DOG BREED IDENTIFICATION USING TRANSFER LEARNING

GROUP MEMBERS:

Thusti Nikhil: 22MH1A0574

M Parimala: 23P35A0412

Lavanya Rajeswari Saride: 22MH1A0563

M Sriram Koteswrao Rao: 22MH1A05J5

1. INTRODUCTION:

1.1 PROJECT OVERVIEWS:

The Dog Breed Identification project leverages transfer learning to classify dog breeds from images. By using a pre-trained convolutional neural network (CNN) model, such as VGG16 or ResNet50, fine-tuned on the dog breed dataset, the project efficiently identifies the breed of a dog from an input image. The process involves preprocessing the images, loading and adapting the pre-trained model, training it on the provided labelled dataset, and evaluating its performance. This approach significantly reduces training time and improves accuracy by utilizing the learned features from large-scale image datasets.

1.2 OBJECTIVES :

The aim of this project is to develop a machine learning model capable of accurately identifying the breed of a dog from an image. This involves leveraging the power of transfer learning to improve accuracy and efficiency in training. Using numpy, keras, seaborn, python, pandas as tools and libraries we can work on the project more effectively. Finally, we can result with the high accuracy of the model and dataset consists of labelled images of dogs belonging to different breeds and this labels are stored in CSV file and the images are stored in a directory.

2. PROJECT INITIALIZTION AND PLANNING PHASE:

2.1 DEFINE PROBLEM STATEMENT:

The problem statement for Dog Breed Identification is to develop an accurate and efficient machine learning model capable of classifying the breed of a dog from a given image. Given a dataset of labeled dog images, the goal is to preprocess the data, train a model using transfer learning techniques, and evaluate its performance to ensure it can reliably distinguish between multiple dog breeds. This solution aims to automate and improve the process of dog breed identification, which is beneficial for applications in veterinary care, pet adoption, and animal research.

Define problem statement- **CLICK HERE**

2.2 PROJECT PROPOSAL (PROPOSED SOLUTION):

The Dog Breed Identification System aims to develop an advanced, user-friendly platform capable of accurately identifying dog breeds from images. This system will leverage machine learning and image recognition technologies to meet the diverse needs of pet owners, veterinarians, shelters, breeders, trainers, law enforcement, and more. The final model will be evaluated and validated to ensure its effectiveness in accurately identifying dog breeds from images.

2.3 INITIAL PROJECT PLANNING :

Project Scope and Objectives:

- **Dataset Preparation:**
  - Collect and preprocess a dataset of labeled dog images.
  - Augment the data to increase diversity and robustness.
- **Model Selection:**
  - Choose a pre-trained convolutional neural network (CNN) model such as VGG16, ResNet50, or InceptionV3 for transfer learning.
- **Model Training:**
  - Fine-tune the selected pre-trained model on the dog breed dataset.
  - Optimize the model's parameters and architecture for better performance.
- **Model Evaluation:**
  - Evaluate the model's accuracy and robustness using validation and test datasets.
  - Implement performance metrics such as accuracy, precision, recall, and F1-score.
- **Deployment:**
  - Develop a user-friendly interface or API for practical use of the model.
  - Deploy the model for real-world applications like veterinary care and pet adoption.

3. DATA COLLECTION AND PREPROCESSING PHASE

3.1 DATA COLLECTION PLAN AND RAW DATA SOURCES IDENTIFIED :

DATA COLLECTION PLAN :

Like we can determine the number of dog breeds to be included and then we can decide the minimum number of images per breed to ensure a balanced dataset. We can collect the images from the kagle dataset and we can also supplement with the additional images from sources like flickr and google images too. Data preprocessing and data augmentation and storage can be done in csv file including image filenames and corresponding breed labels.

RAW DATA SOURCES:

The raw data can be seen in Stanford dogs dataset, it contains 20,000 images of 120 dog breeds with labels and bounding box annotations. Kaggle contains over 10,000 images of 120 breeds with a csv file providing breed labels. And also flickr has high quality images with the ability to search for specific dog breeds. We can also get images from pet adoption websites.

3.2 Data Quality Report :

The completeness can be done by ensuring all dog breeds in the dataset are adequately represented with a sufficient number of images per breed. We can confirm the accuracy of image is correctly labelled with the appropriate dog breed. The standardize image formats and dimensions to maintain uniformly. We can verify that all images are of dogs and not of other animals or irrelevant objects. Using recent and up to date images to ensure the dataset reflects current appearances and characteristics of dog breeds. Ensuring the dataset includes images of dogs in various poses, environments and lighting conditions to improve the models robustness.

