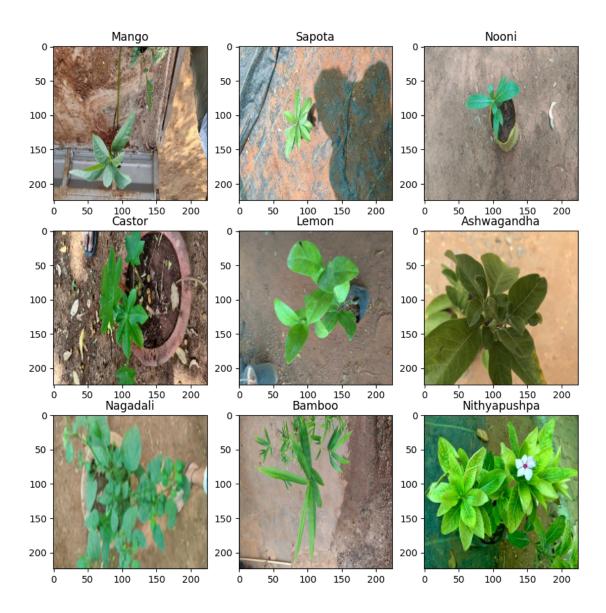
plant-prediction

November 1, 2024

```
[61]: import numpy as np
      import pandas as pd
      #import os
      #for dirname, _, filenames in os.walk('C:/Users/KIIT0001/Desktop/archive/

¬medicinal/Indian Medicinal Leaves Image Datasets/medicinal_plant_dataset'):
           for filename in filenames:
               print(os.path.join(dirname, filename))
 [6]: import tensorflow as tf
 [7]: dataset = tf.keras.utils.image_dataset_from_directory("C:/Users/KIIT0001/
       →Desktop/archive/medicinal/Indian Medicinal Leaves Image Datasets/
       →medicinal_plant_dataset")
     Found 5945 files belonging to 40 classes.
 []: ds_train = tf.keras.utils.image_dataset_from_directory(
          'C:/Users/KIIT0001/Desktop/archive/medicinal/Indian Medicinal Leaves Image⊔
       →Datasets/medicinal_plant_dataset',
          image_size=(224, 224),
          batch_size=16,
          validation_split=0.4,
          subset="training",
          seed=42
     Found 5945 files belonging to 40 classes.
     Using 3567 files for training.
 []: ds_val = tf.keras.utils.image_dataset_from_directory(
          'C:/Users/KIIT0001/Desktop/archive/medicinal/Indian Medicinal Leaves Image
       →Datasets/medicinal_plant_dataset',
          image_size=(224, 224),
          batch_size=16,
          validation_split=0.4,
          subset="validation",
          seed=42
```

```
Found 5945 files belonging to 40 classes.
     Using 2378 files for validation.
[10]: import tensorflow_datasets as tfds
      batch_size = 64
      dataset_name = dataset
      class_names = dataset.class_names
      print(class_names)
     ['Aloevera', 'Amla', 'Amruta_Balli', 'Arali', 'Ashoka', 'Ashwagandha',
     'Avacado', 'Bamboo', 'Basale', 'Betel', 'Betel_Nut', 'Brahmi', 'Castor',
     'Curry_Leaf', 'Doddapatre', 'Ekka', 'Ganike', 'Gauva', 'Geranium', 'Henna',
     'Hibiscus', 'Honge', 'Insulin', 'Jasmine', 'Lemon', 'Lemon_grass', 'Mango',
     'Mint', 'Nagadali', 'Neem', 'Nithyapushpa', 'Nooni', 'Pappaya', 'Pepper',
     'Pomegranate', 'Raktachandini', 'Rose', 'Sapota', 'Tulasi', 'Wood_sorel']
[11]: len(class_names)
[11]: 40
[12]: type(class_names)
[12]: list
[13]: size = (224, 224)
      ds_train = ds_train.map(lambda image, label: (tf.image.resize(image,size), ,__
      ds val = ds train.map(lambda image, label: (tf.image.resize(image,size),,,
       →label))
