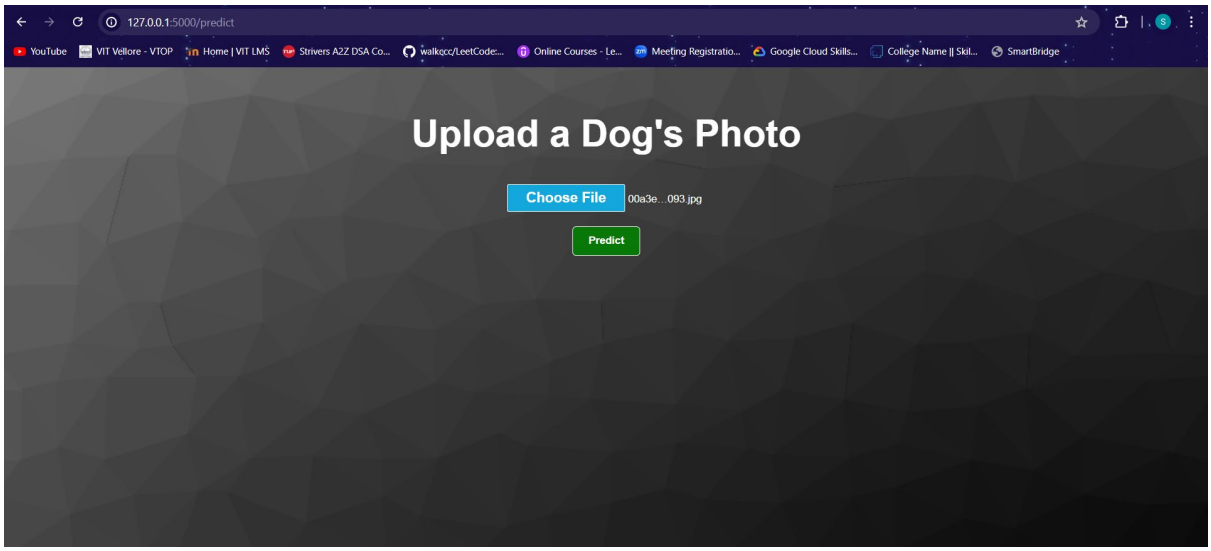
Milestone 5: Results

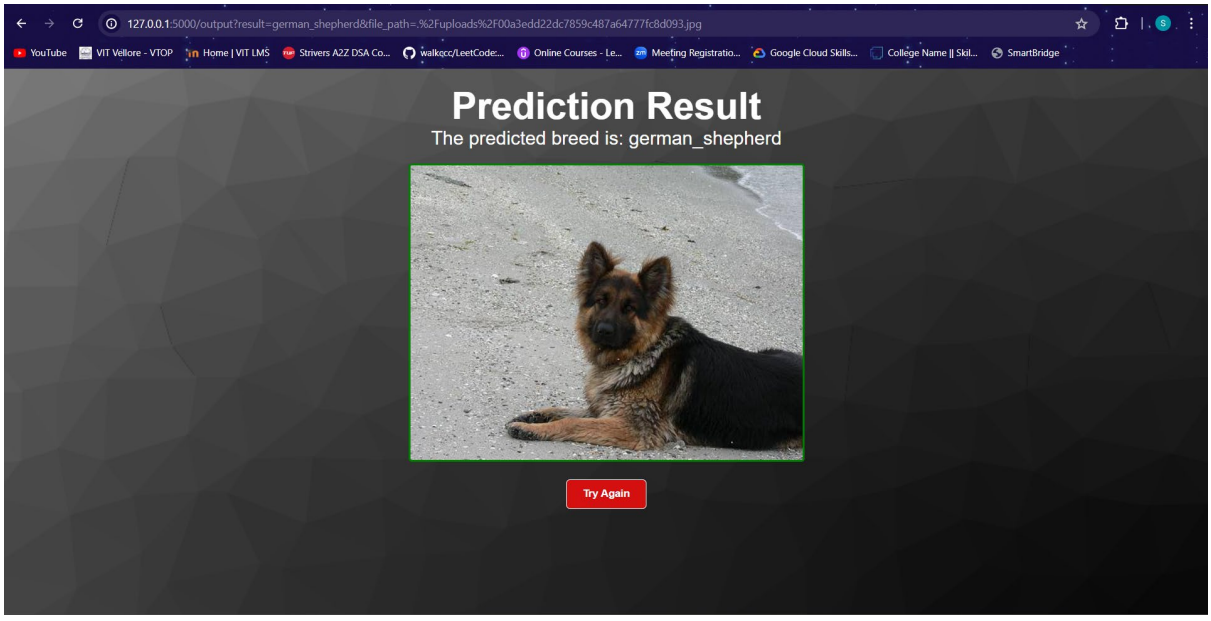
(Screenshots for the output of the Flask App attached below)