3.3 Data Exploration and Preprocessing:

Data Exploration:

Visual Inspection**:** Examine sample images from each breed to understand variations in image quality, size, and labeling accuracy. Statistical Analysis**:** Analyze the distribution of images across different breeds to identify any imbalances or biases in the dataset.

Data Preprocessing:

Resizing**:** Standardize image dimensions to ensure uniform input size for the model (e.g., 224x224 pixels). Normalization**:** Scale pixel values to a range suitable for the neural network, typically between 0 and 1. splitting**:** Divide the dataset into training, validation, and test sets to evaluate model performance effectively.

4 Model Development Phase:

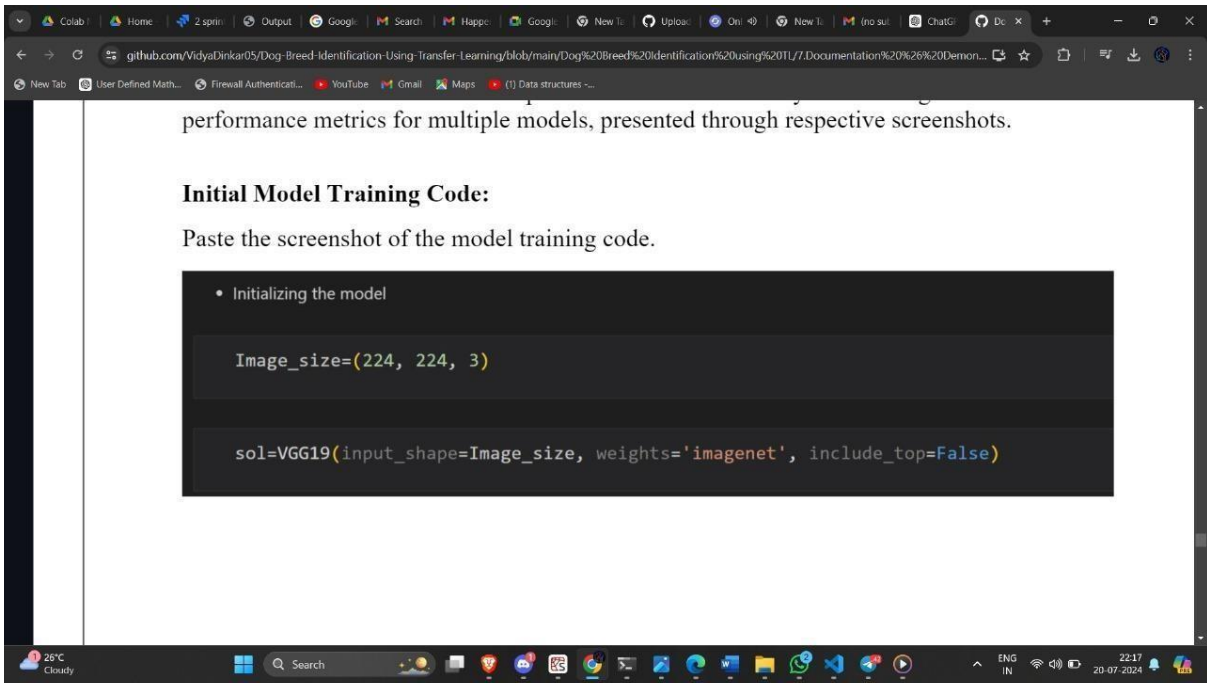
4.1. Model Selection Report

When choosing a model for classification, evaluate various pre-trained convolutional neural network (CNN) models (e.g., VGG16, ResNet50, InceptionV3) based on key metrics such as accuracy, precision, recall, and F1-score. Assess the complexity and size of each model, including the number of parameters and computational requirements. By choose a model that can be easily adapted or scaled to include additional breeds or handle variations in the dataset. By addressing these points in the model selection report, the project ensures the choice of a robust, efficient, and effective model for dog breed identification.

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

Initial Model Training Code, Model Validation and Evaluation Report

Model Training Code:



performance metrics for multiple models, presented through respective screenshots.

