FINAL PROJECT REPORT

1.INTRODUCTION

1.1. PROJECT OVERVIEW:

Objective	To develop a high-accuracy image classification system capable of identifying dog breeds, even with subtle visual differences, using transfer learning.
Scope	The system will classify dog breeds from images and be deployable for use in applications such as pet registration, veterinary support, animal shelter systems, and lost pet recovery.
Problem Statement	
Description	Accurate breed identification is challenging due to the high degree of visual similarity among breeds. This project utilizes pre-trained convolutional neural networks (e.g., ResNet, EfficientNet) fine-tuned on a curated dataset of labeled dog breed images. The goal is to enable reliable, real-time classification by learning fine-grained visual features.
Impact	**Pet owners:** Simplified registration and breed recognition. **Veterinarians:** Tailored health guidance based on breed-specific traits. **Animal shelters:** Faster breed identification for adoption/rescue. **Lost pet services:** Visual matching of found animals with missing pet databases.
Proposed Solution	
Approach	1. **Dataset Collection & Curation** (from open sources like Kaggle/Stanford Dogs) 2. **Data Augmentation** for better generalization 3. **Transfer Learning** using models like ResNet50 or EfficientNetB0 4. **Fine-tuning** with breed-specific layers

	5. **Evaluation** using metrics like accuracy, precision, and recall 6. **Deployment** via a web/mobile interface
Key Features	• High-accuracy classification of over 100 dog breeds • Fine-grained feature recognition (e.g., snout shape, coat texture) • Lightweight, fast inference for mobile/web deployment • Scalable for future addition of new breeds • API support for integration into external applications

1.2.OBJECTIVE:

To develop a high-accuracy image classification system capable of identifying dog breeds, even with subtle visual differences, using transfer learning. It will give High-accuracy classification of over 100 dog breeds, Fine-grained feature recognition (e.g., snout shape, coat texture),Lightweight, fast inference for mobile/web deployment, Scalable for future addition of new breeds and API support for integration into external applications.

2.PROJECT INITIALIZATION AND PLANNING PHASE

2.1.Define Problem Statement:

Accurate identification of dog breeds from images presents a significant challenge due to the high visual similarity between many breeds. Traditional image recognition systems often fail to distinguish between breeds with subtle differences in features such as coat colour, size, or facial structure. This leads to misidentification, which can have practical implications for pet owners, veterinarians, animal shelters, and researchers.

To address this, the project proposes a transfer learning-based image classification model trained on a diverse set of dog breed images. By leveraging pre-trained deep learning architectures and fine-tuning them on a curated dataset, the model aims to learn fine-grained visual patterns that differentiate breeds more effectively. This system can serve multiple real-world use cases:

- Pet registration systems for breed documentation.
- Veterinary clinics for breed-specific medical advice.
- Shelters for faster breed identification and rehoming.
- Lost pet identification through visual search apps.

Visual Similarity confusion between breeds:

Image	Actual Breed	Predicted Breed	Issue
	Labrador Retriever	Golden Retriever	Similar coat color and size

Goal:

To build an intelligent breed classification system using transfer learning that consistently outperforms traditional methods by accurately identifying dog breeds, even among visually similar categories

2.2 Project Proposal (Proposed Solution)

The proposal report aims to build an intelligent breed classification system using transfer learning that consistently outperforms traditional methods by accurately identifying dog breeds, even among visually similar categories.

Approach	7. **Dataset Collection & Curation** (from open sources like Kaggle/Stanford Dogs) 8. **Data Augmentation** for better generalization 9. **Transfer Learning** using models like ResNet50 or EfficientNetB0 10. **Fine-tuning** with breed-specific layers 11. **Evaluation** using metrics like accuracy, precision, and recall 12. **Deployment** via a web/mobile interface
Key Features	• High-accuracy classification of over 100 dog breeds • Fine-grained feature recognition (e.g., snout shape, coat texture) • Lightweight, fast inference for mobile/web deployment • Scalable for future addition of new breeds • API support for integration into external applications

2.3 Initial Project Planning:

Product Backlog, Sprint Schedule, and Estimation (4 Marks)

Sprint Task Table

Sprint	Functional Requirement (Epic)	User Story Number	User Story / Task	Priority	Team Members	Sprint Start Date	Sprint End Date (Planned)
Sprint-1	Data Collection and	SL-3	Understanding & loading data	Low	Dhiraj	13/06/25	14/06/25

Sprint	Functional Requirement (Epic)	User Story Number	User Story / Task	Priority	Team Members	Sprint Start Date	Sprint End Date (Planned)
	Preprocessing						
Sprint-	Data Collection and Preprocessing	SL-4	Data cleaning	High	Dhiraj	13/06/25	14/06/25
Sprint-2	Model Development	SL-8	Training the model	Medium	Nandita	14/06/25	16/06/25
Sprint-2	Model tuning and testing	SL-14	Model testing	Medium	Amrita	17/06/25	17/06/25
Sprint-3	Web integration and Deployment	SL-16	Building HTML templates	Low	Aditi	17/06/25	18/06/25
Sprint-3	Web integration and Deployment	SL-17	Local deployment	Medium	Aditi	17/06/25	18/06/25
Sprint-4	Project Report	SL-20	Report	Medium	Amrita	18/06/25	19/06/25

3. Data Collection and Preprocessing phase

3.1 Data Collection plan and Raw Data sources identified

Elevate your data strategy with the Data Collection plan and the Raw Data Sources report, ensuring meticulous data curation and integrity for informed decision-making in every analysis and decision-making endeavor.