[14]: import matplotlib.pyplot as plt
[15]: plt.figure(figsize = (10,10))
      for images,labels in ds_train.take(1):
          for i in range(9):
              ax = plt.subplot(3,3,i+1)
              plt.imshow(images[i].numpy().astype("uint8"))
              plt.title(class_names[labels[i]])
              plt.axis("on")
```



```
# Concatenate the list of image batches into a NumPy array
      images_array = np.concatenate(images_list, axis=0)
      # Now, 'images_array' contains all the images in a 4D NumPy array, and _{
m L}
       →'labels_array' contains all the labels as a NumPy array
[17]: images_array.shape
[17]: (3567, 224, 224, 3)
[18]: labels_array
[18]: array([18., 25., 25., ..., 20., 1., 2.])
[19]: images_array[0]
[19]: array([[[184.7496 , 180.7496 , 177.7496 ],
              [195.97075, 191.97075, 188.97075],
              [199.6789 , 194.6789 , 190.6789 ],
              [166.30316, 156.30316, 146.30316],
              [172.80484, 162.80484, 152.80484],
              [169.85579, 159.85579, 149.85579]],
             [[190.51427, 186.20624, 182.89821],
              [196.19077, 191.88274, 188.57469],
              [189.06744, 184.06744, 180.06744],
              [167.57985, 157.57985, 147.8879],
              [170.82776, 160.82776, 151.13579],
              [170.25853, 160.25853, 150.25853]],
             [[194.62302, 189.62302, 185.62302],
              [194.40865, 189.40865, 185.40865],
              [181.74083, 176.74083, 172.74083],
              [168.41255, 158.41255, 149.41255],
              [169.27028, 159.27028, 150.27028],
              [172.21446, 162.21446, 152.21446]],
             ...,
             [[208.2597 , 203.2597 , 199.2597 ],
              [219.00333, 211.00333, 208.00333],
              [214.03223, 206.03223, 203.03223],
```

```
[164.251 , 162.02573, 159.46089]],

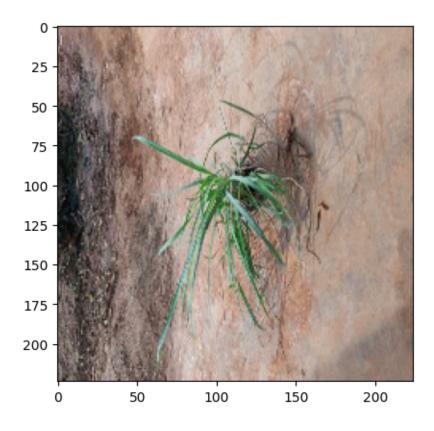
[[216.25323, 209.17728, 205.86926],
[215.01393, 207.01393, 204.01393],
[216.77718, 208.08519, 203.70122],
...,
[168.1254 , 170.1254 , 168.85358],
[180.52542, 178.22838, 179.648 ],
[197.1066 , 193.94708, 189.51361]],

[[225.57068, 217.57068, 214.57068],
[215.28612, 207.28612, 204.28612],
[190.13632, 181.13632, 176.13632],
...,
[173.1664 , 175.1664 , 173.77357],
[172.84341, 170.84341, 172.87906],
[184.34416, 179.54948, 175.15842]]], dtype=float32)

[20]: plt.imshow(images_array[2].astype("uint8"))
plt.axis("on")
```