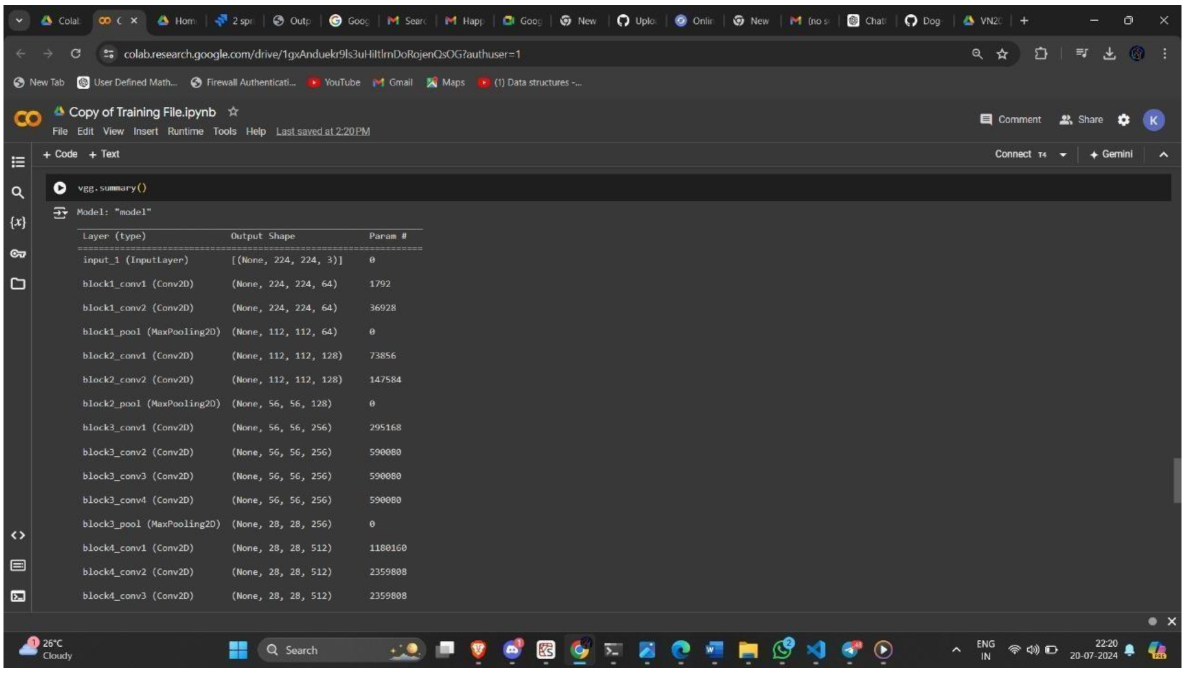
Initial Model Training Code:

Paste the screenshot of the model training code.

- Initializing the model

```
Image_size=(224, 224, 3)
```

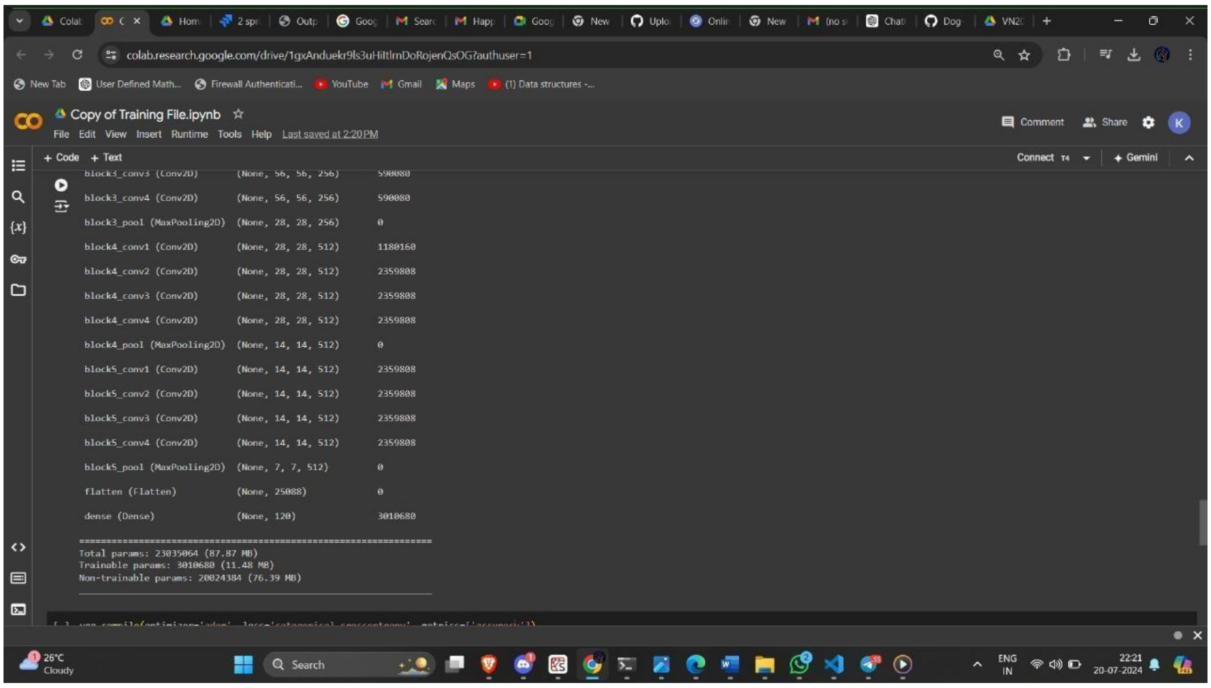
```
sol=VGG19(input_shape=Image_size, weights='imagenet', include_top=False)
```