Data Collection Plan :

Section	Description
Project Overview	Dog Breed Identification using Transfer Learning" aims to develop a robust machine learning model for accurately classifying dog breeds from images. The project leverages transfer learning, a technique that utilizes pre-trained deep learning models as feature extractors, to overcome the challenges of limited training data and computational resources. By fine-tuning a pre-trained convolutional neural network (CNN) on a dataset of dog images, the model learns to distinguish between different breeds with high accuracy. The resulting system provides a valuable tool for dog breed recognition in various applications, including pet care, veterinary medicine, and animal welfare.
Data Collection Plan	The datasets are acquired from Kaggle

Raw Data Sources :

Source Name	Description	Location/URL	Format	Size	Access Permissions
Kaggle Dataset 1	The training dataset consists of folders corresponding to each class containing image data.	https://www.kaggle.com/competitions/dog-breed-identification/	Image	344 MB	Public
Label	Contains the label for all the images in the dataset	https://www.kaggle.com/competitions/dog-breed-identification/	CSV	471 KB	Public
Kaggle Dataset 2	The testing dataset consists of folders corresponding to each class containing image data.	https://www.kaggle.com/datasets/gpiosenka/70-dog-breedsimage-data-set	Image	344 MB	Public
Dogs	Contains the label for all the images in the dataset	https://www.kaggle.com/datasets/gpiosenka/70-dog-breedsimage-data-set	CSV	471 KB	Public

3.2 Data Quality Report:

The Data Quality Report Template will summarize data quality issues from the selected source, including severity levels and resolution plans. It will aid in systematically identifying and rectifying data discrepancies.

Data Source	Data Quality Issue	Severity	Resolution Plan
Kaggle Dataset 1	The testing data was unlabelled.	Moderate	Separate data were used to verify the accuracy of the model
Kaggle Dataset 1	The dataset had more than required classes	Low	The data of required classes were filtered
Kaggle Dataset 1	The data were not classified into folders	Low	The data were filtered into folders using os module functions
Kaggle Dataset 2	The labels were not matching with training dataset	Low	Used string modification functions to normalize the labels

3.3. Data Processing:

The images will be preprocessed by resizing, normalizing, converting color space and batch normalizing. These steps will enhance data quality, promote model generalization, and improve convergence during neural network training, ensuring robust and efficient performance across various computer vision tasks.

Section	Description
Data Overview	The dataset contains 10,222 images categorized into 120 classes. For training purposes, only 20 of these classes were selected, comprising a total of 1,683 images.
Resizing	The images were resized to 224 × 224 pixels to ensure uniformity.
Normalization	Pixel values were normalized to a target range of 0 to 1.
Color Space Conversion	The images are taken BGR format
Batch Normalization	A batch size of 32 was used during model training.
Data Preprocessing Code Screenshots	

Loading Data

```
!rm -rf /content/subset
```

```
!pip install -q kaggle
```

```
!mkdir ~/.kaggle
```

```
!cp kaggle.json ~/.kaggle
```

```
!kaggle competitions download -c dog-breed-identification
```

```
Warning: Your Kaggle API key is readable by other users on this system! To fix this, you can run 'chmod 600 /root/.kaggle/kaggle.json'
Downloading dog-breed-identification.zip to /content
 96% 665M/691M [00:01<00:00, 262MB/s]
100% 691M/691M [00:01<00:00, 379MB/s]
```

```
!unzip /content/dog-breed-identification.zip
```

```
  inflating: train/87a2b416edf49358251c500097885887.jpg
  inflating: train/87a8f6b9a0e618486e67662a133e9e61.jpg
  inflating: train/87b33815ce34f2c2d98b2374c32ce3a5.jpg
  inflating: train/87c3089fb8c7c00ae4ce78b939530f84.jpg
```

Resizing

```
# datagen = ImageDataGenerator ()
generator = train_datagen.flow_from_directory(
  '/content/subset/train',
  target_size=(224, 224), # Adjust target size as needed
  batch_size=32,
  class_mode='categorical',
  shuffle=False, # Ensure order is maintained for class indices
  classes=selected_classes # Specify the selected classes
)
```

Normalization

```
#import image datagenerator library
from tensorflow.keras.preprocessing.image import ImageDataGenerator
train_datagen=ImageDataGenerator(rescale=1./255,shear_range=0.2,zoom_range=0.2,horizontal_flip=True)
```

Batch Normalization

```
# datagen = ImageDataGenerator ()
generator = train_datagen.flow_from_directory(
  '/content/subset/train',
  target_size=(224, 224), # Adjust target size as needed
  batch_size=32,
  class_mode='categorical',
  shuffle=False, # Ensure order is maintained for class indice
  classes=selected_classes # Specify the selected classes
)
```

4.Model Development Phase

4.1.Model Selection Report:

Model	Description
VGG19	VGG19 is a deep CNN with 19 layers, pre-trained on ImageNet. It performs well for image classification tasks and can capture detailed spatial features. However, due to its large size and high number of parameters, it can be slow to train and prone to overfitting on smaller datasets.
MobileNet V2	MobileNetV2 is a lightweight model designed for mobile and low-resource environments. It uses depth-wise separable convolutions and performs well even with limited data. Its smaller size makes it faster to train and less prone to overfitting,
EfficientNe tB0	Balances performance and efficiency using a compound scaling method. Offers better accuracy and lower computational cost compared to VGG19 and MobileNetV2. Suitable for most tasks, especially when both accuracy and speed are important.

4.2.Initial Model Training Code, Model Validation and Evaluation Report

Model Building

```python
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.layers import Dense
from tensorflow.keras.activations import softmax
from keras import activations
```

```python
from tensorflow. keras.applications. vgg19 import VGG19
from tensorflow. keras. layers import Dense, Flatten
from tensorflow. keras.models import Model
from tensorflow.keras.optimizers import Adam
```

```python
Image_size=[224,224]
```

```python
base_model=VGG19(input_shape=Image_size + [3] , weights='imagenet' , include_top = False)
```

```python
for i in base_model.layers:
  i.trainable = False
```

```python
y=Flatten()(base_model.output)
```

```python
output=Dense(20,activation='softmax')(y)
```

```python
vgg19=Model(inputs=base_model.input,outputs=output)
```

Model Validation and Evaluation Report (5 marks):

Model	Summary	Training and Validation Performance Metrics
VGG19		

```python
vgg19.summary()
```

Model: "functional_1"

