

# Classify Palm, Banana and a cat

Author: Shashank K Holla, 1Rv17EC139 shashankholla@outlook.in

This model below is a 3 class image classifier built to classify between a cat, banana and a hand. The model is derived from the popular VGG16 architecture but has been optimized to improve accuracy in this case.

Using the keras library with Tensorflow backend. Make sure to use the same versions to prevent problems

```
In [48]: # Data Augmentation and classes
from keras.preprocessing.image import ImageDataGenerator

# NN Libraries
import numpy as np
import keras
import tensorflow as tf
from keras.models import Sequential
from keras.layers import Conv2D, MaxPooling2D, MaxPool2D
from keras.layers import Activation, Dropout, Flatten, Dense
from keras import backend as K
from keras.optimizers import Adam

# Visualisation
from keras.preprocessing import image
from PIL import Image
import matplotlib.pyplot as plt

# Other
import math
import os
```

```
In [50]: print("Tensorflow:" + tf.__version__)
print("Keras:" + keras.__version__)
```

```
Tensorflow:2.2.0
Keras2.3.0-tf
```

```
In [55]: # Paths
train_data_dir = "../input/banacathand-40n10/Dataset/train/"
validation_data_dir = "../input/banacathand-40n10/Dataset/valid/"
test_data_dir = "../input/banacathand-40n10/Dataset/test/"
```

```
├──train
│   ├──banana - 40
│   ├──cat - 40
│   └──hand - 40
├──valid
│   ├──banana - 10
│   ├──cat - 10
│   └──hand - 10
└──test
    ├──banana
    ├──cat
    └──hand
```

```

In [6]: _inputSize      = (224,224)
        _trainBatchSize = 32
        _validBatchSize = 32

# Image Augmentation. Artificially generate different looking samples from the given samples

        _rescaler      = 1. / 255
        _shearRange     = 0.2
        _zoomRange      = 0.15
        _rotationRange  = 45
        _widthShift     = 0.15
        _heightShift    = 0.15
        _isHorizontalFlip = True
        _isVerticalFlip  = True
        _fillMode        = "nearest"
        _epochs         = 100
        _classes         = {0: 'banana', 1: 'cat', 2: 'hand'}

        _bestSaveModelName = "best.h5"
        _learningRate      = 0.0001

train_batches = ImageDataGenerator( rescale=_rescaler ,
                                    shear_range=_shearRange,
                                    zoom_range=_zoomRange,
                                    rotation_range=_rotationRange,
                                    width_shift_range=_widthShift,
                                    height_shift_range=_heightShift,
                                    horizontal_flip=_isHorizontalFlip,
                                    vertical_flip=_isVerticalFlip,
                                    fill_mode=_fillMode).flow_from_directory(
    train_data_dir,
    target_size = _inputSize,
    batch_size  = _trainBatchSize)

valid_batches = ImageDataGenerator( rescale=_rescaler ,
                                    shear_range=_shearRange,
                                    zoom_range=_zoomRange,
                                    rotation_range=_rotationRange,
                                    width_shift_range=_widthShift,
                                    height_shift_range=_heightShift,
                                    horizontal_flip=_isHorizontalFlip,
                                    vertical_flip=_isVerticalFlip,
                                    fill_mode=_fillMode).flow_from_directory(
    validation_data_dir,
    target_size = _inputSize,
    batch_size  = _trainBatchSize)

```

Found 120 images belonging to 3 classes.  
Found 30 images belonging to 3 classes.

## Visualisation of Data

The dataset has been taken from 4 places and judged to include a variety of photos.

1. Collection from people for hands (online data set was mostly fair hands with white background which might not work well if used to predict unprocessed images)
2. Most of the images scrapped from google images for educational purpose.
3. Kaggle Fruits Dataset - <https://www.kaggle.com/moltean/fruits?> (<https://www.kaggle.com/moltean/fruits?>) 4\*\*. Kaggle Cats And Dogs Dataset - <https://www.kaggle.com/c/dogs-vs-cats> (<https://www.kaggle.com/c/dogs-vs-cats>)

In [52]:

```
filesPerRow = 10

def printDataset(p):
    files = os.listdir(p)
    noOfCols = filesPerRow
    noOfRow = int(len(files) / noOfCols)

    # Generate the subplots
    fig, axs = plt.subplots(noOfRow, noOfCols)
    fig.set_size_inches(10, 10, forward=True)

    # Map each file to subplot
    for i in range(0, len(files)):
        file_name = files[i]
        image = Image.open(f'{p}/{file_name}')
        row = math.floor(i / filesPerRow)
        col = i % filesPerRow
        axs[row, col].imshow(image)
        axs[row, col].axis('off')

    plt.show()
```

Dataset is comprised of training data of 40 images of each class, and 10 images for validation of each class

```
In [6]: printDataset(train_data_dir+ "cat")  
        printDataset(train_data_dir+ "hand")  
        printDataset(train_data_dir+ "banana")
```





Data Augmentation is used to generate more samples from the existing set of samples by using few image processing techniques to stretch, zoom, flip and scale images. This helps the model generalise better by giving more data when dataset is limited.

And for validation 10 images per class

In [57]:

```
filesPerRow = 5

def printDataset2(p):
    files = os.listdir(p)
    noOfCols = filesPerRow
    noOfRow = int(len(files) / noOfCols)

    # Generate the subplots
    fig, axs = plt.subplots(noOfRow, noOfCols)
    fig.set_size_inches(10, 10, forward=True)

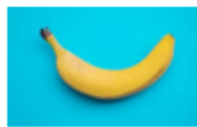
    # Map each file to subplot
    for i in range(0, len(files)):
        file_name = files[i]
        image = Image.open(f'{p}/{file_name}')
        row = math.floor(i / filesPerRow)
        col = i % filesPerRow
        axs[row, col].imshow(image)
        axs[row, col].axis('off')

    plt.show()

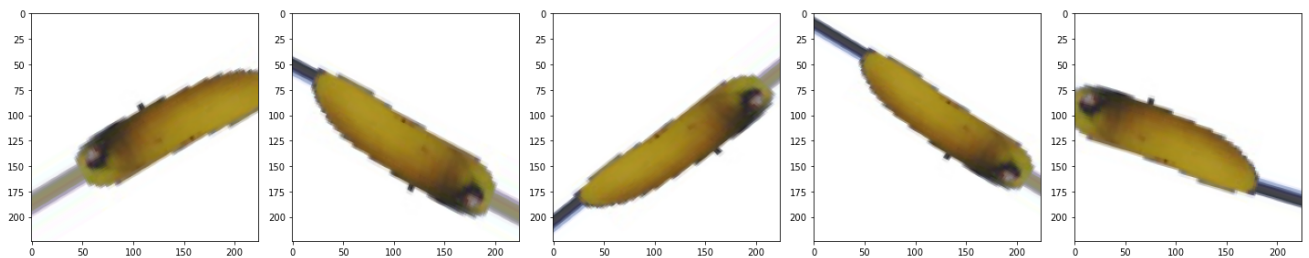
printDataset2(validation_data_dir+ "cat")
printDataset2(validation_data_dir+ "hand")
printDataset2(validation_data_dir+ "banana")
```







```
In [7]: def plotImages(images_arr):  
    fig, axes = plt.subplots(1, 5, figsize=(20,20))  
    axes = axes.flatten()  
    for img, ax in zip( images_arr, axes):  
        ax.imshow(img)  
    plt.tight_layout()  
    plt.show()  
  
augmented_images = [train_batches[0][0][1] for i in range(5)]  
plotImages(augmented_images)
```