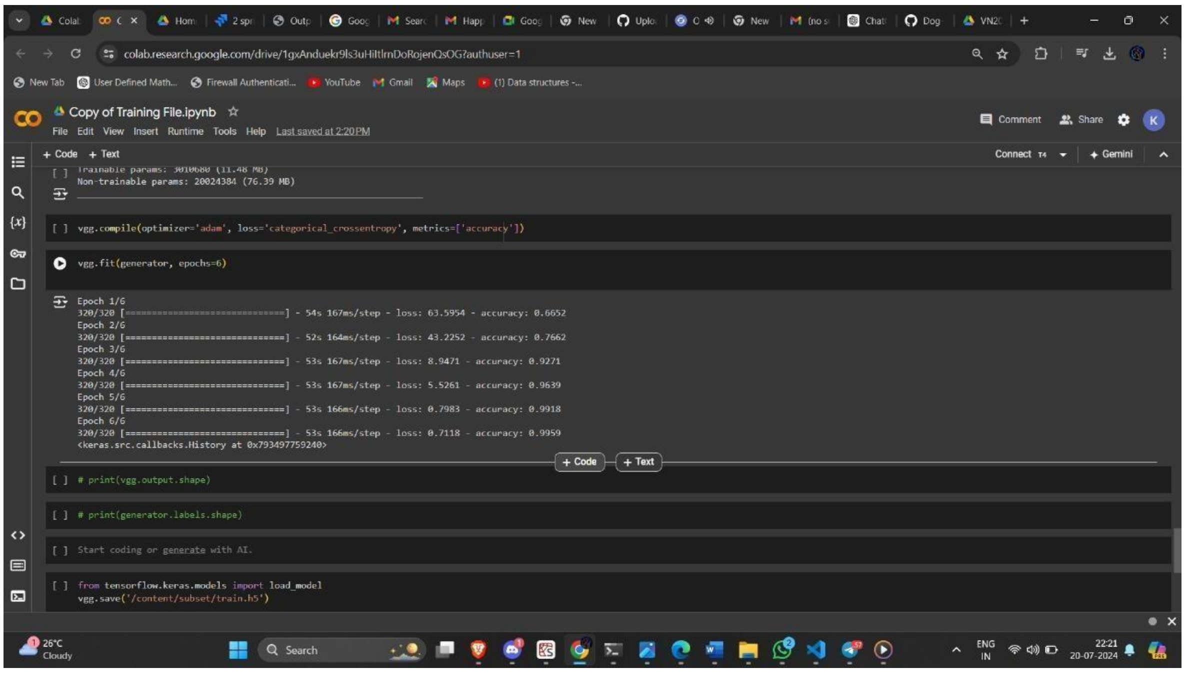


Copy of Training File.ipynb

```
vgg.summary()
```

```
Model: "model"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_1 (InputLayer)        [(None, 224, 224, 3)]     0

 block1_conv1 (Conv2D)       (None, 224, 224, 64)      1792

 block1_conv2 (Conv2D)       (None, 224, 224, 64)      36928

 block1_pool (MaxPooling2D)  (None, 112, 112, 64)      0

 block2_conv1 (Conv2D)       (None, 112, 112, 128)     73856

 block2_conv2 (Conv2D)       (None, 112, 112, 128)     147584

 block2_pool (MaxPooling2D)  (None, 56, 56, 128)       0

 block3_conv1 (Conv2D)       (None, 56, 56, 256)       295168

 block3_conv2 (Conv2D)       (None, 56, 56, 256)       590080

 block3_conv3 (Conv2D)       (None, 56, 56, 256)       590080

 block3_conv4 (Conv2D)       (None, 56, 56, 256)       590080

 block3_pool (MaxPooling2D)  (None, 28, 28, 256)       0

 block4_conv1 (Conv2D)       (None, 28, 28, 512)       1180160

 block4_conv2 (Conv2D)       (None, 28, 28, 512)       2359808

 block4_conv3 (Conv2D)       (None, 28, 28, 512)       2359808
```


```
block3_conv3 (Conv2D)       (None, 56, 56, 256)       590080

block3_conv4 (Conv2D)       (None, 56, 56, 256)       590080

block3_pool (MaxPooling2D)  (None, 28, 28, 256)       0

block4_conv1 (Conv2D)       (None, 28, 28, 512)       1180160

block4_conv2 (Conv2D)       (None, 28, 28, 512)       2359808

block4_conv3 (Conv2D)       (None, 28, 28, 512)       2359808

block4_conv4 (Conv2D)       (None, 28, 28, 512)       2359808

block4_pool (MaxPooling2D)  (None, 14, 14, 512)       0

block5_conv1 (Conv2D)       (None, 14, 14, 512)       2359808

block5_conv2 (Conv2D)       (None, 14, 14, 512)       2359808

block5_conv3 (Conv2D)       (None, 14, 14, 512)       2359808

block5_conv4 (Conv2D)       (None, 14, 14, 512)       2359808

block5_pool (MaxPooling2D)  (None, 7, 7, 512)         0

flatten (Flatten)           (None, 25088)             0

dense (Dense)               (None, 120)               3010680

=================================================================
Total params: 23035064 (87.87 MB)
Trainable params: 3010680 (11.48 MB)
Non-trainable params: 20024384 (76.39 MB)
```


```
Trainable params: 3010680 (11.48 MB)
Non-trainable params: 20024384 (76.39 MB)
```

```
vgg.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])
```

```
vgg.fit(generator, epochs=6)
```

```
Epoch 1/6
320/320 [==============================] - 54s 167ms/step - loss: 63.5954 - accuracy: 0.6652
Epoch 2/6
320/320 [==============================] - 52s 164ms/step - loss: 43.2252 - accuracy: 0.7662
Epoch 3/6
320/320 [==============================] - 53s 167ms/step - loss: 8.9471 - accuracy: 0.9271
Epoch 4/6
320/320 [==============================] - 53s 167ms/step - loss: 5.5261 - accuracy: 0.9639
Epoch 5/6
320/320 [==============================] - 53s 166ms/step - loss: 0.7983 - accuracy: 0.9918
Epoch 6/6
320/320 [==============================] - 53s 166ms/step - loss: 0.7118 - accuracy: 0.9959
<keras.src.callbacks.History at 0x793497759240>
```

```
# print(vgg.output.shape)
```

```
# print(generator.labels.shape)
```

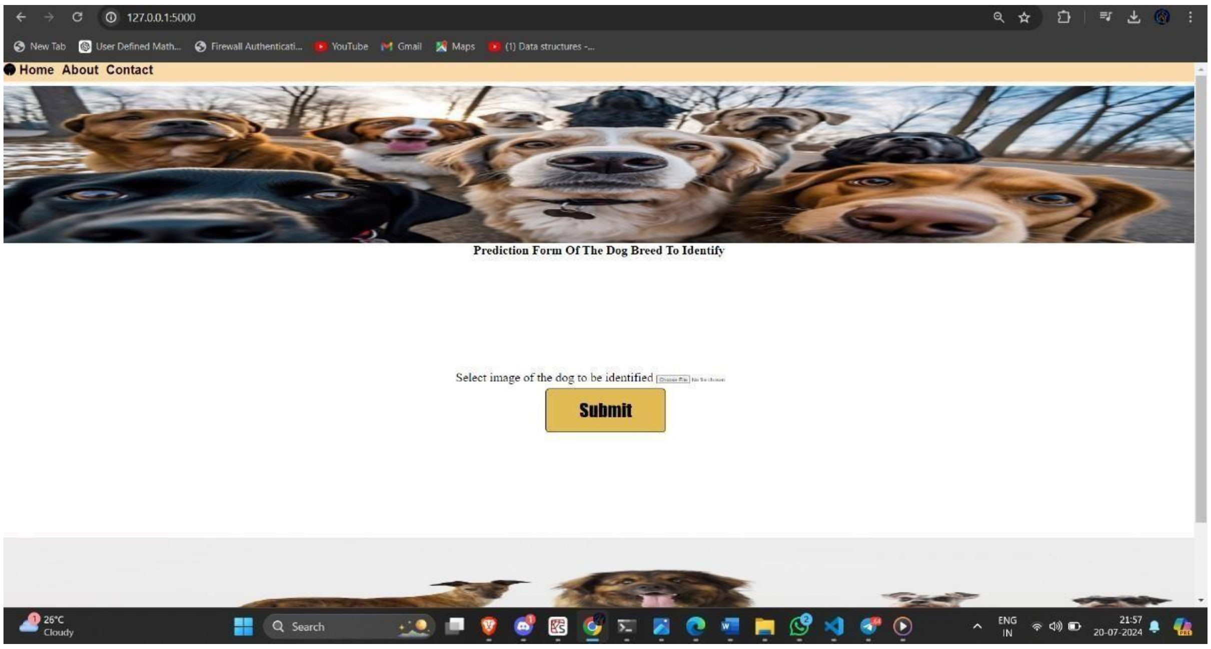
```
from tensorflow.keras.models import load_model
vgg.save('/content/subset/train.h5')
```

5. Model Optimization and Tuning Phase

- **Hyperparameter Tuning:**
    - **Learning Rate:** Adjust the learning rate to find the optimal value that balances convergence speed and stability.
    - **Batch Size:** Experiment with different batch sizes to determine the impact on training efficiency and model performance.
    - **Epochs:** Set an appropriate number of epochs to ensure sufficient training without overfitting.
- **Regularization Techniques:**
    - **Dropout:** Apply dropout to prevent overfitting by randomly dropping neurons during training.
    - **L2 Regularization:** Use L2 regularization to penalize large weights and reduce model complexity.
- **Model Architecture Adjustments:**
    - **Layer Modification:** Experiment with adding or removing layers, or adjusting layer sizes, to improve model performance.
    - **Transfer Learning Adjustments:** Fine-tune different layers of the pre-trained model (e.g., feature extractor vs. classifier layers) to adapt to the specific dog breed dataset.
- **Data Augmentation:**
    - Enhance the dataset with techniques such as rotation, flipping, and color adjustments to improve model robustness and generalization.
- **Optimization Algorithms:**
    - **Optimizer Selection:** Test different optimization algorithms (e.g., Adam, SGD, RMSprop) to find the best fit for the model and dataset.
    - **Learning Rate Schedulers:** Use learning rate schedulers to adjust the learning rate dynamically during training for better convergence.

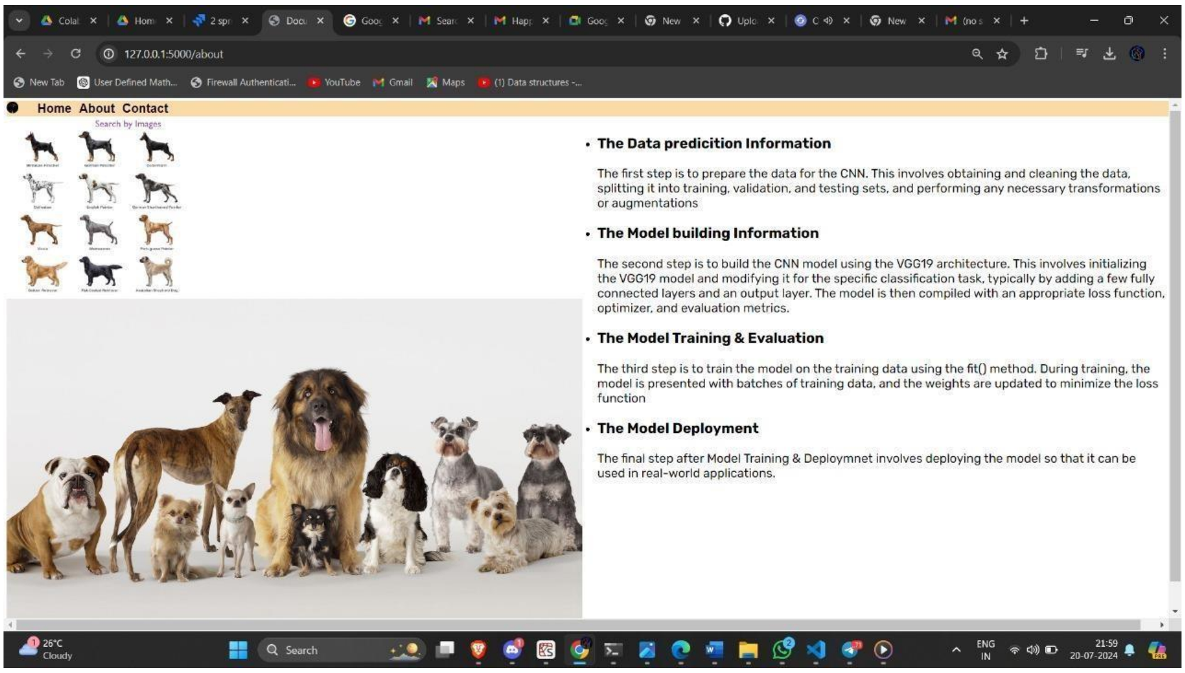
6. Result:

HomePage:



Prediction Form Of The Dog Breed To Identify

About Page:



- **The Data predicition Information**

  The first step is to prepare the data for the CNN. This involves obtaining and cleaning the data, splitting it into training, validation, and testing sets, and performing any necessary transformations or augmentations

- **The Model building Information**

  The second step is to build the CNN model using the VGG19 architecture. This involves initializing the VGG19 model and modifying it for the specific classification task, typically by adding a few fully connected layers and an output layer. The model is then compiled with an appropriate loss function, optimizer, and evaluation metrics.

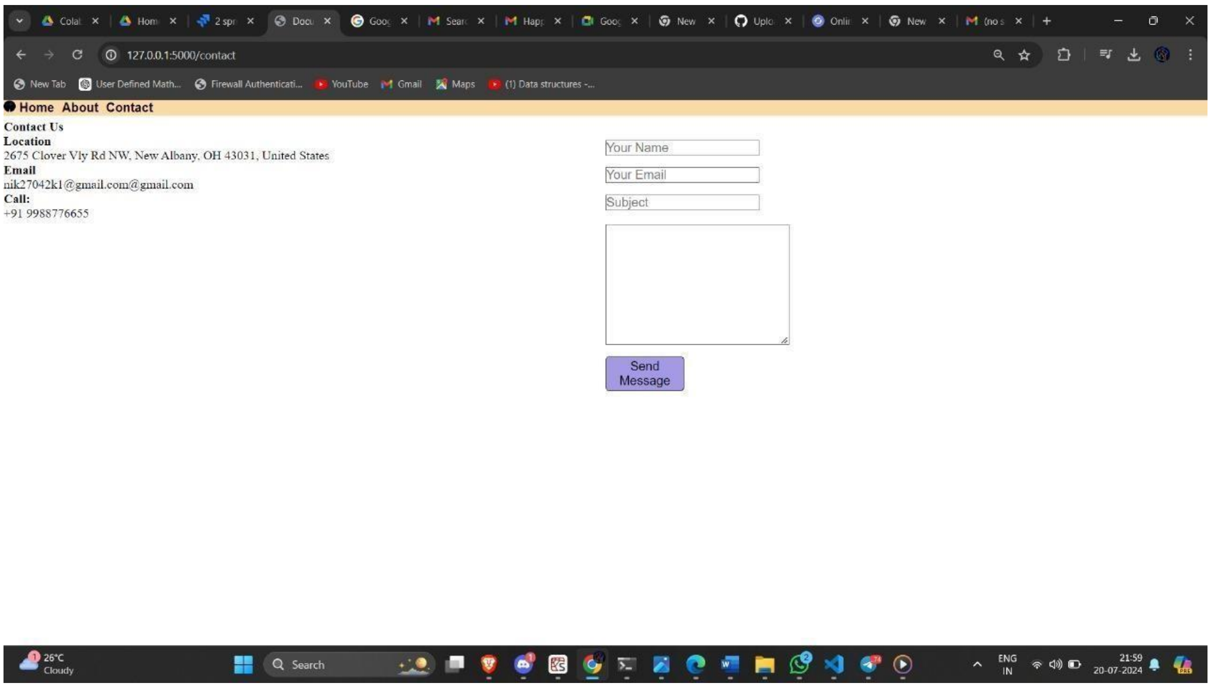
- **The Model Training & Evaluation**

  The third step is to train the model on the training data using the fit() method. During training, the model is presented with batches of training data, and the weights are updated to minimize the loss function

- **The Model Deployment**

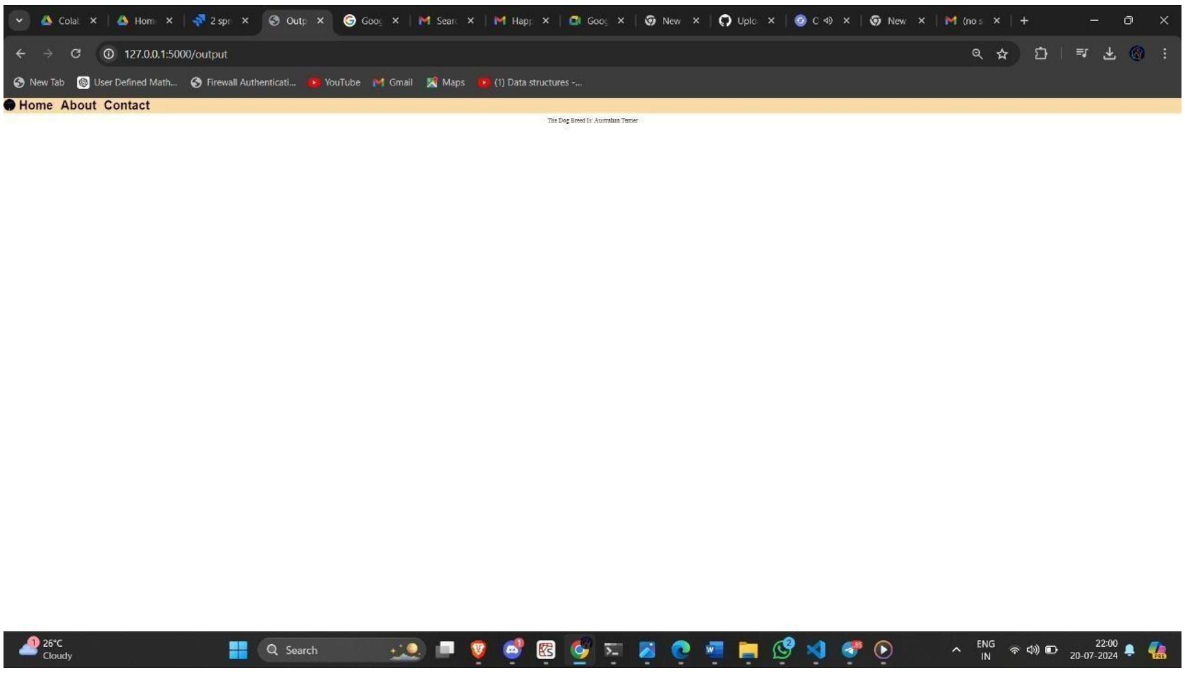
  The final step after Model Training & Deploymnet involves deploying the model so that it can be used in real-world applications.

Contact Page:



Contact Us
Location
2675 Clover Vly Rd NW, New Albany, OH 43031, United States
Email
nik27042k1@gmail.com@gmail.com
Call:
+91 9988776655

Output Page:



The Dog Breed Is: Australian Terrier

7 ADVANTAGES AND DISADVANTAGES

ADVANTAGES

● Integration with Flask:

Using Flask for integration is ideal due to its lightweight nature in Python web frameworks. It's versatile, simplifying the creation of user-friendly interfaces for CSV prediction models. Flask's straightforwardness accelerates model development and deployment significantly.

●Scalability:

Scalability is a strong suit of Flask-based models, designed to manage numerous concurrent user queries for real-time predictions effectively. This makes the model highly applicable in clinical settings with extensive patient populations, ensuring robust performance and scalability.

DISADVANTAGES

●Complexity of Model Building:

Selecting, training, and fine-tuning additional models is essential when incorporating them into a voting classifier. Achieving optimal performance requires careful optimization of each individual model and finding the right balance between them can be challenging.

●Deployment and Upkeep:

Managing a Flask-based application entails ongoing monitoring, maintenance, and updates on the server. This can introduce additional complexity and potentially higher maintenance costs compared to deploying a standalone model.

8 APPLICATIONS :

- **Veterinary Care:**
  - Assist veterinarians in quickly identifying dog breeds, which can aid in diagnosing breed-specific health issues and recommending appropriate care.
- **Pet Adoption and Shelters:**
  - Help animal shelters and adoption centers accurately identify dog breeds, improving breed-specific matchmaking and adoption processes.
- **Pet Insurance:**
  - Facilitate insurance companies in assessing risk and coverage by identifying dog breeds, which can be used to tailor insurance plans and premiums.
- **Breed Research and Conservation:**
  - Support researchers and conservationists in studying breed characteristics, population distributions, and genetic diversity.
- **Dog Breeder Services:**
  - Assist breeders in confirming the breed of dogs in their litters, ensuring accurate breed documentation and certification.
- **Mobile Applications:**
  - Provide a user-friendly tool for dog owners and enthusiasts to identify breeds in real-time using mobile apps, enhancing user engagement and education.

• 9 CONCLUSION :

In summary, The Dog Breed Identification project successfully demonstrates the power of transfer learning and advanced machine learning techniques in classifying dog breeds from images. By leveraging pre-trained convolutional neural networks, the project achieves high accuracy and efficiency in recognizing a wide range of dog breeds. Through thorough data exploration, preprocessing, and model optimization, the project ensures robust performance and generalization. The practical applications of this technology span veterinary care, pet adoption, and mobile applications, offering valuable tools for both professionals and dog enthusiasts. Overall, the project highlights the potential of AI to enhance our interactions with and understanding of the canine world, paving the way for future advancements in image classification and machine learning.

10 FUTURE SCOPE:

The future scope in dog breed identification can be more helpful and profitable project it can be extended the model to identify a broader range of dog breeds including rare and mixed breeds by expanding the dataset and fine tuning the model. Incorporate more advanced architectures or hybrid models to enhance classification accuracy and reduce error rates. It can develop real time identification capabilities for mobile and web applications allowing users to classify dog breeds using their smartphones. We can also implement advanced data augmentation techniques such as generative adversarial networks to further enhance dataset diversity and model robustness.

10. Appendix

10.1. Source Code : CLICK HERE

10.2. GitHub & Project Demo Link

GitHub : CLICK HERE

Project Demo Link: CLICK HERE