[176.33624, 177.51117, 175.89697], [169.93007, 167.97415, 166.96475],

[20]: (-0.5, 223.5, 223.5, -0.5)



```
[21]: class_names[int(labels_array[2])]
[21]: 'Lemon_grass'
     Training the model
[22]: from tensorflow.keras.layers import Input, Dense, Flatten
      from tensorflow.keras.models import Model
      from tensorflow.keras.applications.vgg16 import VGG16
      from tensorflow.keras.applications.vgg16 import preprocess_input
      from tensorflow.keras.preprocessing import image
      from tensorflow.keras.preprocessing.image import ImageDataGenerator
      from tensorflow.keras.models import Sequential
[23]: IMAGE_SIZE = [224,224]
[24]: vgg = VGG16(input_shape=IMAGE_SIZE +[3] , weights = 'imagenet' , include_top = ___
       →False)
[25]: for layer in vgg.layers:
          layer.trainable = False
[26]: x = Flatten()(vgg.output)
[27]: prediction = Dense(len(class_names) , activation = "softmax")(x)
[28]: model = Model(inputs = vgg.input,outputs = prediction)
      model.summary()
```

Model: "functional"

Layer (type)	Output Shape	Param #
<pre>input_layer (InputLayer)</pre>	(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
                                  (None, 56, 56, 256)
block3_conv2 (Conv2D)
                                                                 590,080
block3_conv3 (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_pool (MaxPooling2D)
                                  (None, 14, 14, 512)
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_pool (MaxPooling2D)
                                  (None, 7, 7, 512)
                                                                       0
flatten (Flatten)
                                  (None, 25088)
                                                                       0
dense (Dense)
                                  (None, 40)
                                                               1,003,560
```

Total params: 15,718,248 (59.96 MB)

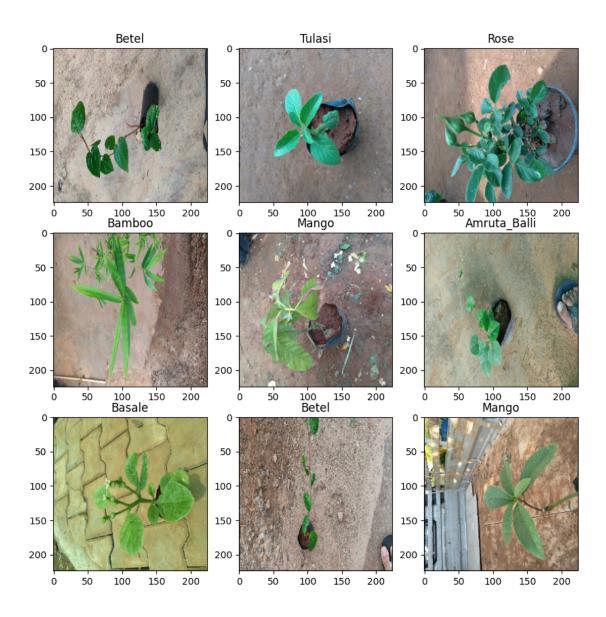
Trainable params: 1,003,560 (3.83 MB)

Non-trainable params: 14,714,688 (56.13 MB)

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

```
[30]: labels_array
```

```
[30]: array([18., 25., 25., ..., 20., 1., 2.])
[31]: # One-hot encode the labels
      labels_one_hot = tf.keras.utils.to_categorical(labels_array, num_classes=40)
[32]: r = model.fit(
          images_array,
          labels_one_hot,
          batch_size=16,
          epochs = 5
      )
     Epoch 1/5
     223/223
                         973s 4s/step -
     accuracy: 0.4400 - loss: 19.5057
     Epoch 2/5
     223/223
                         1035s 5s/step -
     accuracy: 0.9143 - loss: 2.8841
     Epoch 3/5
     223/223
                         593s 3s/step -
     accuracy: 0.9565 - loss: 1.3523
     Epoch 4/5
     223/223
                         455s 2s/step -
     accuracy: 0.9685 - loss: 1.1977
     Epoch 5/5
     223/223
                         453s 2s/step -
     accuracy: 0.9800 - loss: 0.9391
[33]: # Save the entire model, including architecture, weights, and optimizer state
      model.save("my model.h5") # Provide a filename with a '.h5' extension
     WARNING:absl:You are saving your model as an HDF5 file via `model.save()` or
     `keras.saving.save_model(model)`. This file format is considered legacy. We
     recommend using instead the native Keras format, e.g.
     `model.save('my_model.keras')` or `keras.saving.save_model(model,
     'my_model.keras')`.
     Testing model;
[34]: import matplotlib.pyplot as plt
[35]: plt.figure(figsize = (10,10))
      for images,labels in ds_val.take(1):
          for i in range(9):
              ax = plt.subplot(3,3,i+1)
              plt.imshow(images[i].numpy().astype("uint8"))
              plt.title(class_names[labels[i]])
              plt.axis("on")
```