This model is inspired from the famous VGG16 model but has been modified to reduce the layers for this application. It has an input layer of (224,224,3) with 64 output filters followed by another layer with 64 filters and "same" padding meaning the output is the same dimension as input. It is followed by a max pooling layer with stride length of (2,2). This is followed by 3 sets of similar layers with increasing number of filters to capture smaller features. Two more convolutional Dense layers with 2048 units each and ends with a 3 unit Dense layer to get the 3 classes required.

```
In [14]: model = tf.keras.Sequential()

model.add(Conv2D(input_shape=(224,224,3),filters=64,kernel_size=(3,3),padding="same",
activation="relu"))
model.add(Conv2D(filters=64,kernel_size=(3,3),padding="same", activation="relu"))
model.add(MaxPool2D(pool_size=(2,2),strides=(2,2)))

model.add(Conv2D(filters=128, kernel_size=(3,3), padding="same", activation="relu"))
model.add(MaxPool2D(pool_size=(2,2),strides=(2,2)))

model.add(Conv2D(filters=256, kernel_size=(3,3), padding="same", activation="relu"))
model.add(Conv2D(filters=256, kernel_size=(3,3), padding="same", activation="relu"))
model.add(MaxPool2D(pool_size=(2,2),strides=(2,2)))

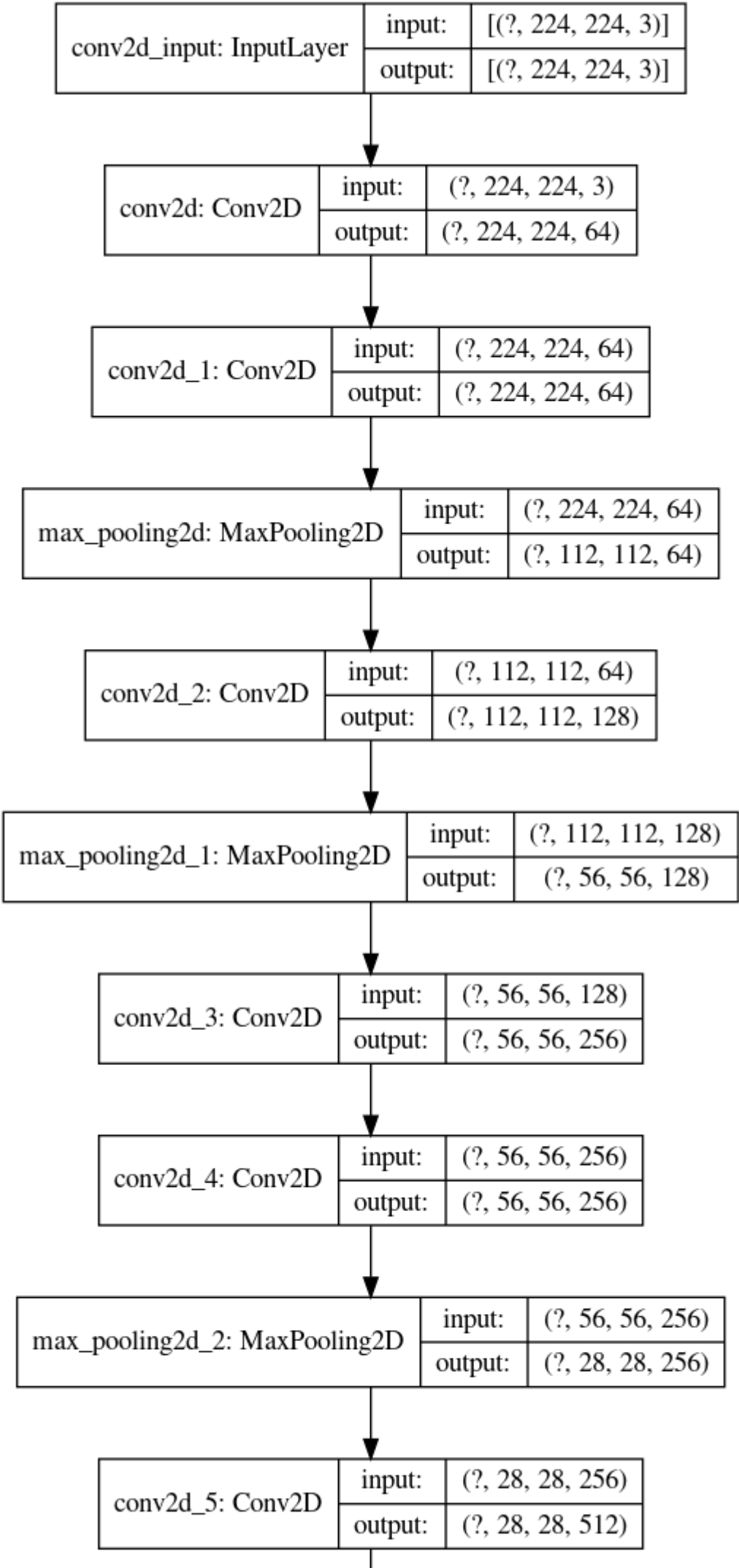
model.add(Conv2D(filters=512, kernel_size=(3,3), padding="same", activation="relu"))
model.add(Conv2D(filters=512, kernel_size=(3,3), padding="same", activation="relu"))
model.add(MaxPool2D(pool_size=(2,2),strides=(2,2)))

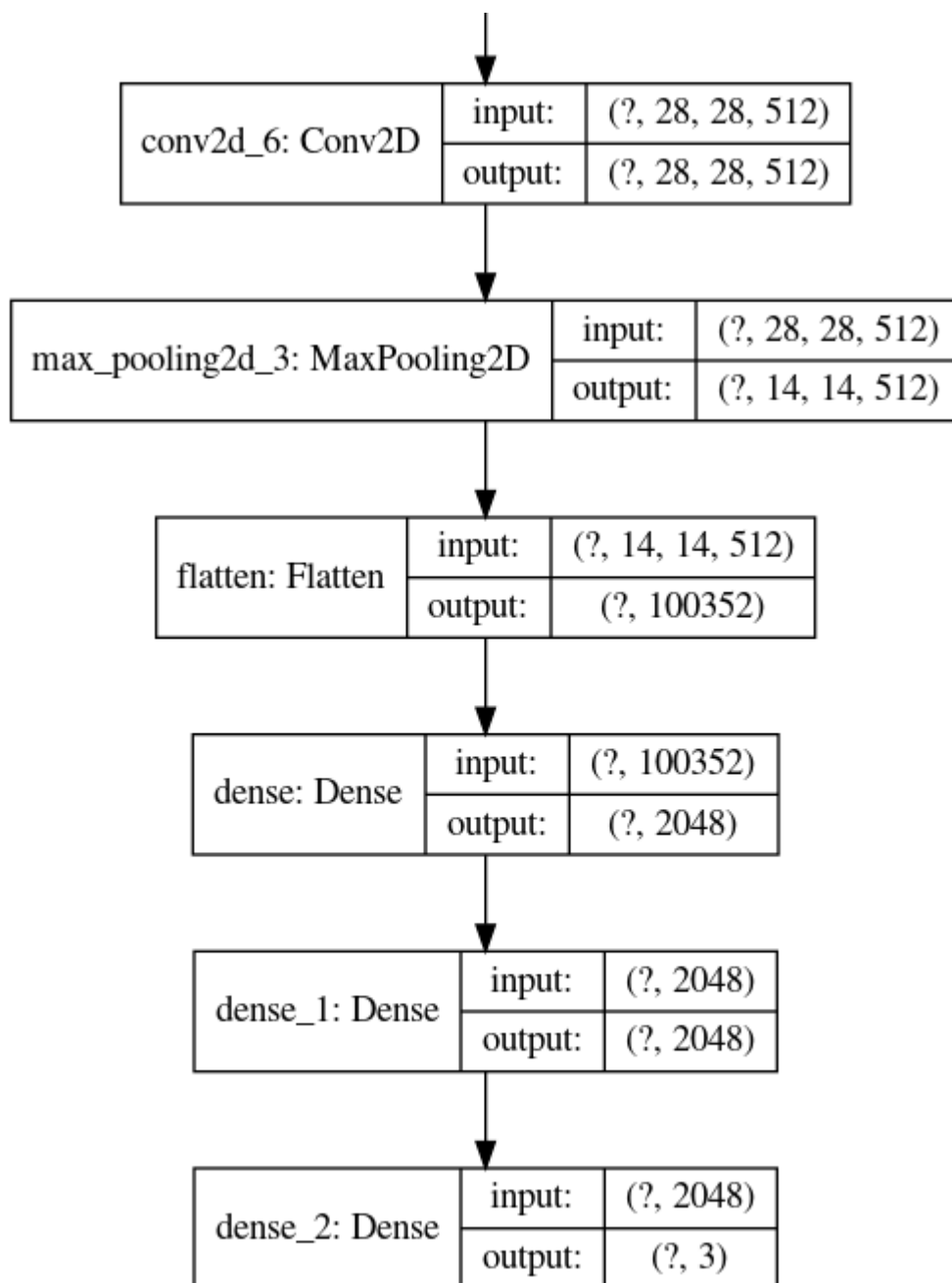
model.add(Flatten())
model.add(Dense(units=2048,activation="relu"))
model.add(Dense(units=2048,activation="relu"))
model.add(Dense(units=3, activation="softmax"))
```

A visualization of the model.

```
In [10]: from keras.utils.vis_utils import plot_model
plot_model(model, to_file='model_plot.png', show_shapes=True, show_layer_names=True)
```

Out[10]:





Adam optimizer is used after very poor results after using SGD which gives erratic accuracy changes. A ModelCheckPoint call back is used to save the best model based on minimum Validation lose

```
In [ ]: ## Getting poor results with SGD. Switching back to Adam.

#opt = keras.optimizers.SGD(lr=1e-4, momentum=0.9)
#model.compile(loss="categorical_crossentropy",optimizer=opt,metrics=["accuracy"])
#model.fit_generator(train_batches, steps_per_epoch=16, validation_data=valid_batches, validation_steps=4, epochs=10, verbose=1)
```

```
In [15]: opt = tf.keras.optimizers.Adam(lr=_learningRate)

mcp_save = tf.keras.callbacks.ModelCheckpoint(_bestSaveModelName, save_best_only=True, monitor='val_loss', mode='min')

model.compile(optimizer=opt, loss=keras.losses.categorical_crossentropy, metrics=['accuracy'])
history = model.fit_generator(train_batches, validation_data=valid_batches, epochs=_epochs, verbose=1, callbacks=[mcp_save])
```