app_efficientNetB7.py

```python
from flask import Flask, render_template, request, redirect, url_for, send_from_directory
from keras.applications.efficientnet import preprocess_input
from tensorflow.keras.preprocessing.image import load_img, img_to_array
import numpy as np
import os
import tensorflow as tf

os.environ['TF_ENABLE_ONEDNN_OPTS'] = '0'

app = Flask(__name__)

model_path = 'dogbreed_efficientNetB7.h5'
model = tf.keras.models.load_model(model_path)

UPLOAD_FOLDER = './uploads/'
if not os.path.exists(UPLOAD_FOLDER):
    os.makedirs(UPLOAD_FOLDER)

app.config['UPLOAD_FOLDER'] = UPLOAD_FOLDER

class_labels = ['boston_bull', 'dingo', 'pekinese', 'bluetick', 'golden_retriever', 'bedlington_terrier', 'bora

def model_predict(img_path, model):
    img = load_img(img_path, target_size=(224, 224))
    x = img_to_array(img)
    x = preprocess_input(x)
    preds = model.predict(np.array([x]))
    predicted_class = class_labels[np.argmax(preds)]

    return predicted_class

@app.route('/')
def index():
    return render_template('index.html')

@app.route('/predict', methods=['GET', 'POST'])
def predict():
    if request.method == 'POST':
        file = request.files['file']
        if file:
            file_path = os.path.join(app.config['UPLOAD_FOLDER'], file.filename)
            file.save(file_path)
            predicted_class= model_predict(file_path, model)
            return redirect(url_for('output', result=predicted_class, file_path=file_path))
    return render_template('predict.html')

@app.route('/output')
def output():
    result = request.args.get('result')
    file_path = request.args.get('file_path')
    return render_template('output.html', result=result, file_path=file_path)

@app.route('/uploads/<filename>')
def uploaded_file(filename):
    return send_from_directory('uploads', filename)

if __name__ == '__main__':
    app.run(debug=True)
```


127.0.0.1:5000
YouTube
VIT Vellore - VTOP
Home | VIT LMS
Strivers A2Z DSA Co...
walkccc/LeetCode...
Online Courses - Le...
Meeting Registratio...
Google Cloud Skills...
College Name || Skil...
SmartBridge
DOG BREED.
Home
About
Contact
Inspect
Dog Breed Identification.
Identification of Different Dog Breeds


127.0.0.1:5000/predict
YouTube
VIT Vellore - VTOP
Home | VIT LMS
Strivers A2Z DSA Co...
walkccc/LeetCode...
Online Courses - Le...
Meeting Registratio...
Google Cloud Skills...
College Name || Skil...
SmartBridge
Upload a Dog's Photo
Choose File
00a3e...093.jpg
Predict


127.0.0.1:5000/output?result=german_shepherd&file_path=%2Fuploads%2F00a3edd22dc7859c487a64777fc8d093.jpg
YouTube
VIT Vellore - VTOP
Home | VIT LMS
Strivers A2Z DSA Co...
walkccc/LeetCode...
Online Courses - Le...
Meeting Registratio...
Google Cloud Skills...
College Name || Skil...
SmartBridge
Prediction Result
The predicted breed is: german_shepherd
Try Again

7. Advantages & Disadvantages

Advantages:

- Accuracy: Utilizing advanced transfer learning techniques with pre-trained models ensures high accuracy in breed identification.

- Efficiency: Pre-trained models like MobileNetV2 and EfficientNetB7 offer efficient computation, making them suitable for deployment on various devices.

- User-Friendly: The web-based deployment provides an accessible interface for users to identify dog breeds easily.

Disadvantages:

- Data Dependency: The model's performance is heavily reliant on the quality and diversity of the training data.

- Resource Intensive: Training deep learning models can be resource-intensive, requiring significant computational power and memory.

- Maintenance: Keeping the model updated with new data and breeds can be challenging and time-consuming.

8. Conclusion

The Dog Breed Classification project successfully demonstrates the application of advanced machine learning techniques to accurately identify dog breeds from images. By leveraging pre-trained models and a robust dataset, the project provides a reliable tool for veterinarians, rescue organizations, and pet owners. The deployment as a web application ensures accessibility and usability.

9. Future Scope

- Model Improvement: Continuously improving the model by incorporating new data and exploring more advanced architectures.

- Mobile Application: Developing a mobile application version for easier access and usability on handheld devices.

- Integration with Veterinary Systems: Integrating the model with veterinary systems to assist in clinical decision-making and pet care management.

- Real-time Identification: Enhancing the model to support real-time breed identification through live camera feeds.

GitHub & Project Demo Link

- GitHub Repository: https://github.com/sjainpropy9724/Dog-Breed-Identification-using-Transfer-Learning

- Project Demo: https://drive.google.com/file/d/1JLaK8uAg_qrk32SacO3nw8unJ6niehCO/view?usp=sharing