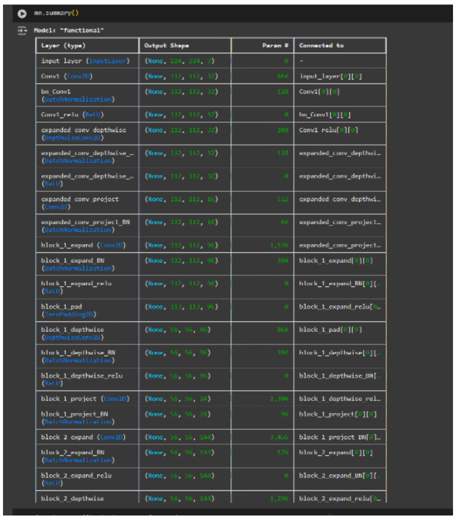
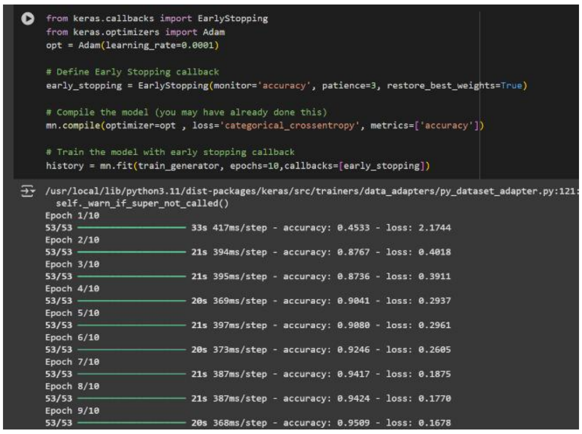
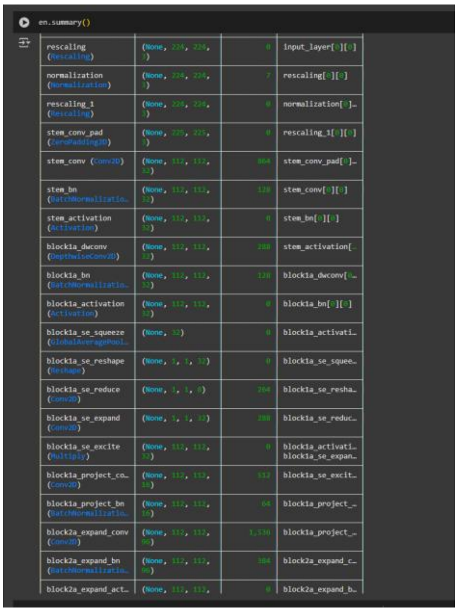
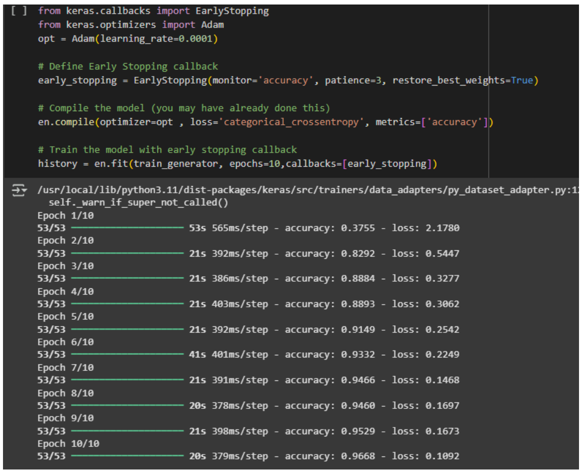
Layer (type)	Output Shape	Param #
input_layer_1 (InputLayer)	(None, 224, 224, 3)	0
block1_conv1 (Conv2D)	(None, 224, 224, 64)	1,792
block1_conv2 (Conv2D)	(None, 224, 224, 64)	36,928
block1_pool (MaxPooling2D)	(None, 112, 112, 64)	0
block2_conv1 (Conv2D)	(None, 112, 112, 128)	73,856
block2_conv2 (Conv2D)	(None, 112, 112, 128)	147,584
block2_pool (MaxPooling2D)	(None, 56, 56, 128)	0
block3_conv1 (Conv2D)	(None, 56, 56, 256)	295,168
block3_conv2 (Conv2D)	(None, 56, 56, 256)	590,080
block3_conv3 (Conv2D)	(None, 56, 56, 256)	590,080
block3_conv4 (Conv2D)	(None, 56, 56, 256)	590,080
block3_pool (MaxPooling2D)	(None, 28, 28, 256)	0
block4_conv1 (Conv2D)	(None, 28, 28, 512)	1,180,160
block4_conv2 (Conv2D)	(None, 28, 28, 512)	2,359,808
block4_conv3 (Conv2D)	(None, 28, 28, 512)	2,359,808
block4_conv4 (Conv2D)	(None, 28, 28, 512)	2,359,808
block4_pool (MaxPooling2D)	(None, 14, 14, 512)	0
block5_conv1 (Conv2D)	(None, 14, 14, 512)	2,359,808
block5_conv2 (Conv2D)	(None, 14, 14, 512)	2,359,808
block5_conv3 (Conv2D)	(None, 14, 14, 512)	2,359,808
block5_conv4 (Conv2D)	(None, 14, 14, 512)	2,359,808
block5_pool (MaxPooling2D)	(None, 7, 7, 512)	0
flatten_1 (Flatten)	(None, 25088)	0
dense_1 (Dense)	(None, 20)	501,780

Total params: 20,526,164 (78.30 MB)
Trainable params: 501,780 (1.91 MB)
Non-trainable params: 20,024,384 (76.39 MB)

```python
from keras.callbacks import EarlyStopping
from keras.optimizers import Adam
opt = Adam(learning_rate=0.0001)

# Define Early Stopping callback
early_stopping = EarlyStopping(monitor='accuracy', patience=3, restore_best_weights=True)

# Compile the model (you may have already done this)
vgg19.compile(optimizer=opt , loss='categorical_crossentropy', metrics=['accuracy'])

# Train the model with early stopping callback
history = vgg19.fit(generator, epochs=50,callbacks=[early_stopping])
```

```
Epoch 1/50
53/53 ━━━━━━━━━━━━━━━━━━━━ 27s 476ms/step - accuracy: 0.5952 - loss: 2.0641
Epoch 2/50
53/53 ━━━━━━━━━━━━━━━━━━━━ 24s 456ms/step - accuracy: 0.9821 - loss: 0.0747
Epoch 3/50
53/53 ━━━━━━━━━━━━━━━━━━━━ 24s 457ms/step - accuracy: 0.9716 - loss: 0.0978
Epoch 4/50
53/53 ━━━━━━━━━━━━━━━━━━━━ 24s 455ms/step - accuracy: 0.9732 - loss: 0.0928
Epoch 5/50
53/53 ━━━━━━━━━━━━━━━━━━━━ 41s 460ms/step - accuracy: 0.9820 - loss: 0.0710
```