Epoch 1/100  
4/4 [=====] - 22s 6s/step - loss: 1.1264 - accuracy: 0.2750  
- val\_loss: 1.0937 - val\_accuracy: 0.3333  
Epoch 2/100  
4/4 [=====] - 34s 8s/step - loss: 1.0876 - accuracy: 0.4333  
- val\_loss: 1.0758 - val\_accuracy: 0.3333  
Epoch 3/100  
4/4 [=====] - 38s 9s/step - loss: 1.0315 - accuracy: 0.4250  
- val\_loss: 1.0096 - val\_accuracy: 0.5333  
Epoch 4/100  
4/4 [=====] - 4s 932ms/step - loss: 0.9610 - accuracy: 0.55  
00 - val\_loss: 1.1263 - val\_accuracy: 0.4000  
Epoch 5/100  
4/4 [=====] - 35s 9s/step - loss: 0.9585 - accuracy: 0.4583  
- val\_loss: 0.8561 - val\_accuracy: 0.6333  
Epoch 6/100  
4/4 [=====] - 39s 10s/step - loss: 0.8255 - accuracy: 0.650  
0 - val\_loss: 0.7784 - val\_accuracy: 0.6333  
Epoch 7/100  
4/4 [=====] - 39s 10s/step - loss: 0.7629 - accuracy: 0.625  
0 - val\_loss: 0.6698 - val\_accuracy: 0.7000  
Epoch 8/100  
4/4 [=====] - 40s 10s/step - loss: 0.6779 - accuracy: 0.616  
7 - val\_loss: 0.6643 - val\_accuracy: 0.6667  
Epoch 9/100  
4/4 [=====] - 39s 10s/step - loss: 0.6159 - accuracy: 0.650  
0 - val\_loss: 0.5726 - val\_accuracy: 0.6000  
Epoch 10/100  
4/4 [=====] - 39s 10s/step - loss: 0.5671 - accuracy: 0.650  
0 - val\_loss: 0.5485 - val\_accuracy: 0.6667  
Epoch 11/100  
4/4 [=====] - 4s 881ms/step - loss: 0.5526 - accuracy: 0.70  
00 - val\_loss: 0.5541 - val\_accuracy: 0.7000  
Epoch 12/100  
4/4 [=====] - 33s 8s/step - loss: 0.5085 - accuracy: 0.7167  
- val\_loss: 0.4685 - val\_accuracy: 0.8333  
Epoch 13/100  
4/4 [=====] - 40s 10s/step - loss: 0.4976 - accuracy: 0.708  
3 - val\_loss: 0.4219 - val\_accuracy: 0.7333  
Epoch 14/100  
4/4 [=====] - 3s 834ms/step - loss: 0.4730 - accuracy: 0.75  
00 - val\_loss: 0.5732 - val\_accuracy: 0.7333  
Epoch 15/100  
4/4 [=====] - 34s 9s/step - loss: 0.6346 - accuracy: 0.6750  
- val\_loss: 0.3689 - val\_accuracy: 0.9000  
Epoch 16/100  
4/4 [=====] - 4s 992ms/step - loss: 0.5345 - accuracy: 0.67  
50 - val\_loss: 0.3980 - val\_accuracy: 0.7667  
Epoch 17/100  
4/4 [=====] - 3s 855ms/step - loss: 0.4664 - accuracy: 0.78  
33 - val\_loss: 0.4186 - val\_accuracy: 0.6667  
Epoch 18/100  
4/4 [=====] - 14s 4s/step - loss: 0.4635 - accuracy: 0.7417  
- val\_loss: 0.3916 - val\_accuracy: 0.7667  
Epoch 19/100  
4/4 [=====] - 48s 12s/step - loss: 0.4401 - accuracy: 0.741  
7 - val\_loss: 0.6837 - val\_accuracy: 0.8667  
Epoch 20/100  
4/4 [=====] - 31s 8s/step - loss: 0.3942 - accuracy: 0.8500  
- val\_loss: 0.4533 - val\_accuracy: 0.9333  
Epoch 21/100  
4/4 [=====] - 41s 10s/step - loss: 0.3525 - accuracy: 0.858  
3 - val\_loss: 0.3299 - val\_accuracy: 0.9000



Epoch 22/100  
4/4 [=====] - 4s 1s/step - loss: 0.5262 - accuracy: 0.7500  
- val\_loss: 0.7232 - val\_accuracy: 0.8667  
Epoch 23/100  
4/4 [=====] - 4s 907ms/step - loss: 0.3608 - accuracy: 0.82  
50 - val\_loss: 0.4020 - val\_accuracy: 0.8667  
Epoch 24/100  
4/4 [=====] - 29s 7s/step - loss: 0.3199 - accuracy: 0.8917  
- val\_loss: 0.3236 - val\_accuracy: 0.8000  
Epoch 25/100  
4/4 [=====] - 35s 9s/step - loss: 0.3691 - accuracy: 0.8250  
- val\_loss: 0.2953 - val\_accuracy: 0.9000  
Epoch 26/100  
4/4 [=====] - 39s 10s/step - loss: 0.3766 - accuracy: 0.808  
3 - val\_loss: 0.2506 - val\_accuracy: 0.9333  
Epoch 27/100  
4/4 [=====] - 38s 10s/step - loss: 0.2771 - accuracy: 0.891  
7 - val\_loss: 0.2092 - val\_accuracy: 0.9333  
Epoch 28/100  
4/4 [=====] - 40s 10s/step - loss: 0.2582 - accuracy: 0.916  
7 - val\_loss: 0.1496 - val\_accuracy: 0.9333  
Epoch 29/100  
4/4 [=====] - 4s 938ms/step - loss: 0.2607 - accuracy: 0.87  
50 - val\_loss: 0.1817 - val\_accuracy: 0.9667  
Epoch 30/100  
4/4 [=====] - 4s 948ms/step - loss: 0.2616 - accuracy: 0.89  
17 - val\_loss: 0.2454 - val\_accuracy: 0.9333  
Epoch 31/100  
4/4 [=====] - 4s 877ms/step - loss: 0.2902 - accuracy: 0.88  
33 - val\_loss: 0.1730 - val\_accuracy: 0.9333  
Epoch 32/100  
4/4 [=====] - 4s 910ms/step - loss: 0.2318 - accuracy: 0.88  
33 - val\_loss: 0.2902 - val\_accuracy: 0.9000  
Epoch 33/100  
4/4 [=====] - 3s 801ms/step - loss: 0.2632 - accuracy: 0.91  
67 - val\_loss: 0.4056 - val\_accuracy: 0.9000  
Epoch 34/100  
4/4 [=====] - 4s 888ms/step - loss: 0.2279 - accuracy: 0.93  
33 - val\_loss: 0.4149 - val\_accuracy: 0.9333  
Epoch 35/100  
4/4 [=====] - 3s 775ms/step - loss: 0.2394 - accuracy: 0.89  
17 - val\_loss: 0.4100 - val\_accuracy: 0.9333  
Epoch 36/100  
4/4 [=====] - 4s 908ms/step - loss: 0.2181 - accuracy: 0.89  
17 - val\_loss: 0.3223 - val\_accuracy: 0.9000  
Epoch 37/100  
4/4 [=====] - 3s 817ms/step - loss: 0.1685 - accuracy: 0.90  
83 - val\_loss: 0.3053 - val\_accuracy: 0.9333  
Epoch 38/100  
4/4 [=====] - 3s 835ms/step - loss: 0.1913 - accuracy: 0.92  
50 - val\_loss: 0.1841 - val\_accuracy: 0.9333  
Epoch 39/100  
4/4 [=====] - 3s 762ms/step - loss: 0.2235 - accuracy: 0.88  
33 - val\_loss: 0.1548 - val\_accuracy: 0.9667  
Epoch 40/100  
4/4 [=====] - 3s 717ms/step - loss: 0.1815 - accuracy: 0.93  
33 - val\_loss: 0.2712 - val\_accuracy: 0.9333  
Epoch 41/100  
4/4 [=====] - 4s 924ms/step - loss: 0.1739 - accuracy: 0.91  
67 - val\_loss: 0.3831 - val\_accuracy: 0.8667  
Epoch 42/100  
4/4 [=====] - 3s 819ms/step - loss: 0.2032 - accuracy: 0.89  
17 - val\_loss: 0.3390 - val\_accuracy: 0.9000