```
[36]: import numpy as np

[37]: # Initialize empty lists to store images and labels
    images_list_v = []
    labels_list_v = []

# Iterate through the dataset
for image_batch, label_batch in ds_val:
    # Append the image batch to the images list
    images_list_v.append(image_batch.numpy())

# Append the label batch to the labels list
    labels_list_v.append(label_batch.numpy())
```

```
# Concatenate the list of image batches into a NumPy array
images_array_v = np.concatenate(images_list_v, axis=0)

# Concatenate the list of label batches into a NumPy array
labels_array_v = np.concatenate(labels_list_v, axis=0)

# Now, 'images_array' contains all the images in a 4D NumPy array, and_
____'labels_array' contains all the corresponding labels as a NumPy array
```

[38]: images_array_v.shape

[38]: (3567, 224, 224, 3)

[39]: labels_array_v.shape

[39]: (3567,)

[40]: # One-hot encode the labels labels_one_hot_v = tf.keras.utils.to_categorical(labels_array_v, num_classes=40)

[41]: model_new = tf.keras.models.load_model("my_model.h5")

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.

[42]: model_new.summary()

Model: "functional"

Layer (type)	Output Shape	Param #
<pre>input_layer (InputLayer)</pre>	(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_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_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_pool (MaxPooling2D)	(None, 7, 7, 512)	0
flatten (Flatten)	(None, 25088)	0

Total params: 15,718,250 (59.96 MB)

Trainable params: 1,003,560 (3.83 MB)

Non-trainable params: 14,714,688 (56.13 MB)

Optimizer params: 2 (12.00 B)

[43]: model_new.evaluate(images_array_v,labels_one_hot_v)

112/112 449s 4s/step - accuracy: 0.9888 - loss: 0.7650

[43]: [0.45777466893196106, 0.9873843789100647]

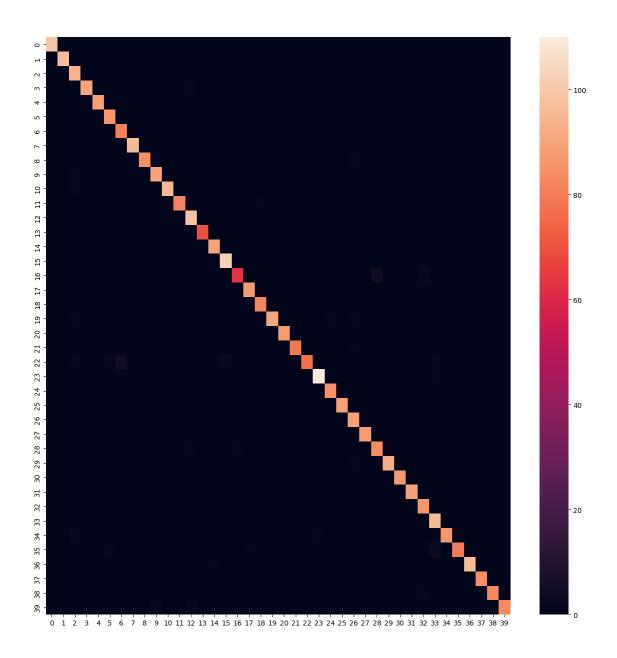
```
[44]: |y_pred = model_new.predict(images_array_v)
     112/112
                           454s 4s/step
[49]: y_pred
[49]: array([[0., 0., 0., ..., 0., 0., 0.],
              [0., 1., 0., ..., 0., 0., 0.]
              [0., 0., 0., ..., 0., 0., 0.]
              [0., 0., 0., ..., 0., 0., 0.]
              [0., 0., 0., ..., 0., 0., 0.]
              [0., 1., 0., ..., 0., 0., 0.]], dtype=float32)
[46]: from sklearn.metrics import confusion_matrix , classification_report
      import numpy as np
      y_pred_classes = [np.argmax(element) for element in y_pred]
      print("Classification Report: \n", classification_report(labels_array_v,_
        →y_pred_classes))
     Classification Report:
                     precision
                                    recall f1-score
                                                        support
                 0
                          1.00
                                     1.00
                                                1.00
                                                            99
                 1
                          1.00
                                     1.00
                                                1.00
                                                            97
                 2
                          0.94
                                     1.00
                                                0.97
                                                            94
                 3
                          1.00
                                     0.99
                                                0.99
                                                            91
                 4
                          1.00
                                     1.00
                                                1.00
                                                            89
                 5
                          0.98
                                     1.00
                                                0.99
                                                            86
                 6
                          0.94
                                     1.00
                                                0.97
                                                            81
                 7
                          1.00
                                     1.00
                                                1.00
                                                            96
                 8
                          1.00
                                     0.98
                                                0.99
                                                            87
                 9
                          0.97
                                     0.99
                                                0.98
                                                            91
                          1.00
                                                0.99
                                                            96
                10
                                     0.99
                11
                          1.00
                                     0.99
                                                0.99
                                                            83
                12
                          0.96
                                     1.00
                                                0.98
                                                            98
                13
                          1.00
                                     1.00
                                                1.00
                                                            70
                14
                          0.99
                                     1.00
                                                0.99
                                                            90
                15
                          0.98
                                     1.00
                                                0.99
                                                            103
                16
                          0.98
                                     0.91
                                                0.95
                                                             69
                17
                          0.99
                                     1.00
                                                0.99
                                                            88
                18
                          0.99
                                     1.00
                                                0.99
                                                            82
                19
                          1.00
                                     0.97
                                                0.98
                                                            94
                20
                          1.00
                                     1.00
                                                1.00
                                                            88
                21
                          1.00
                                     0.99
                                                0.99
                                                            80
                22
                          1.00
                                     0.89
                                                0.94
                                                            87
                          0.99
                23
                                     0.99
                                                0.99
                                                           111
```