Saving the model

MobileNetV2		
EfficientNetB0		

```
from keras.callbacks import EarlyStopping
from keras.optimizers import Adam
opt = Adam(learning_rate=0.0001)

# Define Early Stopping callback
early_stopping = EarlyStopping(monitor='accuracy', patience=3, restore_best_weights=True)

# Compile the model (you may have already done this)
mn.compile(optimizer=opt , loss='categorical_crossentropy', metrics=['accuracy'])

# Train the model with early stopping callback
history = mn.fit(train_generator, epochs=10,callbacks=[early_stopping])

/usr/local/lib/python3.11/dist-packages/keras/src/trainers/data_adapters/py_dataset_adapter.py:121:
  self._warn_if_super_not_called()
Epoch 1/10
53/53 ━━━━━━━━━━━━━━━━━━━━ 33s 417ms/step - accuracy: 0.4533 - loss: 2.1744
Epoch 2/10
53/53 ━━━━━━━━━━━━━━━━━━━━ 21s 394ms/step - accuracy: 0.8767 - loss: 0.4018
Epoch 3/10
53/53 ━━━━━━━━━━━━━━━━━━━━ 21s 395ms/step - accuracy: 0.8736 - loss: 0.3911
Epoch 4/10
53/53 ━━━━━━━━━━━━━━━━━━━━ 20s 369ms/step - accuracy: 0.9041 - loss: 0.2937
Epoch 5/10
53/53 ━━━━━━━━━━━━━━━━━━━━ 21s 397ms/step - accuracy: 0.9080 - loss: 0.2961
Epoch 6/10
53/53 ━━━━━━━━━━━━━━━━━━━━ 20s 373ms/step - accuracy: 0.9246 - loss: 0.2605
Epoch 7/10
53/53 ━━━━━━━━━━━━━━━━━━━━ 21s 387ms/step - accuracy: 0.9417 - loss: 0.1875
Epoch 8/10
53/53 ━━━━━━━━━━━━━━━━━━━━ 21s 387ms/step - accuracy: 0.9424 - loss: 0.1770
Epoch 9/10
53/53 ━━━━━━━━━━━━━━━━━━━━ 20s 368ms/step - accuracy: 0.9509 - loss: 0.1678
```

```
from keras.callbacks import EarlyStopping
from keras.optimizers import Adam
opt = Adam(learning_rate=0.0001)

# Define Early Stopping callback
early_stopping = EarlyStopping(monitor='accuracy', patience=3, restore_best_weights=True)

# Compile the model (you may have already done this)
en.compile(optimizer=opt , loss='categorical_crossentropy', metrics=['accuracy'])

# Train the model with early stopping callback
history = en.fit(train_generator, epochs=10,callbacks=[early_stopping])

/usr/local/lib/python3.11/dist-packages/keras/src/trainers/data_adapters/py_dataset_adapter.py:1
  self._warn_if_super_not_called()
Epoch 1/10
53/53 ━━━━━━━━━━━━━━━━━━━━ 53s 565ms/step - accuracy: 0.3755 - loss: 2.1780
Epoch 2/10
53/53 ━━━━━━━━━━━━━━━━━━━━ 21s 392ms/step - accuracy: 0.8292 - loss: 0.5447
Epoch 3/10
53/53 ━━━━━━━━━━━━━━━━━━━━ 21s 386ms/step - accuracy: 0.8884 - loss: 0.3277
Epoch 4/10
53/53 ━━━━━━━━━━━━━━━━━━━━ 21s 403ms/step - accuracy: 0.8893 - loss: 0.3062
Epoch 5/10
53/53 ━━━━━━━━━━━━━━━━━━━━ 21s 392ms/step - accuracy: 0.9149 - loss: 0.2542
Epoch 6/10
53/53 ━━━━━━━━━━━━━━━━━━━━ 41s 401ms/step - accuracy: 0.9332 - loss: 0.2249
Epoch 7/10
53/53 ━━━━━━━━━━━━━━━━━━━━ 21s 391ms/step - accuracy: 0.9466 - loss: 0.1468
Epoch 8/10
53/53 ━━━━━━━━━━━━━━━━━━━━ 20s 378ms/step - accuracy: 0.9460 - loss: 0.1697
Epoch 9/10
53/53 ━━━━━━━━━━━━━━━━━━━━ 21s 398ms/step - accuracy: 0.9529 - loss: 0.1673
Epoch 10/10
53/53 ━━━━━━━━━━━━━━━━━━━━ 20s 379ms/step - accuracy: 0.9668 - loss: 0.1092
```

5.Model Optimization and Tuning Phase

5.1.Tuning Documentation:

Model	Tuned Hyperparameters

<table>
<tr>
<td>VGG19</td>
<td>

```
from keras.callbacks import EarlyStopping
from keras.optimizers import Adam
opt = Adam(learning_rate=0.0001)

# Define Early Stopping callback
early_stopping = EarlyStopping(monitor='accuracy', patience=3, restore_best_weights=True)

# Compile the model (you may have already done this)
vgg19.compile(optimizer=opt , loss='categorical_crossentropy', metrics=['accuracy'])

# Train the model with early stopping callback
history = vgg19.fit(generator, epochs=50,callbacks=[early_stopping])
```

1. Batch Size = 32
2. Epochs = 50
3. Learning Rate = 0.0001
4. Optimizer: Adam optimizer
5. Loss Function: categorical crossentropy
6. Image Size = (224 × 224).

</td>
</tr>
<tr>
<td>MobileNetV2</td>
<td>

```
from keras.callbacks import EarlyStopping
from keras.optimizers import Adam
opt = Adam(learning_rate=0.0001)

# Define Early Stopping callback
early_stopping = EarlyStopping(monitor='accuracy', patience=3, restore_best_weights=True)

# Compile the model (you may have already done this)
mn.compile(optimizer=opt , loss='categorical_crossentropy', metrics=['accuracy'])

# Train the model with early stopping callback
history = mn.fit(train_generator, epochs=10,callbacks=[early_stopping])
```

1. Batch Size = 32
2. Epochs = 10
3. Learning Rate = 0.0001
4. Optimizer: Adam optimizer
5. Loss Function: categorical crossentropy
6. Image Size = (224 × 224).

</td>
</tr>
</table>

<table>
<tr>
<td>EfficientNet B0</td>
<td>

```
from keras.callbacks import EarlyStopping
from keras.optimizers import Adam
opt = Adam(learning_rate=0.0001)

# Define Early Stopping callback
early_stopping = EarlyStopping(monitor='accuracy', patience=3, restore_best_weights=True)

# Compile the model (you may have already done this)
en.compile(optimizer=opt , loss='categorical_crossentropy', metrics=['accuracy'])

# Train the model with early stopping callback
history = en.fit(train_generator, epochs=10,callbacks=[early_stopping])
```

1. Batch Size = 32
2. Epochs = 10
3. Learning Rate = 0.0001
4. Optimizer: Adam optimizer
5. Loss Function: categorical crossentropy
6. Image Size = (224 × 224).

</td>
</tr>
</table>

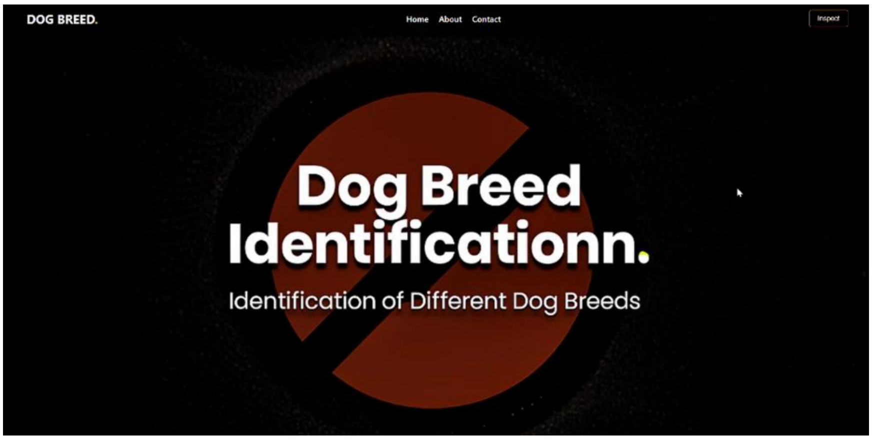
5.2. Final Model Selection Justification:

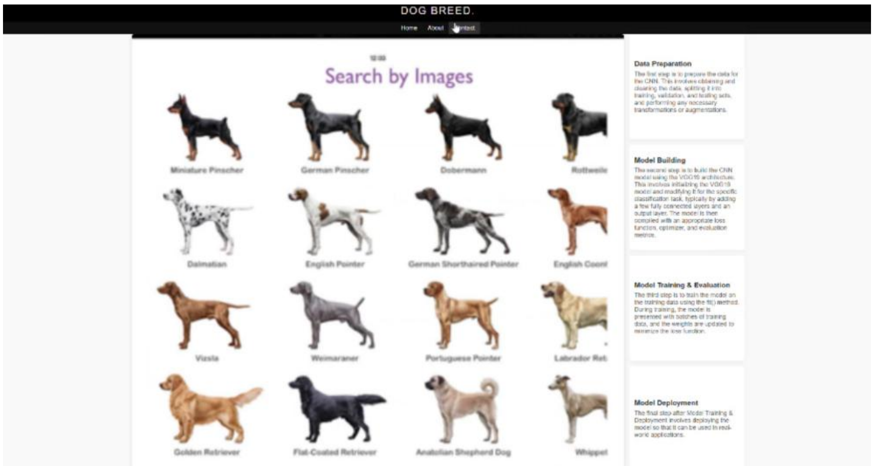
Final Model	Reasoning
MobileNetV2	For this project, MobileNetV2 was chosen as the final model for dog breed classification using transfer learning. This decision was based on a combination of empirical performance and architectural advantages. Among the evaluated models, MobileNetV2 achieved the highest training and testing accuracy, demonstrating strong generalization capabilities even on a relatively small dataset of 1683 images across 20 classes. Its lightweight architecture, which uses depth-wise separable convolutions, allows it to maintain high efficiency while reducing the number of trainable parameters compared to larger models like VGG19. This made it particularly well-suited for our limited data scenario, where larger models tend to overfit. Additionally, MobileNetV2's

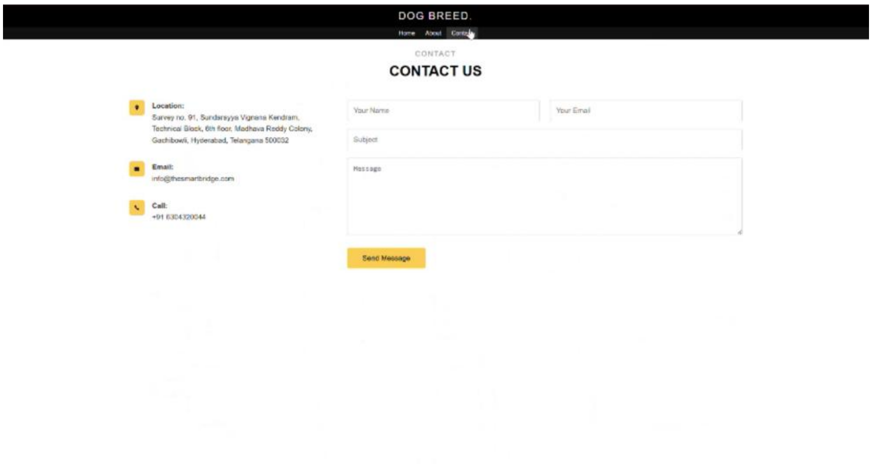
	pretrained weights on ImageNet allow it to transfer rich feature representations, significantly improving convergence speed and accuracy. The model is also highly compatible with deployment environments due to its low computational footprint, making it an ideal choice for real-time applications on mobile or web platforms.

6.Result

6.1.Output Screenshots:






DOG BREED.
Home
About
CONTACT
CONTACT US
Location:
Survey no. 91, Sundarayya Vignana Kendram, Technical Block, 6th floor, Madhava Reddy Colony, Gachibowli, Hyderabad, Telangana 500032
Email:
info@thesmartbridge.com
Call:
+91 6304320044
Your Name
Your Email
Subject
Message
Send Message


DOG BREED.
Home
About
Contact
Dog Breed Classifier
Choose File shitzu.jpg
Prediction:
Shih-tzu

7.Advantages and Disadvantages

Advantages

1. **High Accuracy on Similar Breeds:**
   Transfer learning enables the model to recognize fine-grained visual features, improving accuracy even for look-alike breeds.

2. **Reduced Training Time and Data Requirement:**
   Using pre-trained models drastically cuts down the need for massive datasets and training time.

3. **Scalability:**
   New breeds can be added to the system by fine-tuning with additional images, making the system adaptable.

4. **Real-World Utility:**
   Helps in pet registration, lost pet recovery, breed-specific health recommendations, and adoption processes.

5. **Cross-Platform Deployment:**
   Can be integrated into web/mobile apps, veterinary software, and shelter databases.

6. **Cost-Effective:**
   Eliminates the need for manual breed identification by experts, reducing time and resources.

DISADVANTAGES

1. **Bias from Pre-trained Models:**
   If the pre-trained model was trained on biased data (e.g., underrepresented breeds), it may lead to misclassifications.
2. **Dependence on Image Quality:**
   Poor lighting, angles, or occlusions (e.g., accessories or dirt) can affect the model's performance.
3. **Limited to Visual Features:**
   The system can't account for genetic or behavioral traits that may also define a breed.
4. **Maintenance Overhead:**
   As new breeds emerge or breed standards evolve, the model will require updates and re-training.
5. **Overfitting Risk:**
   Without proper data augmentation and regularization, the model may overfit to specific features in the training dataset.

6. **Computation Requirements:**
   Training and even inference may need powerful hardware, especially for high-resolution images or real-time use.

8.Conclusion

The proposed dog breed identification system leverages transfer learning to accurately classify dog breeds from images, addressing the limitations of traditional image recognition methods. By fine-tuning pre-trained deep learning models on a curated dataset, the system can detect subtle visual distinctions between breeds, offering a practical solution for pet owners, veterinarians, shelters, and animal welfare applications. While challenges such as image quality and model bias exist, the advantages in terms of accuracy, efficiency, and real-world impact make this a valuable and scalable tool. With proper data management and model updates, the system holds strong potential for broad adoption and continued improvement.

9.Future Scope

1. **Real-Time Mobile Applications:**
   Deploy the model in lightweight mobile apps for instant breed recognition through smartphone cameras.
2. **Mixed Breed Detection:**
   Enhance the model to identify and estimate breed composition in mixed-breed dogs using ensemble or hybrid models.
3. **Integration with Veterinary Systems:**
   Link with vet databases to provide instant breed-specific health tips and vaccination schedules.
4. **Lost & Found Pet Platforms:**
   Implement visual matching systems in pet recovery platforms to compare found pet images with missing pet reports.
5. **Global Breed Expansion:**
   Expand the dataset to include lesser-known and region-specific dog breeds for broader international application.
6. **Explainable AI Features:**
   Add interpretability to the model using Grad-CAM or similar methods to highlight the features that influenced breed predictions.
7. **Voice and Behavior Analysis Integration:**
   Combine visual identification with audio cues or behavior data for a more holistic breed assessment.
8. **Cloud-Based API Services:**
   Offer the model as a cloud API that can be integrated into third-party apps and services like pet adoption platforms and smart pet cameras.

10.Appendix

10.1 Source Code

Data collection and Preprocessing¶

In [ ]:

```
!rm -rf /content/subset
```

In [ ]:

```
!pip install -q kaggle
```

In [ ]:

```
!mkdir ~/.kaggle
```

In [ ]:

```
!cp kaggle.json ~/.kaggle
```

In [ ]:

```
!kaggle competitions download -c dog-breed-identification
```

```
Warning: Your Kaggle API key is readable by other users on this system! To
fix this, you can run 'chmod 600 /root/.kaggle/kaggle.json'
Downloading dog-breed-identification.zip to /content
 96% 665M/691M [00:01<00:00, 262MB/s]
100% 691M/691M [00:01<00:00, 379MB/s]
```

In [ ]:

```
!unzip /content/dog-breed-identification.zip
```

```
Streaming output truncated to the last 5000 lines.
  inflating: train/83bc62b0fffa99a9c94ba0b67a5f7395.jpg
  inflating: train/83bcff6b55ee179a7c123fa6103c377a.jpg
  inflating: train/83be6d622ab74a5e7e08b53eb8fd566a.jpg
  inflating: train/83c2d7419b0429b9fe953bc1b6cddbec.jpg
  inflating: train/83cf7d7cd2a759a93e2ffd95bea9c6fb.jpg
  inflating: train/83d405858f0931722ef21e8ac0adee4d.jpg
  inflating: train/83d4125a4c3c7dc5956563276cb1cd74.jpg
```

```
  inflating: train/83f0bb565b2186dbcc6a9d009cb26ff2.jpg
  inflating: train/83fad0718581a696132c96c166472627.jpg
  inflating: train/83fbbcc9a612e3f712b1ba199da61f20.jpg
  inflating: train/8403d8936430c2f05ab7d74d23c2c0cb.jpg
  inflating: train/8406d837b2d7fac1c3cd621abb4c4f9e.jpg
  inflating: train/840b67d26e5e43f8eb6430f62d4ba1ac.jpg
  inflating: train/840db91ba4600148f3dcb06ec419b421.jpg
  inflating: train/840dbad5a691c22611d85b2488bf4cbb.jpg

  inflating: train/ffe2ca6c940cddfee68fa3cc6c63213f.jpg
  inflating: train/ffe5f6d8e2bff356e9482a80a6e29aac.jpg
  inflating: train/fff43b07992508bc822f33d8ffd902ae.jpg
```

In [ ]:

```
import os
import shutil
import sys
import pandas as pd
```

In [ ]:

```
dataset_dir = '/content/train'
test_data_dir='/content/test'
labels = pd.read_csv('/content/labels.csv')
```

In [ ]:

```
def make_dir(x):
  if os.path.exists(x) == False:
    os.makedirs (x)


base_dir = './subset'
make_dir (base_dir)
```

In [ ]:

```
train_dir = os.path. join(base_dir, 'train')
test_dir=os.path.join(base_dir,'test')
```

```
make_dir(train_dir)
make_dir(test_dir)
```

In [ ]:

```
selected_classes = [ 'affenpinscher', 'beagle', 'appenzeller', 'basset',
'bluetick', 'boxer', 'cairn', 'doberman', 'german_shepherd', 'golden_retriever',
'kelpie', 'komondor', 'leonberg',
'mexican_hairless', 'pug', 'redbone', 'shih-tzu', 'toy_poodle', 'vizsla',
'whippet']
len(selected_classes)
```

Out[ ]:

20

In [ ]:

```
breeds = labels.breed. unique()
for breed in selected_classes:
 # Make folder for each breed
 _= os.path.join(train_dir, breed)
 make_dir(_)

 # Copy images to the corresponding folders
 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)
```

In [ ]:

```
#import image datagenerator library
from tensorflow.keras.preprocessing.image import ImageDataGenerator
train_datagen=ImageDataGenerator(rescale=1./255,shear_range=0.2,zoo
m_range=0.2,horizontal_flip=True)
```

In [ ]:

```
# datagen = ImageDataGenerator ()
generator = train_datagen.flow_from_directory(
  '/content/subset/train',
  target_size=(224, 224), # Adjust target size as needed
  batch_size=32,
  class_mode='categorical',
  shuffle=False, # Ensure order is maintained for class indices
  classes=selected_classes # Specify the selected classes
)
# test_datagen=ImageDataGenerator(rescale=1./255)
# test_generator = test_datagen.flow_from_directory(
#   '/content/subset/test',
#   target_size=(224, 224), # Adjust target size as needed
#   batch_size=32,
#   class_mode='categorical',
#   shuffle=False, # Ensure order is maintained for class indices
#   classes=selected_classes # Specify the selected classes
# )
```

Found 1683 images belonging to 20 classes.
Found 0 images belonging to 20 classes.

Model Building¶

MobileNetV2¶

In [ ]:

```
import tensorflow as tf
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.applications import MobileNetV2
from tensorflow.keras.applications.mobilenet_v2 import preprocess_input
from tensorflow.keras.layers import GlobalAveragePooling2D, Dropout,
Dense
from tensorflow.keras.models import Model
from tensorflow.keras.callbacks import EarlyStopping
```

In [ ]:

```
from tensorflow. keras. layers import Dense, Flatten
from tensorflow. keras.models import Model
from tensorflow.keras.optimizers import Adam
```

In [ ]:

```
Image_size=[224,224]
```

In [ ]:

```
base_model=MobileNetV2(input_shape=Image_size + [3] ,
weights='imagenet' , include_top = False)
```

```
Downloading data from https://storage.googleapis.com/tensorflow/keras-applications/mobilenet_v2/mobilenet_v2_weights_tf_dim_ordering_tf_kernels_1.0_224_no_top.h5
9406464/9406464 ━━━━━━━━━━━━━━━━━━━━ 0s
0us/step
```

In [ ]:

```
for i in base_model.layers:
  i.trainable = False
```

In [ ]:

```
y=Flatten()(base_model.output)
```

In [ ]:

```
output=Dense(20,activation='softmax')(y)
```

In [ ]:

```
mn=Model(inputs=base_model.input,outputs=output)
```

In [ ]:

```
mn.summary()
```

Model: "functional"

Layer (type)	Output Shape	Param #	Connected to
input_layer (InputLayer)	(None, 224, 224, 3)	0	-
Conv1 (Conv2D)	(None, 112, 112, 32)	864	input_layer[0][0]
bn_Conv1 (BatchNormalization)	(None, 112, 112, 32)	128	Conv1[0][0]
Conv1_relu (ReLU)	(None, 112, 112, 32)	0	bn_Conv1[0][0]
expanded_conv_depthwise (DepthwiseConv2D)	(None, 112, 112, 32)	288	Conv1_relu[0][0]
expanded_conv_depthwise_… (BatchNormalization)	(None, 112, 112, 32)	128	expanded_conv_depthwi…
expanded_conv_depthwise_… (ReLU)	(None, 112, 112, 32)	0	expanded_conv_depthwi…

```
────────────────┼───────────────────────┤
│ expanded_conv_project    │ (None, 112, 112, 16)  │        512 │
expanded_conv_depthwi… │
│ (Conv2D)            │             │         │             │
 ├──────────────────────────┼───────────────────────┼
────────────────┼───────────────────────┤
│ expanded_conv_project_BN │ (None, 112, 112, 16)  │         64 │
expanded_conv_project… │
│ (BatchNormalization)     │             │         │             │
 ├──────────────────────────┼───────────────────────┼
────────────────┼───────────────────────┤
│ block_1_expand (Conv2D)  │ (None, 112, 112, 96)  │      1,536 │
│ flatten (Flatten)        │ (None, 62720)         │          0 │ out_relu[0][0]         │
 ├──────────────────────────┼───────────────────────┼
────────────────┼───────────────────────┤
│ dense (Dense)            │ (None, 20)            │  1,254,420 │ flatten[0][0]          │
└──────────────────────────┴───────────────────────┴
────────────────┴───────────────────────┘
```

Total params: 3,512,404 (13.40 MB)

Trainable params: 1,254,420 (4.79 MB)

Non-trainable params: 2,257,984 (8.61 MB)

In [ ]:

```
from keras.callbacks import EarlyStopping
from keras.optimizers import Adam
opt = Adam(learning_rate=0.0001)

# Define Early Stopping callback
early_stopping = EarlyStopping(monitor='accuracy', patience=3,
restore_best_weights=True)

# Compile the model (you may have already done this)
mn.compile(optimizer=opt , loss='categorical_crossentropy',
```

```
metrics=['accuracy'])

# Train the model with early stopping callback
history = mn.fit(train_generator, epochs=10,callbacks=[early_stopping])
```

```
/usr/local/lib/python3.11/dist-packages/keras/src/trainers/data_adapters/py_dataset_adapter.py:121: UserWarning: Your `PyDataset` class should call `super().__init__(**kwargs)` in its constructor. `**kwargs` can include `workers`, `use_multiprocessing`, `max_queue_size`. Do not pass these arguments to `fit()`, as they will be ignored.
  self._warn_if_super_not_called()
```

```
Epoch 1/10
53/53 ━━━━━━━━━━━━━━━━━━━━ 37s 487ms/step - accuracy: 0.4396 - loss: 2.2295
Epoch 2/10
53/53 ━━━━━━━━━━━━━━━━━━━━ 23s 427ms/step - accuracy: 0.8593 - loss: 0.4512
Epoch 3/10
53/53 ━━━━━━━━━━━━━━━━━━━━ 23s 430ms/step - accuracy: 0.8943 - loss: 0.3610
Epoch 4/10
53/53 ━━━━━━━━━━━━━━━━━━━━ 22s 409ms/step - accuracy: 0.9083 - loss: 0.2969
Epoch 5/10
53/53 ━━━━━━━━━━━━━━━━━━━━ 22s 417ms/step - accuracy: 0.9211 - loss: 0.2452
Epoch 6/10
53/53 ━━━━━━━━━━━━━━━━━━━━ 22s 424ms/step - accuracy: 0.9331 - loss: 0.1990
Epoch 7/10
53/53 ━━━━━━━━━━━━━━━━━━━━ 23s 429ms/step - accuracy: 0.9091 - loss: 0.2969
Epoch 8/10
53/53 ━━━━━━━━━━━━━━━━━━━━ 21s 401ms/step -
```

accuracy: 0.9403 - loss: 0.2139
Epoch 9/10
53/53 ━━━━━━━━━━━━━━━━━━━━ 42s 426ms/step - accuracy: 0.9530 - loss: 0.1671
Epoch 10/10
53/53 ━━━━━━━━━━━━━━━━━━━━ 22s 413ms/step - accuracy: 0.9558 - loss: 0.1240

In [ ]:

```
mn.save("mn.h5")
```

Testing¶

In [ ]:

```
!pip install -q kaggle
```

In [ ]:

```
!mkdir ~/.kaggle
```

In [ ]:

```
!cp kaggle.json ~/.kaggle
```

In [ ]:

```
!kaggle datasets download gpiosenka/70-dog-breedsimage-data-set
```

Warning: Your Kaggle API key is readable by other users on this system! To fix this, you can run 'chmod 600 /root/.kaggle/kaggle.json'
Dataset URL: https://www.kaggle.com/datasets/gpiosenka/70-dog-breedsimage-data-set
License(s): CC0-1.0
Downloading 70-dog-breedsimage-data-set.zip to /content
 81% 174M/215M [00:00<00:00, 656MB/s]
100% 215M/215M [00:00<00:00, 542MB/s]

In [ ]:

```
!unzip /content/70-dog-breedsimage-data-set.zip
```

```
Streaming output truncated to the last 5000 lines.
  inflating: train/Dhole/085.jpg
  inflating: train/Dhole/086.jpg
  inflating: train/Dhole/087.jpg
  inflating: train/Dhole/088.jpg
  inflating: train/Dhole/089.jpg
  inflating: train/Dhole/090.jpg
  inflating: train/Dhole/091.jpg
  inflating: train/Dhole/092.jpg
  inflating: train/Dhole/093.jpg
  inflating: train/Dhole/094.jpg
  inflating: train/Dhole/095.jpg
  inflating: train/Dhole/096.jpg
  inflating: train/Dhole/097.jpg
  inflating: train/Dhole/098.jpg
  inflating: train/Dhole/099.jpg
  inflating: train/Dhole/100.jpg
  inflating: train/Dhole/101.jpg
  inflating: train/Dhole/102.jpg
  inflating:
  inflating: valid/Yorkie/09.jpg
  inflating: valid/Yorkie/10.jpg
```

In [ ]:

```
import os
import shutil
import sys
import pandas as pd
```

In [ ]:

```
!rm -rf /content/filtered_test
```

In [ ]:

```
import os
import shutil
```

```
# Path to the original test folder
source_dir = '/content/test'

# Path where the filtered classes will be copied
target_dir = '/content/filtered_test'

# List of selected class names to keep
selected_classes = [ 'affenpinscher', 'beagle', 'appenzeller', 'basset',
'bluetick', 'boxer', 'cairn', 'doberman', 'german_shepherd', 'golden_retriever',
'kelpie', 'komondor', 'leonberg',
'mexican_hairless', 'pug', 'redbone', 'shih-tzu', 'toy_poodle', 'vizsla',
'whippet']

# Create target directory if it doesn't exist
os.makedirs(target_dir, exist_ok=True)

for class_name in selected_classes:
  print("Name:",class_name.replace('_',' ').title())
  src_class_path = os.path.join(source_dir, class_name.replace('_',' ').title())
  dst_class_path = os.path.join(target_dir, class_name)

  # Check if the class folder exists in source
  if os.path.exists(src_class_path):
    shutil.copytree(src_class_path, dst_class_path)
    # print(f"Copied: {class_name}")
  else:
    os.makedirs(dst_class_path, exist_ok=True)
    # print(f"Created empty folder: {class_name}")
```

Testing MobileNetV5¶

In [ ]:

```
import tensorflow as tf
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.models import load_model
```

```
# Load the trained model
model = load_model('mn.h5')

# Image size and batch settings
image_size = (224, 224)
batch_size = 32

#import image datagenerator library
from tensorflow.keras.applications.mobilenet_v2 import preprocess_input
from tensorflow.keras.preprocessing.image import ImageDataGenerator
datagen=ImageDataGenerator(
    preprocessing_function=preprocess_input,
    rotation_range=30,
    zoom_range=0.2,
    width_shift_range=0.2,
    height_shift_range=0.2,
    shear_range=0.2,
    horizontal_flip=True,
    fill_mode='nearest',
    validation_split=0.2
)

# Testing data
test_generator = datagen.flow_from_directory(
    '/content/filtered_test',
    target_size=(224, 224),
    batch_size=32,
    class_mode='categorical',
    shuffle=True
)
# Evaluate the model
loss, accuracy = model.evaluate(test_generator)
```

```
print(f"Test Loss: {loss:.4f}")
print(f"Test Accuracy: {accuracy:.4f}")
```

WARNING:absl:Compiled the loaded model, but the compiled metrics have yet to be built. `model.compile_metrics` will be empty until you train or evaluate the model.

4/4 ━━━━━━━━━━━━━━━━━━━━ 7s 677ms/step - accuracy: 0.9797 - loss: 0.0551
Test Loss: 0.0815
Test Accuracy: 0.9727

10.2 Github and Project Demo link:

Github:

https://github.com/dhirajskitchen/Dog-Breed-Identification-using-Transfer-Learning

Project Demo Link:

https://drive.google.com/file/d/1FMe_he8XyxUlTZLFeM_gNfz7G_cw8atH/view