Epoch 43/100  
4/4 [=====] - 3s 799ms/step - loss: 0.2178 - accuracy: 0.9167 - val\_loss: 0.2200 - val\_accuracy: 0.9667  
Epoch 44/100  
4/4 [=====] - 3s 836ms/step - loss: 0.2428 - accuracy: 0.8667 - val\_loss: 0.5805 - val\_accuracy: 0.9000  
Epoch 45/100  
4/4 [=====] - 3s 866ms/step - loss: 0.1921 - accuracy: 0.9083 - val\_loss: 0.4188 - val\_accuracy: 0.9000  
Epoch 46/100  
4/4 [=====] - 4s 891ms/step - loss: 0.1866 - accuracy: 0.9000 - val\_loss: 0.5072 - val\_accuracy: 0.9000  
Epoch 47/100  
4/4 [=====] - 3s 854ms/step - loss: 0.2100 - accuracy: 0.9083 - val\_loss: 0.1535 - val\_accuracy: 0.9333  
Epoch 48/100  
4/4 [=====] - 21s 5s/step - loss: 0.1470 - accuracy: 0.9333 - val\_loss: 0.1213 - val\_accuracy: 0.9333  
Epoch 49/100  
4/4 [=====] - 34s 8s/step - loss: 0.1236 - accuracy: 0.9333 - val\_loss: 0.1194 - val\_accuracy: 0.9333  
Epoch 50/100  
4/4 [=====] - 41s 10s/step - loss: 0.1481 - accuracy: 0.9583 - val\_loss: 0.0627 - val\_accuracy: 1.0000  
Epoch 51/100  
4/4 [=====] - 38s 10s/step - loss: 0.1672 - accuracy: 0.9250 - val\_loss: 0.0510 - val\_accuracy: 1.0000  
Epoch 52/100  
4/4 [=====] - 4s 982ms/step - loss: 0.1947 - accuracy: 0.9333 - val\_loss: 0.0967 - val\_accuracy: 0.9667  
Epoch 53/100  
4/4 [=====] - 4s 1s/step - loss: 0.1681 - accuracy: 0.9167 - val\_loss: 0.1339 - val\_accuracy: 0.9333  
Epoch 54/100  
4/4 [=====] - 4s 996ms/step - loss: 0.2885 - accuracy: 0.8667 - val\_loss: 0.5296 - val\_accuracy: 0.8667  
Epoch 55/100  
4/4 [=====] - 4s 947ms/step - loss: 0.1958 - accuracy: 0.9333 - val\_loss: 1.0038 - val\_accuracy: 0.8667  
Epoch 56/100  
4/4 [=====] - 4s 966ms/step - loss: 0.2913 - accuracy: 0.8500 - val\_loss: 1.0915 - val\_accuracy: 0.9333  
Epoch 57/100  
4/4 [=====] - 3s 831ms/step - loss: 0.1830 - accuracy: 0.9167 - val\_loss: 1.1960 - val\_accuracy: 0.9000  
Epoch 58/100  
4/4 [=====] - 4s 888ms/step - loss: 0.1818 - accuracy: 0.9167 - val\_loss: 0.1871 - val\_accuracy: 0.9333  
Epoch 59/100  
4/4 [=====] - 4s 952ms/step - loss: 0.1771 - accuracy: 0.9333 - val\_loss: 0.3573 - val\_accuracy: 0.9333  
Epoch 60/100  
4/4 [=====] - 4s 888ms/step - loss: 0.1630 - accuracy: 0.9333 - val\_loss: 0.3929 - val\_accuracy: 0.9000  
Epoch 61/100  
4/4 [=====] - 3s 847ms/step - loss: 0.1264 - accuracy: 0.9417 - val\_loss: 0.4938 - val\_accuracy: 0.9000  
Epoch 62/100  
4/4 [=====] - 3s 872ms/step - loss: 0.1140 - accuracy: 0.9583 - val\_loss: 0.6114 - val\_accuracy: 0.9000  
Epoch 63/100  
4/4 [=====] - 3s 783ms/step - loss: 0.1154 - accuracy: 0.9333 - val\_loss: 1.2162 - val\_accuracy: 0.9000

Epoch 64/100  
4/4 [=====] - 3s 844ms/step - loss: 0.1063 - accuracy: 0.95  
83 - val\_loss: 1.0034 - val\_accuracy: 0.9000  
Epoch 65/100  
4/4 [=====] - 3s 839ms/step - loss: 0.0820 - accuracy: 0.97  
50 - val\_loss: 1.0575 - val\_accuracy: 0.9000  
Epoch 66/100  
4/4 [=====] - 3s 843ms/step - loss: 0.1188 - accuracy: 0.94  
17 - val\_loss: 2.2247 - val\_accuracy: 0.9000  
Epoch 67/100  
4/4 [=====] - 4s 1s/step - loss: 0.0859 - accuracy: 0.9667  
- val\_loss: 1.6789 - val\_accuracy: 0.9000  
Epoch 68/100  
4/4 [=====] - 4s 888ms/step - loss: 0.0674 - accuracy: 0.96  
67 - val\_loss: 1.8637 - val\_accuracy: 0.8667  
Epoch 69/100  
4/4 [=====] - 3s 858ms/step - loss: 0.0570 - accuracy: 0.97  
50 - val\_loss: 1.6713 - val\_accuracy: 0.9000  
Epoch 70/100  
4/4 [=====] - 3s 845ms/step - loss: 0.0821 - accuracy: 0.97  
50 - val\_loss: 1.5420 - val\_accuracy: 0.9000  
Epoch 71/100  
4/4 [=====] - 3s 855ms/step - loss: 0.0495 - accuracy: 0.98  
33 - val\_loss: 1.4587 - val\_accuracy: 0.8333  
Epoch 72/100  
4/4 [=====] - 3s 809ms/step - loss: 0.0662 - accuracy: 0.97  
50 - val\_loss: 1.5145 - val\_accuracy: 0.9000  
Epoch 73/100  
4/4 [=====] - 3s 807ms/step - loss: 0.1061 - accuracy: 0.95  
83 - val\_loss: 1.7428 - val\_accuracy: 0.8667  
Epoch 74/100  
4/4 [=====] - 4s 907ms/step - loss: 0.0641 - accuracy: 0.95  
83 - val\_loss: 0.3655 - val\_accuracy: 0.9667  
Epoch 75/100  
4/4 [=====] - 3s 822ms/step - loss: 0.0678 - accuracy: 0.97  
50 - val\_loss: 0.5452 - val\_accuracy: 0.9333  
Epoch 76/100  
4/4 [=====] - 3s 812ms/step - loss: 0.0960 - accuracy: 0.95  
00 - val\_loss: 1.6132 - val\_accuracy: 0.8333  
Epoch 77/100  
4/4 [=====] - 4s 893ms/step - loss: 0.0795 - accuracy: 0.97  
50 - val\_loss: 0.6466 - val\_accuracy: 0.9333  
Epoch 78/100  
4/4 [=====] - 3s 753ms/step - loss: 0.0470 - accuracy: 0.99  
17 - val\_loss: 0.2600 - val\_accuracy: 0.9667  
Epoch 79/100  
4/4 [=====] - 3s 828ms/step - loss: 0.0551 - accuracy: 0.97  
50 - val\_loss: 0.6218 - val\_accuracy: 0.8667  
Epoch 80/100  
4/4 [=====] - 3s 754ms/step - loss: 0.0963 - accuracy: 0.95  
83 - val\_loss: 1.5088 - val\_accuracy: 0.9000  
Epoch 81/100  
4/4 [=====] - 4s 927ms/step - loss: 0.0604 - accuracy: 0.97  
50 - val\_loss: 2.0167 - val\_accuracy: 0.8667  
Epoch 82/100  
4/4 [=====] - 4s 933ms/step - loss: 0.0788 - accuracy: 0.97  
50 - val\_loss: 0.9017 - val\_accuracy: 0.9000  
Epoch 83/100  
4/4 [=====] - 3s 849ms/step - loss: 0.4276 - accuracy: 0.85  
83 - val\_loss: 1.4734 - val\_accuracy: 0.9000  
Epoch 84/100  
4/4 [=====] - 3s 826ms/step - loss: 0.2948 - accuracy: 0.87  
50 - val\_loss: 0.4746 - val\_accuracy: 0.9000

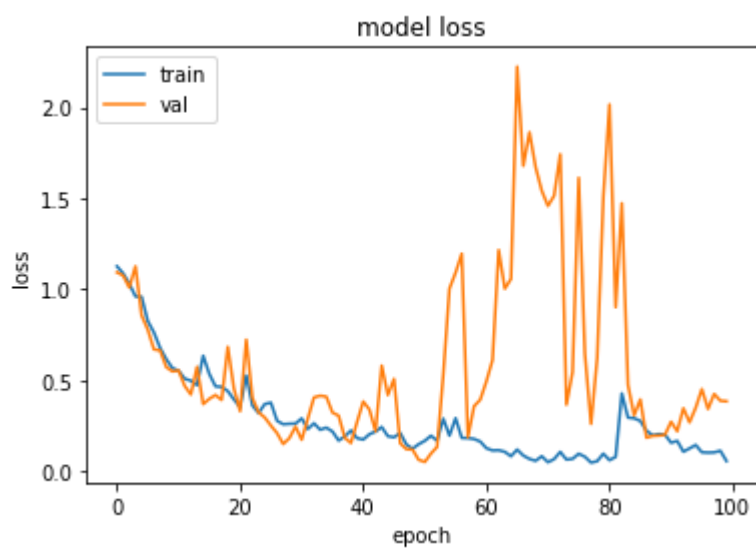
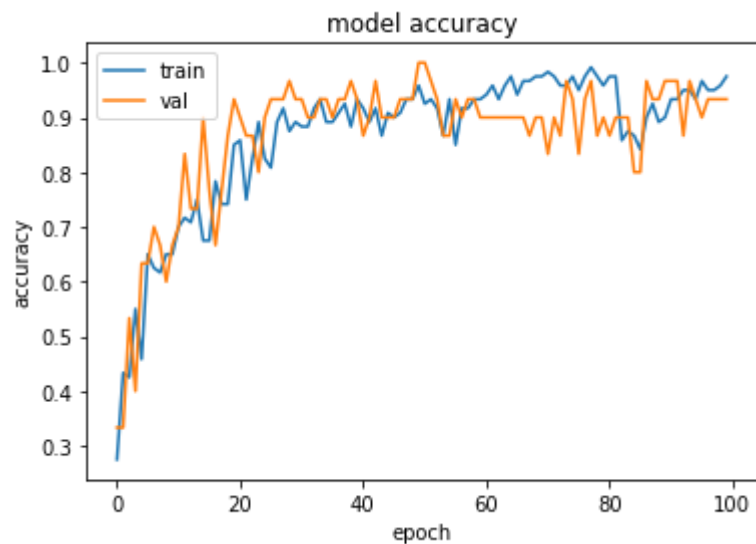
```

Epoch 85/100
4/4 [=====] - 4s 913ms/step - loss: 0.2910 - accuracy: 0.86
67 - val_loss: 0.3071 - val_accuracy: 0.8000
Epoch 86/100
4/4 [=====] - 3s 804ms/step - loss: 0.2763 - accuracy: 0.84
17 - val_loss: 0.3945 - val_accuracy: 0.8000
Epoch 87/100
4/4 [=====] - 3s 870ms/step - loss: 0.2224 - accuracy: 0.90
00 - val_loss: 0.1843 - val_accuracy: 0.9667
Epoch 88/100
4/4 [=====] - 3s 745ms/step - loss: 0.1971 - accuracy: 0.92
50 - val_loss: 0.1943 - val_accuracy: 0.9333
Epoch 89/100
4/4 [=====] - 3s 768ms/step - loss: 0.2042 - accuracy: 0.89
17 - val_loss: 0.1958 - val_accuracy: 0.9333
Epoch 90/100
4/4 [=====] - 4s 947ms/step - loss: 0.2016 - accuracy: 0.90
00 - val_loss: 0.1998 - val_accuracy: 0.9667
Epoch 91/100
4/4 [=====] - 3s 817ms/step - loss: 0.1564 - accuracy: 0.93
33 - val_loss: 0.2721 - val_accuracy: 0.9667
Epoch 92/100
4/4 [=====] - 3s 804ms/step - loss: 0.1663 - accuracy: 0.93
33 - val_loss: 0.2196 - val_accuracy: 0.9667
Epoch 93/100
4/4 [=====] - 3s 869ms/step - loss: 0.1073 - accuracy: 0.95
00 - val_loss: 0.3457 - val_accuracy: 0.8667
Epoch 94/100
4/4 [=====] - 3s 797ms/step - loss: 0.1252 - accuracy: 0.95
00 - val_loss: 0.2684 - val_accuracy: 0.9667
Epoch 95/100
4/4 [=====] - 3s 862ms/step - loss: 0.1440 - accuracy: 0.93
33 - val_loss: 0.3491 - val_accuracy: 0.9333
Epoch 96/100
4/4 [=====] - 4s 1s/step - loss: 0.1040 - accuracy: 0.9667
- val_loss: 0.4512 - val_accuracy: 0.9000
Epoch 97/100
4/4 [=====] - 4s 897ms/step - loss: 0.1021 - accuracy: 0.95
00 - val_loss: 0.3420 - val_accuracy: 0.9333
Epoch 98/100
4/4 [=====] - 4s 936ms/step - loss: 0.1033 - accuracy: 0.95
00 - val_loss: 0.4247 - val_accuracy: 0.9333
Epoch 99/100
4/4 [=====] - 3s 822ms/step - loss: 0.1121 - accuracy: 0.95
83 - val_loss: 0.3874 - val_accuracy: 0.9333
Epoch 100/100
4/4 [=====] - 3s 795ms/step - loss: 0.0559 - accuracy: 0.97
50 - val_loss: 0.3844 - val_accuracy: 0.9333

```

A very erratic validation loss can be seen but the accuracy climbs up steadily and plateaus around 95%

```
In [16]: plt.plot(history.history['accuracy'])
plt.plot(history.history['val_accuracy'])
plt.title('model accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train', 'val'], loc='upper left')
plt.show()
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'val'], loc='upper left')
plt.show()
```



**Check Accuracy against 30 test images**

```
In [17]: test_batches = ImageDataGenerator(rescale=1. / 255,
      shear_range=0.5,
      zoom_range=0.5,
      rotation_range=45,
      width_shift_range=.15,
      height_shift_range=.15,
      horizontal_flip=True,
      vertical_flip=True).flow_from_directory(test_data_dir, target_size=(224,224), batch_size=10)
d = model.evaluate_generator(test_batches)
print("Loss: {} and Accuracy: {:.02f}".format(d[0],d[1]*100))
```

Found 29 images belonging to 3 classes.

Loss: 0.4342779219150543 and Accuracy: 86.20689511299133

```
In [30]: tr = model.evaluate_generator(train_batches)
v = model.evaluate_generator(valid_batches)
test = model.evaluate_generator(test_batches)

print("Train Loss: {} and Accuracy: {:.02f}".format(tr[0],tr[1]*100))
print("Valid Loss: {} and Accuracy: {:.02f}".format(v[0],v[1]*100))
print("Test Loss: {} and Accuracy: {:.02f}".format(test[0],test[1]*100))
```

Train Loss: 0.06878527253866196 and Accuracy: 96.66666388511658

Valid Loss: 0.4679800570011139 and Accuracy: 93.33333373069763

Test Loss: 0.5713502168655396 and Accuracy: 75.86206793785095

Poor test accuracy. Over fitting could be a problem. Too complex layers might result in overfitting

```
In [ ]: model.save("VGGBananaM1.h5")
```

Checking for random image to test

```
In [63]: from keras.preprocessing import image
from IPython.display import Image

import numpy as np
img = image.load_img('../input/bananacathand/Dataset/train/cat/cat.23.jpg', target_size=(224,224))
display(img)
x = image.img_to_array(img)
x = np.expand_dims(x, axis=0)
x = x*(1./255)
images = np.vstack([x])

classes = model.predict(images)
print(classes*100)
print(valid_batches.class_indices)
print(_classes[np.argmax(classes)])
```



```
[[2.2680389e-03 9.9996552e+01 1.1849966e-03]]
{'banana': 0, 'cat': 1, 'hand': 2}
cat
```

```
In [ ]: #For saving the model

# print(tf.__version__)
# from keras.models import model_from_json
# loaded_model = tf.keras.models.load_model("best.h5")
# json_model = loaded_model.to_json()
# with open('BananaWeights_model.json', 'w') as json_file:
#     json_file.write(json_model)
# #saving the weights of the model
# loaded_model.save_weights('BananaWeights.h5')
```

```
In [ ]: # json_file = open('BananaWeights_model.json', 'r')
# loaded_model_json = json_file.read()
# json_file.close()
# loaded_model = model_from_json(loaded_model_json)
# # Load weights into new model
# loaded_model.load_weights("BananaWeights.h5")
# loaded_model.compile(optimizer=opt, loss=keras.losses.categorical_crossentropy, metrics=['accuracy'])
# loaded_model.evaluate_generator(train_batches)
```

Now I test with the test set that is out of the 150 training images to get an idea

```
In [36]: print(model)
from keras.preprocessing import image
import numpy as np

for c in os.listdir("../input/bananacathand/Dataset/test/cat"):
    print(c)
    img = image.load_img("../input/bananacathand/Dataset/test/cat/" +c, target_size=(224,224))
    x = image.img_to_array(img)
    x = np.expand_dims(x, axis=0)
    x = x*(1./255)
    images = np.vstack([x])
    classes = model.predict(images)
    print(_classes[np.argmax(classes)])
    print()
```

<tensorflow.python.keras.engine.sequential.Sequential object at 0x7f6bd1662dd0>

cat.25.jpg  
cat

cat.8.jpg  
cat

cat.36.jpg  
cat

rscat2.jpg  
cat

vatx.jpg  
cat

cat.17.jpg  
cat

cat-banana.jpg  
banana

cat.26.jpg  
hand

cat.44.jpg  
cat

cat.13.jpg  
cat

cat.15.jpg  
cat

cat.11.jpg  
cat

cat.3.jpg  
hand

cathand.jpg  
hand



## Trying to reduce complexity to achieve faster training speed and lesser model size

I feel this model is too complex for the need. Thus need to reduce layers to improve the problem of overfitting. Trying to play around with filters

```
In [38]: model2 = tf.keras.Sequential()

model2.add(Conv2D(input_shape=(224,224,3),filters=32,kernel_size=(3,3),padding="same",
, activation="relu"))
model2.add(Conv2D(filters=32,kernel_size=(3,3),padding="same", activation="relu"))
model2.add(MaxPool2D(pool_size=(2,2),strides=(2,2)))

model2.add(Conv2D(filters=64, kernel_size=(3,3), padding="same", activation="relu"))
model2.add(MaxPool2D(pool_size=(2,2),strides=(2,2)))

model2.add(Conv2D(filters=128, kernel_size=(3,3), padding="same", activation="relu"))
model2.add(Conv2D(filters=128, kernel_size=(3,3), padding="same", activation="relu"))
model2.add(MaxPool2D(pool_size=(2,2),strides=(2,2)))

model2.add(Conv2D(filters=256, kernel_size=(3,3), padding="same", activation="relu"))
model2.add(Conv2D(filters=256, kernel_size=(3,3), padding="same", activation="relu"))
model2.add(MaxPool2D(pool_size=(2,2),strides=(2,2)))

model2.add(Flatten())
model2.add(Dense(units=1024,activation="relu"))
model2.add(Dense(units=1024,activation="relu"))

model2.add(Dense(units=3, activation="softmax"))
```

```
In [39]: _bestSaveModelName2 = "best2.h5"
opt = tf.keras.optimizers.Adam(lr=_learningRate)

mcp_save = tf.keras.callbacks.ModelCheckpoint(_bestSaveModelName2, save_best_only=True,
monitor='val_loss', mode='min')

model2.compile(optimizer=opt, loss=keras.losses.categorical_crossentropy, metrics=['accuracy'])
history = model2.fit_generator(train_batches, validation_data=valid_batches, epochs=_epochs,
verbose=1, callbacks=[mcp_save])
```

Epoch 1/100  
4/4 [=====] - 5s 1s/step - loss: 1.0986 - accuracy: 0.3250  
- val\_loss: 1.0883 - val\_accuracy: 0.3333  
Epoch 2/100  
4/4 [=====] - 5s 1s/step - loss: 1.0818 - accuracy: 0.3333  
- val\_loss: 1.0691 - val\_accuracy: 0.6333  
Epoch 3/100  
4/4 [=====] - 5s 1s/step - loss: 1.0674 - accuracy: 0.4917  
- val\_loss: 1.0414 - val\_accuracy: 0.6667  
Epoch 4/100  
4/4 [=====] - 5s 1s/step - loss: 0.9774 - accuracy: 0.5500  
- val\_loss: 0.9840 - val\_accuracy: 0.6000  
Epoch 5/100  
4/4 [=====] - 6s 2s/step - loss: 0.9079 - accuracy: 0.6083  
- val\_loss: 0.9058 - val\_accuracy: 0.6333  
Epoch 6/100  
4/4 [=====] - 8s 2s/step - loss: 0.8675 - accuracy: 0.5333  
- val\_loss: 0.7517 - val\_accuracy: 0.7000  
Epoch 7/100  
4/4 [=====] - 13s 3s/step - loss: 0.7699 - accuracy: 0.6083  
- val\_loss: 0.6746 - val\_accuracy: 0.6667  
Epoch 8/100  
4/4 [=====] - 5s 1s/step - loss: 0.7202 - accuracy: 0.6250  
- val\_loss: 0.6703 - val\_accuracy: 0.6333  
Epoch 9/100  
4/4 [=====] - 13s 3s/step - loss: 0.6604 - accuracy: 0.7000  
- val\_loss: 0.5811 - val\_accuracy: 0.7667  
Epoch 10/100  
4/4 [=====] - 6s 1s/step - loss: 0.6051 - accuracy: 0.7333  
- val\_loss: 0.5572 - val\_accuracy: 0.6333  
Epoch 11/100  
4/4 [=====] - 13s 3s/step - loss: 0.5683 - accuracy: 0.6833  
- val\_loss: 0.5118 - val\_accuracy: 0.9333  
Epoch 12/100  
4/4 [=====] - 5s 1s/step - loss: 0.5232 - accuracy: 0.7500  
- val\_loss: 0.4465 - val\_accuracy: 0.6667  
Epoch 13/100  
4/4 [=====] - 3s 821ms/step - loss: 0.5417 - accuracy: 0.68  
33 - val\_loss: 0.4525 - val\_accuracy: 0.8000  
Epoch 14/100  
4/4 [=====] - 5s 1s/step - loss: 0.4989 - accuracy: 0.7917  
- val\_loss: 0.3535 - val\_accuracy: 0.9333  
Epoch 15/100  
4/4 [=====] - 4s 876ms/step - loss: 0.5088 - accuracy: 0.71  
67 - val\_loss: 0.3629 - val\_accuracy: 0.9333  
Epoch 16/100  
4/4 [=====] - 5s 1s/step - loss: 0.4493 - accuracy: 0.8000  
- val\_loss: 0.3481 - val\_accuracy: 0.9667  
Epoch 17/100  
4/4 [=====] - 13s 3s/step - loss: 0.4152 - accuracy: 0.7917  
- val\_loss: 0.2591 - val\_accuracy: 0.9667  
Epoch 18/100  
4/4 [=====] - 3s 827ms/step - loss: 0.3623 - accuracy: 0.85  
83 - val\_loss: 0.2900 - val\_accuracy: 0.8667  
Epoch 19/100  
4/4 [=====] - 3s 855ms/step - loss: 0.3871 - accuracy: 0.80  
83 - val\_loss: 0.2979 - val\_accuracy: 0.9333  
Epoch 20/100  
4/4 [=====] - 5s 1s/step - loss: 0.3586 - accuracy: 0.8250  
- val\_loss: 0.1820 - val\_accuracy: 1.0000  
Epoch 21/100  
4/4 [=====] - 4s 887ms/step - loss: 0.3271 - accuracy: 0.85  
83 - val\_loss: 0.2786 - val\_accuracy: 0.9000

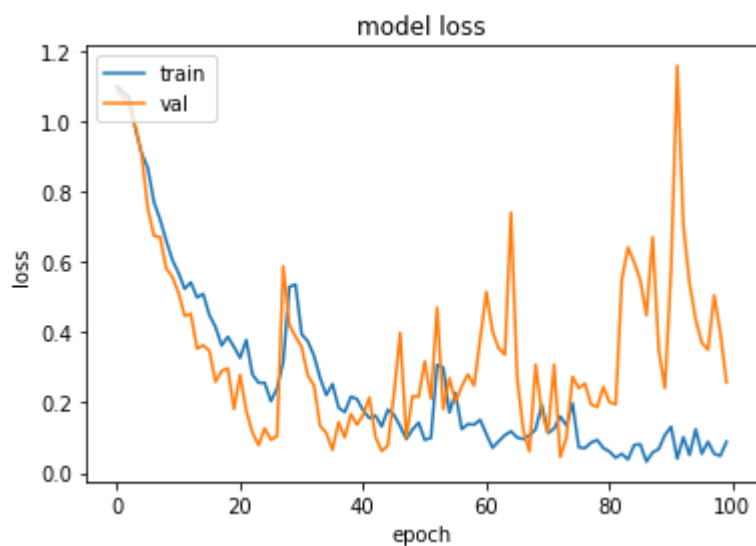
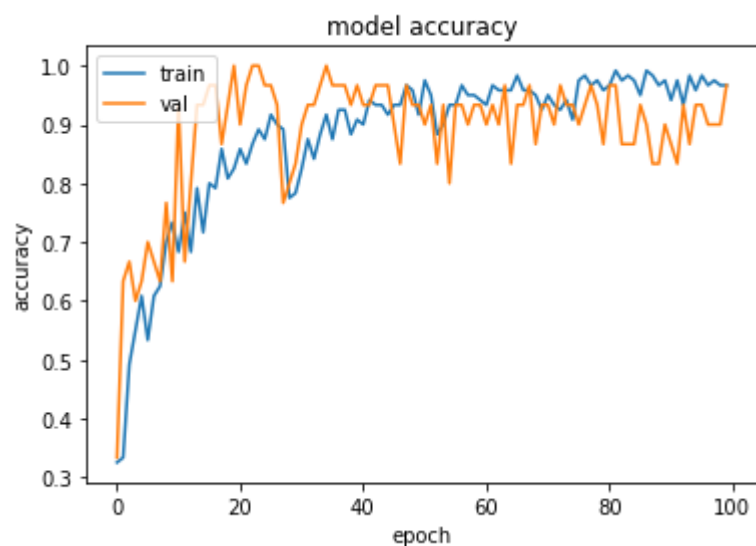
Epoch 22/100  
4/4 [=====] - 5s 1s/step - loss: 0.3780 - accuracy: 0.8333  
- val\_loss: 0.1777 - val\_accuracy: 0.9667  
Epoch 23/100  
4/4 [=====] - 5s 1s/step - loss: 0.2803 - accuracy: 0.8667  
- val\_loss: 0.1148 - val\_accuracy: 1.0000  
Epoch 24/100  
4/4 [=====] - 5s 1s/step - loss: 0.2566 - accuracy: 0.8917  
- val\_loss: 0.0793 - val\_accuracy: 1.0000  
Epoch 25/100  
4/4 [=====] - 4s 925ms/step - loss: 0.2561 - accuracy: 0.87  
50 - val\_loss: 0.1270 - val\_accuracy: 0.9667  
Epoch 26/100  
4/4 [=====] - 4s 1s/step - loss: 0.2040 - accuracy: 0.9167  
- val\_loss: 0.0944 - val\_accuracy: 0.9667  
Epoch 27/100  
4/4 [=====] - 3s 848ms/step - loss: 0.2404 - accuracy: 0.90  
00 - val\_loss: 0.1051 - val\_accuracy: 0.9333  
Epoch 28/100  
4/4 [=====] - 4s 878ms/step - loss: 0.3156 - accuracy: 0.89  
17 - val\_loss: 0.5875 - val\_accuracy: 0.7667  
Epoch 29/100  
4/4 [=====] - 4s 926ms/step - loss: 0.5289 - accuracy: 0.77  
50 - val\_loss: 0.4203 - val\_accuracy: 0.8000  
Epoch 30/100  
4/4 [=====] - 3s 859ms/step - loss: 0.5357 - accuracy: 0.78  
33 - val\_loss: 0.3876 - val\_accuracy: 0.8333  
Epoch 31/100  
4/4 [=====] - 4s 936ms/step - loss: 0.3941 - accuracy: 0.82  
50 - val\_loss: 0.3581 - val\_accuracy: 0.9000  
Epoch 32/100  
4/4 [=====] - 3s 850ms/step - loss: 0.3744 - accuracy: 0.87  
50 - val\_loss: 0.2765 - val\_accuracy: 0.9333  
Epoch 33/100  
4/4 [=====] - 4s 971ms/step - loss: 0.3333 - accuracy: 0.84  
17 - val\_loss: 0.2494 - val\_accuracy: 0.9333  
Epoch 34/100  
4/4 [=====] - 3s 874ms/step - loss: 0.2699 - accuracy: 0.88  
33 - val\_loss: 0.1337 - val\_accuracy: 0.9667  
Epoch 35/100  
4/4 [=====] - 3s 746ms/step - loss: 0.2215 - accuracy: 0.91  
67 - val\_loss: 0.1143 - val\_accuracy: 1.0000  
Epoch 36/100  
4/4 [=====] - 5s 1s/step - loss: 0.2528 - accuracy: 0.8750  
- val\_loss: 0.0658 - val\_accuracy: 0.9667  
Epoch 37/100  
4/4 [=====] - 4s 893ms/step - loss: 0.1857 - accuracy: 0.92  
50 - val\_loss: 0.1448 - val\_accuracy: 0.9667  
Epoch 38/100  
4/4 [=====] - 4s 920ms/step - loss: 0.1733 - accuracy: 0.92  
50 - val\_loss: 0.1012 - val\_accuracy: 0.9667  
Epoch 39/100  
4/4 [=====] - 4s 884ms/step - loss: 0.2171 - accuracy: 0.88  
33 - val\_loss: 0.1676 - val\_accuracy: 0.9333  
Epoch 40/100  
4/4 [=====] - 5s 1s/step - loss: 0.2099 - accuracy: 0.9083  
- val\_loss: 0.1373 - val\_accuracy: 0.9667  
Epoch 41/100  
4/4 [=====] - 3s 870ms/step - loss: 0.1776 - accuracy: 0.90  
00 - val\_loss: 0.1662 - val\_accuracy: 0.9333  
Epoch 42/100  
4/4 [=====] - 3s 782ms/step - loss: 0.1561 - accuracy: 0.94  
17 - val\_loss: 0.2147 - val\_accuracy: 0.9333

Epoch 43/100  
4/4 [=====] - 4s 909ms/step - loss: 0.1630 - accuracy: 0.93  
33 - val\_loss: 0.1023 - val\_accuracy: 0.9667  
Epoch 44/100  
4/4 [=====] - 6s 1s/step - loss: 0.1324 - accuracy: 0.9333  
- val\_loss: 0.0623 - val\_accuracy: 0.9667  
Epoch 45/100  
4/4 [=====] - 4s 941ms/step - loss: 0.1801 - accuracy: 0.91  
67 - val\_loss: 0.0784 - val\_accuracy: 0.9667  
Epoch 46/100  
4/4 [=====] - 3s 768ms/step - loss: 0.1652 - accuracy: 0.93  
33 - val\_loss: 0.2259 - val\_accuracy: 0.9000  
Epoch 47/100  
4/4 [=====] - 3s 725ms/step - loss: 0.1332 - accuracy: 0.93  
33 - val\_loss: 0.3982 - val\_accuracy: 0.8333  
Epoch 48/100  
4/4 [=====] - 4s 929ms/step - loss: 0.0964 - accuracy: 0.96  
67 - val\_loss: 0.1003 - val\_accuracy: 0.9667  
Epoch 49/100  
4/4 [=====] - 3s 830ms/step - loss: 0.1236 - accuracy: 0.95  
83 - val\_loss: 0.2188 - val\_accuracy: 0.9333  
Epoch 50/100  
4/4 [=====] - 4s 885ms/step - loss: 0.1432 - accuracy: 0.91  
67 - val\_loss: 0.2168 - val\_accuracy: 0.9333  
Epoch 51/100  
4/4 [=====] - 3s 777ms/step - loss: 0.0944 - accuracy: 0.97  
50 - val\_loss: 0.3174 - val\_accuracy: 0.9000  
Epoch 52/100  
4/4 [=====] - 3s 834ms/step - loss: 0.0998 - accuracy: 0.95  
00 - val\_loss: 0.2104 - val\_accuracy: 0.9333  
Epoch 53/100  
4/4 [=====] - 4s 890ms/step - loss: 0.3075 - accuracy: 0.88  
33 - val\_loss: 0.4697 - val\_accuracy: 0.8333  
Epoch 54/100  
4/4 [=====] - 3s 838ms/step - loss: 0.2995 - accuracy: 0.90  
00 - val\_loss: 0.1811 - val\_accuracy: 0.9333  
Epoch 55/100  
4/4 [=====] - 3s 759ms/step - loss: 0.1722 - accuracy: 0.93  
33 - val\_loss: 0.2699 - val\_accuracy: 0.8000  
Epoch 56/100  
4/4 [=====] - 3s 838ms/step - loss: 0.2272 - accuracy: 0.93  
33 - val\_loss: 0.2017 - val\_accuracy: 0.9333  
Epoch 57/100  
4/4 [=====] - 4s 875ms/step - loss: 0.1247 - accuracy: 0.96  
67 - val\_loss: 0.2463 - val\_accuracy: 0.9333  
Epoch 58/100  
4/4 [=====] - 4s 985ms/step - loss: 0.1392 - accuracy: 0.95  
00 - val\_loss: 0.2804 - val\_accuracy: 0.9000  
Epoch 59/100  
4/4 [=====] - 4s 959ms/step - loss: 0.1376 - accuracy: 0.95  
00 - val\_loss: 0.2485 - val\_accuracy: 0.9333  
Epoch 60/100  
4/4 [=====] - 4s 922ms/step - loss: 0.1512 - accuracy: 0.94  
17 - val\_loss: 0.3811 - val\_accuracy: 0.9333  
Epoch 61/100  
4/4 [=====] - 3s 800ms/step - loss: 0.1106 - accuracy: 0.93  
33 - val\_loss: 0.5145 - val\_accuracy: 0.9000  
Epoch 62/100  
4/4 [=====] - 3s 841ms/step - loss: 0.0718 - accuracy: 0.96  
67 - val\_loss: 0.4034 - val\_accuracy: 0.9333  
Epoch 63/100  
4/4 [=====] - 4s 894ms/step - loss: 0.0902 - accuracy: 0.95  
83 - val\_loss: 0.3541 - val\_accuracy: 0.9000

Epoch 64/100  
4/4 [=====] - 3s 766ms/step - loss: 0.1076 - accuracy: 0.9583 - val\_loss: 0.3365 - val\_accuracy: 0.9667  
Epoch 65/100  
4/4 [=====] - 3s 867ms/step - loss: 0.1186 - accuracy: 0.9583 - val\_loss: 0.7398 - val\_accuracy: 0.8333  
Epoch 66/100  
4/4 [=====] - 4s 947ms/step - loss: 0.1011 - accuracy: 0.9833 - val\_loss: 0.2717 - val\_accuracy: 0.9333  
Epoch 67/100  
4/4 [=====] - 4s 934ms/step - loss: 0.0965 - accuracy: 0.9583 - val\_loss: 0.1224 - val\_accuracy: 0.9333  
Epoch 68/100  
4/4 [=====] - 5s 1s/step - loss: 0.1071 - accuracy: 0.9583 - val\_loss: 0.0615 - val\_accuracy: 0.9667  
Epoch 69/100  
4/4 [=====] - 4s 923ms/step - loss: 0.1239 - accuracy: 0.9500 - val\_loss: 0.3079 - val\_accuracy: 0.8667  
Epoch 70/100  
4/4 [=====] - 3s 848ms/step - loss: 0.1945 - accuracy: 0.9250 - val\_loss: 0.1737 - val\_accuracy: 0.9333  
Epoch 71/100  
4/4 [=====] - 3s 872ms/step - loss: 0.1135 - accuracy: 0.9500 - val\_loss: 0.1155 - val\_accuracy: 0.9333  
Epoch 72/100  
4/4 [=====] - 4s 901ms/step - loss: 0.1262 - accuracy: 0.9333 - val\_loss: 0.3075 - val\_accuracy: 0.9000  
Epoch 73/100  
4/4 [=====] - 6s 1s/step - loss: 0.1612 - accuracy: 0.9250 - val\_loss: 0.0459 - val\_accuracy: 0.9667  
Epoch 74/100  
4/4 [=====] - 4s 944ms/step - loss: 0.1351 - accuracy: 0.9417 - val\_loss: 0.1007 - val\_accuracy: 0.9333  
Epoch 75/100  
4/4 [=====] - 4s 928ms/step - loss: 0.1979 - accuracy: 0.9083 - val\_loss: 0.2734 - val\_accuracy: 0.9333  
Epoch 76/100  
4/4 [=====] - 3s 827ms/step - loss: 0.0733 - accuracy: 0.9750 - val\_loss: 0.2411 - val\_accuracy: 0.9000  
Epoch 77/100  
4/4 [=====] - 3s 754ms/step - loss: 0.0707 - accuracy: 0.9833 - val\_loss: 0.2545 - val\_accuracy: 0.9333  
Epoch 78/100  
4/4 [=====] - 4s 887ms/step - loss: 0.0864 - accuracy: 0.9667 - val\_loss: 0.1951 - val\_accuracy: 0.9667  
Epoch 79/100  
4/4 [=====] - 12s 3s/step - loss: 0.0942 - accuracy: 0.9750 - val\_loss: 0.1874 - val\_accuracy: 0.9333  
Epoch 80/100  
4/4 [=====] - 4s 875ms/step - loss: 0.0711 - accuracy: 0.9583 - val\_loss: 0.2443 - val\_accuracy: 0.8667  
Epoch 81/100  
4/4 [=====] - 4s 926ms/step - loss: 0.0610 - accuracy: 0.9667 - val\_loss: 0.2011 - val\_accuracy: 0.9667  
Epoch 82/100  
4/4 [=====] - 3s 832ms/step - loss: 0.0437 - accuracy: 0.9917 - val\_loss: 0.1952 - val\_accuracy: 0.9667  
Epoch 83/100  
4/4 [=====] - 4s 1s/step - loss: 0.0545 - accuracy: 0.9750 - val\_loss: 0.5485 - val\_accuracy: 0.8667  
Epoch 84/100  
4/4 [=====] - 4s 900ms/step - loss: 0.0387 - accuracy: 0.9833 - val\_loss: 0.6406 - val\_accuracy: 0.8667

Epoch 85/100  
4/4 [=====] - 4s 913ms/step - loss: 0.0798 - accuracy: 0.97  
50 - val\_loss: 0.5991 - val\_accuracy: 0.8667  
Epoch 86/100  
4/4 [=====] - 4s 975ms/step - loss: 0.0818 - accuracy: 0.95  
00 - val\_loss: 0.5482 - val\_accuracy: 0.9333  
Epoch 87/100  
4/4 [=====] - 3s 805ms/step - loss: 0.0325 - accuracy: 0.99  
17 - val\_loss: 0.4480 - val\_accuracy: 0.9000  
Epoch 88/100  
4/4 [=====] - 4s 955ms/step - loss: 0.0586 - accuracy: 0.98  
33 - val\_loss: 0.6700 - val\_accuracy: 0.8333  
Epoch 89/100  
4/4 [=====] - 3s 874ms/step - loss: 0.0683 - accuracy: 0.96  
67 - val\_loss: 0.3493 - val\_accuracy: 0.8333  
Epoch 90/100  
4/4 [=====] - 4s 891ms/step - loss: 0.1084 - accuracy: 0.97  
50 - val\_loss: 0.2413 - val\_accuracy: 0.9000  
Epoch 91/100  
4/4 [=====] - 4s 894ms/step - loss: 0.1313 - accuracy: 0.94  
17 - val\_loss: 0.5786 - val\_accuracy: 0.8667  
Epoch 92/100  
4/4 [=====] - 3s 846ms/step - loss: 0.0412 - accuracy: 0.97  
50 - val\_loss: 1.1572 - val\_accuracy: 0.8333  
Epoch 93/100  
4/4 [=====] - 4s 958ms/step - loss: 0.1017 - accuracy: 0.93  
33 - val\_loss: 0.7028 - val\_accuracy: 0.9333  
Epoch 94/100  
4/4 [=====] - 3s 871ms/step - loss: 0.0516 - accuracy: 0.98  
33 - val\_loss: 0.5390 - val\_accuracy: 0.8667  
Epoch 95/100  
4/4 [=====] - 4s 887ms/step - loss: 0.1245 - accuracy: 0.95  
83 - val\_loss: 0.4355 - val\_accuracy: 0.9333  
Epoch 96/100  
4/4 [=====] - 4s 880ms/step - loss: 0.0548 - accuracy: 0.98  
33 - val\_loss: 0.3702 - val\_accuracy: 0.9333  
Epoch 97/100  
4/4 [=====] - 3s 772ms/step - loss: 0.0891 - accuracy: 0.96  
67 - val\_loss: 0.3504 - val\_accuracy: 0.9000  
Epoch 98/100  
4/4 [=====] - 4s 903ms/step - loss: 0.0548 - accuracy: 0.97  
50 - val\_loss: 0.5050 - val\_accuracy: 0.9000  
Epoch 99/100  
4/4 [=====] - 3s 856ms/step - loss: 0.0491 - accuracy: 0.96  
67 - val\_loss: 0.3989 - val\_accuracy: 0.9000  
Epoch 100/100  
4/4 [=====] - 4s 898ms/step - loss: 0.0890 - accuracy: 0.96  
67 - val\_loss: 0.2578 - val\_accuracy: 0.9667

```
In [65]: plt.plot(history.history['accuracy'])
plt.plot(history.history['val_accuracy'])
plt.title('model accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train', 'val'], loc='upper left')
plt.show()
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'val'], loc='upper left')
plt.show()
```





```
In [47]: bestModel = tf.keras.models.load_model("best2.h5")
d = bestModel.evaluate_generator(train_batches)
print("Train: Loss: {} and Accuracy: {:02}".format(d[0],d[1]*100))

d = bestModel.evaluate_generator(valid_batches)
print("Valid: Loss: {} and Accuracy: {:02}".format(d[0],d[1]*100))

d = bestModel.evaluate_generator(test_batches)
print("Test: Loss: {} and Accuracy: {:02}".format(d[0],d[1]*100))
```

Train: Loss: 0.17853008210659027 and Accuracy: 93.33333373069763  
Valid: Loss: 0.05634515359997749 and Accuracy: 96.66666388511658  
Test: Loss: 0.713640570640564 and Accuracy: 86.20689511299133

The model is achieving better accuracy with test data set.

#### References:

- 1.<https://keras.io/api/layers/> (<https://keras.io/api/layers/>)
- 2.<https://www.kaggle.com/moltean/fruits?> (<https://www.kaggle.com/moltean/fruits?>)
- 3.<https://www.kaggle.com/c/dogs-vs-cats> (<https://www.kaggle.com/c/dogs-vs-cats>)
- 4.<https://neurohive.io/en/popular-networks/vgg16/> (<https://neurohive.io/en/popular-networks/vgg16/>)
- 5.<https://www.geeksforgeeks.org/vgg-16-cnn-model/> (<https://www.geeksforgeeks.org/vgg-16-cnn-model/>)