```
24
                    0.99
                               1.00
                                         0.99
                                                      85
          25
                    1.00
                               1.00
                                          1.00
                                                      89
          26
                    0.96
                               1.00
                                         0.98
                                                      89
          27
                    1.00
                               1.00
                                          1.00
                                                      88
          28
                    0.95
                               0.98
                                         0.97
                                                      86
          29
                               0.99
                                                      93
                    1.00
                                         0.99
          30
                    1.00
                               1.00
                                          1.00
                                                      88
          31
                    1.00
                               1.00
                                          1.00
                                                      89
          32
                    0.97
                               1.00
                                         0.98
                                                      86
          33
                    0.95
                               1.00
                                         0.97
                                                      96
          34
                               0.97
                                         0.98
                                                      89
                    1.00
          35
                    1.00
                               0.94
                                         0.97
                                                      85
          36
                    1.00
                               0.99
                                         0.99
                                                      97
          37
                    1.00
                               1.00
                                          1.00
                                                      85
          38
                    1.00
                               0.98
                                         0.99
                                                      85
          39
                    0.99
                               0.95
                                         0.97
                                                      87
                                          0.99
                                                    3567
    accuracy
   macro avg
                    0.99
                               0.99
                                          0.99
                                                    3567
weighted avg
                    0.99
                               0.99
                                         0.99
                                                    3567
```

```
[56]: import seaborn as sns

plt.figure(figsize=(15,15))
    sns.heatmap(confusion_matrix(labels_array_v, y_pred_classes))
```

[56]: <Axes: >



[]: