

```
!nvidia-smi
```

```
Fri Apr 22 15:44:09 2022
```

NVIDIA-SMI 460.32.03				Driver Version: 460.32.03			CUDA Version: 11.2								

GPU	Name		Persistence-M		Bus-Id	Disp.A	Volatile	Uncorr.	ECC						
Fan	Temp	Perf	Pwr:Usage/Cap		Memory-Usage		GPU-Util	Compute	M.						
								MIG	M.						
=====															
0	Tesla	K80	Off		00000000:00:04.0	Off			0						
N/A	72C	P8	71W / 149W		0MiB / 11441MiB		0%	Default	N/A						

Processes:															
GPU	GI	CI	PID	Type	Process name				GPU Memory						
		ID	ID			Usage									
=====															
No running processes found															

```
USE_GPU = 1
```

```
# • Import • TensorFlow •
```

```
import • tensorflow • as • tf
```

```
# • Print • the • installed • TensorFlow • version
```

```
print(f'TensorFlow • version: • {tf.__version__}\n')
```

```
# • Get • all • GPU • devices • on • this • server
```

```
gpu_devices = • tf.config.list_physical_devices('GPU')
```

```
# • Print • the • name • and • the • type • of • all • GPU • devices
```

```
print('Available • GPU • Devices:')
```

```
for • gpu • in • gpu_devices:
```

```
• • • print(' • ', • gpu.name, • gpu.device_type)
```

```
• • • •
```

```
# • Set • only • the • GPU • specified • as • USE_GPU • to • be • visible
```

```
# • tf.config.set_visible_devices(gpu_devices[USE_GPU], • 'GPU')
```

```
# • Get • all • visible • GPU • • devices • on • this • server
```

```
visible_devices = • tf.config.get_visible_devices('GPU')
```

```
# • Print • the • name • and • the • type • of • all • visible • GPU • devices
```

```
print('\nVisible • GPU • Devices:')
```

```
for • gpu • in • visible_devices:
```

```
• • • print(' • ', • gpu.name, • gpu.device_type)
```

```
• • • •
```

```
# • Set • the • visible • device(s) • to • not • allocate • all • available • memory • at • once,
```

```
# • but • rather • let • the • memory • grow • whenever • needed
```

```
for • gpu • in • visible_devices:
```

```
• • • • tf.config.experimental.set_memory_growth(gpu, • True)
```

TensorFlow version: 2.8.0

Available GPU Devices:
/physical_device:GPU:0 GPU

Visible GPU Devices:
/physical_device:GPU:0 GPU

```
%matplotlib inline
```

```
import os
from pathlib import Path
import numpy as np
import matplotlib.pyplot as plt
import matplotlib.image as mpimg
```

```
from google.colab import drive
drive.mount('/content/drive/')
```

Drive already mounted at /content/drive/; to attempt to forcibly remount, call drive.mount(",



```
path = os.getcwd()
print(path)
```

```
/content
```

```
class_names = ['agricultural', 'airplane', 'baseballdiamond', 'beach', 'buildings',
               'chaparral', 'denseresidential', 'forest', 'freeway', 'golfcourse',
               'harbor', 'intersection', 'mediumresidential', 'mobilehomepark',
               'overpass', 'parkinglot', 'river', 'runway', 'sparseresidential',
               'storagetanks', 'tenniscourt']
```

```
os.chdir("drive/MyDrive/Challenge_dataset/train/")
```

```
print(os.getcwd())
print(os.path.join(os.path.dirname("__file__"), os.path.pardir))
path = os.path.abspath(os.path.join(os.path.dirname("__file__"), os.path.pardir))
os.chdir(path)
print(os.getcwd())
```

```
/content/drive/MyDrive/Challenge_dataset/train
..
/content/drive/MyDrive/Challenge_dataset
```

```
os.chdir(os.getcwd()+ "/train")
```

```
import cv2 as cv
from skimage import io
```

```

X = []
y = []
error = []
counter = 0

for c in class_names:
    os.chdir(os.getcwd() + "/" + c)
    print(os.getcwd())
    files = os.listdir(os.getcwd())
    print(files)
    for file in files: #遍历文件夹
        img = cv.imread(file)
        if(img.shape == (256, 256, 3)):
            X.append(img)
            y.append(counter)
        else:
            error.append(c + file)
    os.chdir(os.path.abspath(os.path.join(os.path.dirname("__file__"), os.path.pardir)))
    print(os.getcwd())
    counter += 1

/content/drive/MyDrive/Challenge_dataset/train/baseballdiamond
['baseballdiamond01.tif', 'baseballdiamond02.tif', 'baseballdiamond03.tif', 'baseballdiamc
/content/drive/MyDrive/Challenge_dataset/train
/content/drive/MyDrive/Challenge_dataset/train/beach
['beach00.tif', 'beach01.tif', 'beach02.tif', 'beach03.tif', 'beach04.tif', 'beach05.tif',
/content/drive/MyDrive/Challenge_dataset/train
/content/drive/MyDrive/Challenge_dataset/train/buildings
['buildings00.tif', 'buildings01.tif', 'buildings02.tif', 'buildings03.tif', 'buildings04.
/content/drive/MyDrive/Challenge_dataset/train
/content/drive/MyDrive/Challenge_dataset/train/chaparral
['chaparral00.tif', 'chaparral01.tif', 'chaparral02.tif', 'chaparral03.tif', 'chaparral04.
/content/drive/MyDrive/Challenge_dataset/train
/content/drive/MyDrive/Challenge_dataset/train/denseresidential
['denseresidential01.tif', 'denseresidential02.tif', 'denseresidential03.tif', 'denseresid
/content/drive/MyDrive/Challenge_dataset/train
/content/drive/MyDrive/Challenge_dataset/train/forest
['forest01.tif', 'forest00.tif', 'forest02.tif', 'forest03.tif', 'forest04.tif', 'forest05
/content/drive/MyDrive/Challenge_dataset/train
/content/drive/MyDrive/Challenge_dataset/train/freeway
['freeway01.tif', 'freeway00.tif', 'freeway02.tif', 'freeway03.tif', 'freeway04.tif', 'fre
/content/drive/MyDrive/Challenge_dataset/train
/content/drive/MyDrive/Challenge_dataset/train/golfcourse
['golfcourse00.tif', 'golfcourse01.tif', 'golfcourse02.tif', 'golfcourse03.tif', 'golfcour
/content/drive/MyDrive/Challenge_dataset/train
/content/drive/MyDrive/Challenge_dataset/train/harbor
['harbor01.tif', 'harbor02.tif', 'harbor03.tif', 'harbor04.tif', 'harbor05.tif', 'harbor06
/content/drive/MyDrive/Challenge_dataset/train
/content/drive/MyDrive/Challenge_dataset/train/intersection
['intersection01.tif', 'intersection02.tif', 'intersection03.tif', 'intersection04.tif', '
/content/drive/MyDrive/Challenge_dataset/train
/content/drive/MyDrive/Challenge_dataset/train/mediumresidential
['mediumresidential00.tif', 'mediumresidential01.tif', 'mediumresidential02.tif', 'mediumr
/content/drive/MyDrive/Challenge_dataset/train
/content/drive/MyDrive/Challenge_dataset/train/mobilehomepark
['mobilehomepark00.tif', 'mobilehomepark01.tif', 'mobilehomepark02.tif', 'mobilehomepark03
/content/drive/MyDrive/Challenge_dataset/train
/content/drive/MyDrive/Challenge_dataset/train/overnass

```

```

/content/drive/MyDrive/Challenge_dataset/train/overpass
['overpass00.tif', 'overpass01.tif', 'overpass02.tif', 'overpass03.tif', 'overpass04.tif',
/content/drive/MyDrive/Challenge_dataset/train
/content/drive/MyDrive/Challenge_dataset/train/parkinglot
['parkinglot01.tif', 'parkinglot02.tif', 'parkinglot03.tif', 'parkinglot04.tif', 'parkingl
/content/drive/MyDrive/Challenge_dataset/train
/content/drive/MyDrive/Challenge_dataset/train/river
['river00.tif', 'river01.tif', 'river02.tif', 'river03.tif', 'river04.tif', 'river05.tif',
/content/drive/MyDrive/Challenge_dataset/train
/content/drive/MyDrive/Challenge_dataset/train/runway
['runway01.tif', 'runway02.tif', 'runway03.tif', 'runway04.tif', 'runway05.tif', 'runway06
/content/drive/MyDrive/Challenge_dataset/train
/content/drive/MyDrive/Challenge_dataset/train/sparseresidential
['sparseresidential00.tif', 'sparseresidential01.tif', 'sparseresidential02.tif', 'sparser
/content/drive/MyDrive/Challenge_dataset/train
/content/drive/MyDrive/Challenge_dataset/train/storagetanks
['storagetanks00.tif', 'storagetanks01.tif', 'storagetanks02.tif', 'storagetanks03.tif', '
/content/drive/MyDrive/Challenge_dataset/train
/content/drive/MyDrive/Challenge_dataset/train/tenniscourt
['tenniscourt00.tif', 'tenniscourt01.tif', 'tenniscourt02.tif', 'tenniscourt03.tif', 'tenn
/content/drive/MyDrive/Challenge_dataset/train

```

```

X = np.array(X)
y = np.array(y)
print(X.shape, y.shape)

(1076, 256, 256, 3) (1076,)

print(X[1].shape)

(256, 256, 3)

os.chdir(os.path.abspath(os.path.join(os.path.dirname("__file__"), os.path.pardir)))
os.getcwd()

'/content/drive/MyDrive/Challenge_dataset'

os.getcwd()

'/content/drive/MyDrive/Challenge_dataset'

with open('train.npy', 'wb') as f:
    np.save(f, X)
    np.save(f, y)

os.chdir(os.getcwd()+"/test")

print(os.getcwd())

/content/drive/MyDrive/Challenge_dataset/test

```



```

/content/drive/MyDrive/Challenge_dataset/test
/content/drive/MyDrive/Challenge_dataset/test/overpass
['overpass88.tif', 'overpass89.tif', 'overpass90.tif', 'overpass91.tif', 'overpass92.tif',
/content/drive/MyDrive/Challenge_dataset/test
/content/drive/MyDrive/Challenge_dataset/test/parkinglot
['parkinglot87.tif', 'parkinglot88.tif', 'parkinglot89.tif', 'parkinglot90.tif', 'parkingl
/content/drive/MyDrive/Challenge_dataset/test
/content/drive/MyDrive/Challenge_dataset/test/river
['river87.tif', 'river88.tif', 'river89.tif', 'river90.tif', 'river91.tif', 'river92.tif',
/content/drive/MyDrive/Challenge_dataset/test
/content/drive/MyDrive/Challenge_dataset/test/runway
['runway89.tif', 'runway90.tif', 'runway91.tif', 'runway92.tif', 'runway93.tif', 'runway94
/content/drive/MyDrive/Challenge_dataset/test
/content/drive/MyDrive/Challenge_dataset/test/sparseresidential
['sparseresidential87.tif', 'sparseresidential88.tif', 'sparseresidential89.tif', 'sparser
/content/drive/MyDrive/Challenge_dataset/test
/content/drive/MyDrive/Challenge_dataset/test/storagetanks
['storagetanks87.tif', 'storagetanks88.tif', 'storagetanks89.tif', 'storagetanks90.tif', '
/content/drive/MyDrive/Challenge_dataset/test
/content/drive/MyDrive/Challenge_dataset/test/tenniscourt
['tenniscourt91.tif', 'tenniscourt92.tif', 'tenniscourt93.tif', 'tenniscourt94.tif', 'tenn
/content/drive/MyDrive/Challenge_dataset/test

```

```

X_test = np.array(X_test)
y_test = np.array(y_test)
print(X_test.shape, y_test.shape)

```

```

(276, 256, 256, 3) (276,)

```

```

print(X_test[1].shape)
print(y_test[1])

```

```

(256, 256, 3)
0

```

```

os.chdir(os.path.abspath(os.path.join(os.path.dirname("__file__"), os.path.pardir)))
os.getcwd()

```

```

'/content/drive/MyDrive/Challenge_dataset'

```

```

with open('test.npy', 'wb') as f:
    np.save(f, X_test)
    np.save(f, y_test)

```

```

print(X[0])

```

```

[[[ 45  41  44]
   [ 56  50  53]
   [ 50  44  47]
   ...
   [122 126 125]
   [130 137 137]
   [111 119 119]]

```

```

[[ 42  38  41]
 [ 46  43  46]
 [ 45  41  44]
 ...
 [ 81  83  83]
 [118 124 124]
 [126 131 135]]

[[ 43  39  42]
 [ 44  41  44]
 [ 44  40  43]
 ...
 [ 91  95  90]
 [ 98 103  99]
 [ 97  99 101]]

...

[[175 173 175]
 [189 191 190]
 [221 223 223]
 ...
 [136 144 144]
 [126 135 135]
 [118 123 124]]

[[120 113 120]
 [150 147 151]
 [165 166 168]
 ...
 [117 121 123]
 [117 121 126]
 [124 129 133]]

[[127 118 128]
 [110 103 113]
 [118 114 122]
 ...
 [ 99 101 101]
 [ 94  95  99]
 [127 129 135]]]

```

```
#####
```

```

# Normalize pixel values to be between 0 and 1
X, X_test = X / 255.0, X_test / 255.0

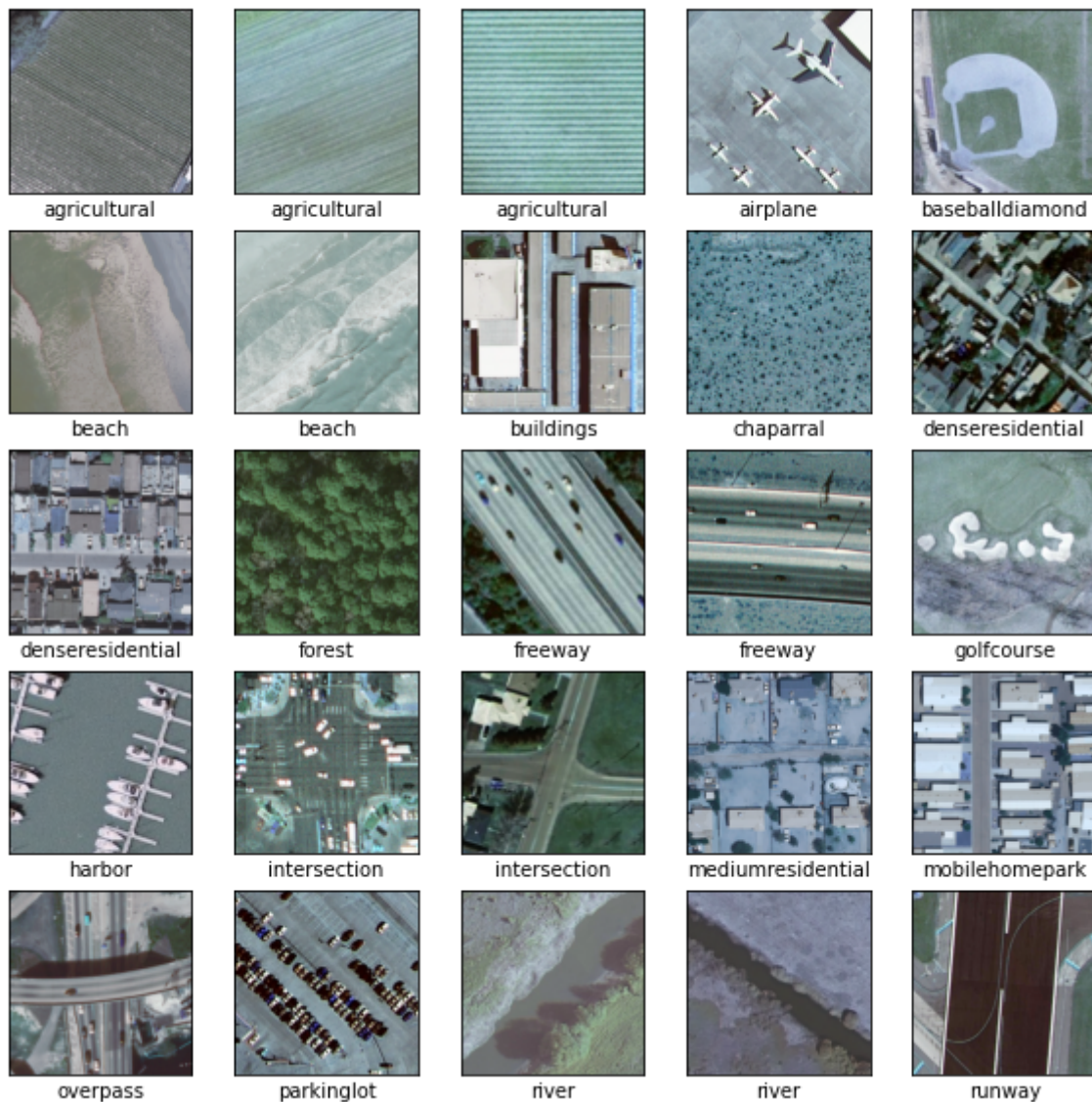
```

```

plt.figure(figsize=(10,10))
for i in range(0, 25):
    plt.subplot(5,5,i+1)
    plt.xticks([])
    plt.yticks([])
    plt.grid(False)
    plt.imshow(X[i*40])
    # The CIFAR labels happen to be arrays,
    # which is why you need the extra index

```

```
plt.xlabel(class_names[y[i*40]])
plt.show()
```



```
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2)

# Instantiate the ResNet50 model
conv_base = tf.keras.applications.resnet.ResNet50(input_shape=(256, 256, 3),
                                                    include_top=False,
                                                    weights='imagenet')

# freeze the layers
for layer in conv_base.layers:
    layer.trainable = False

names = []
for layer in conv_base.layers:
    names.append(layer.name)
```



```
names[-1] # getting the name of the last conv layer
```

```
'conv5_block3_out'
```

```
last_layer = conv_base.get_layer('conv5_block3_out')
print('last layer output shape: ', last_layer.output_shape)
last_output = last_layer.output
```

```
last layer output shape: (None, 8, 8, 2048)
```

```
from tensorflow.keras.models import Model
from tensorflow.keras.layers import Dense, Flatten, ReLU, GlobalAveragePooling2D, Input
```

```
inputs = Input(shape = (256, 256, 3))
x = conv_base(inputs)
x = GlobalAveragePooling2D()(x)
x = Flatten()(x)
# Add a fully connected layer with 512 hidden units and ReLU activation
x = Dense(512, activation='relu')(x)
# Add a final sigmoid layer for classification
output = Dense(len(class_names), activation='softmax')(x)
```

```
model = Model(inputs, output)
```

```
model.summary()
```

```
Model: "model"
```

Layer (type)	Output Shape	Param #
=====		
input_2 (InputLayer)	[(None, 256, 256, 3)]	0
resnet50 (Functional)	(None, 8, 8, 2048)	23587712
global_average_pooling2d (GlobalAveragePooling2D)	(None, 2048)	0
flatten (Flatten)	(None, 2048)	0
dense (Dense)	(None, 512)	1049088
dense_1 (Dense)	(None, 21)	10773
=====		
Total params: 24,647,573		
Trainable params: 1,059,861		
Non-trainable params: 23,587,712		
=====		

```
from tensorflow.keras.optimizers import RMSprop
```

```
# compile the model
model.compile(optimizer=RMSprop(lr=0.001),
```

```

..... loss='SparseCategoricalCrossentropy',
..... metrics=['accuracy'])

```

```

/usr/local/lib/python3.7/dist-packages/keras/optimizer_v2/rmsprop.py:130: UserWarning: The `
super(RMSprop, self).__init__(name, **kwargs)

```

```
X_train[1].shape
```

```
(256, 256, 3)
```

```

print(X_train.shape, y_train.shape)
print(X_test.shape, y_test.shape)

```

```

(860, 256, 256, 3) (860,)
(216, 256, 256, 3) (216,)
numpy.ndarray

```

```

history = model.fit(x = X_train,
                    y = y_train.reshape(860,1),
                    validation_data=(X_test, y_test.reshape(216,1)),
                    epochs=100)

```

```

27/27 [=====] - 11s 395ms/step - loss: 1.0142 - accuracy: 0.6593
Epoch 73/100
27/27 [=====] - 11s 393ms/step - loss: 1.0401 - accuracy: 0.6488
Epoch 74/100
27/27 [=====] - 11s 412ms/step - loss: 1.0356 - accuracy: 0.6605
Epoch 75/100
27/27 [=====] - 11s 394ms/step - loss: 1.0121 - accuracy: 0.6651
Epoch 76/100
27/27 [=====] - 11s 395ms/step - loss: 0.9968 - accuracy: 0.6686
Epoch 77/100
27/27 [=====] - 11s 394ms/step - loss: 0.9732 - accuracy: 0.6849
Epoch 78/100
27/27 [=====] - 11s 394ms/step - loss: 0.9994 - accuracy: 0.6721
Epoch 79/100
27/27 [=====] - 11s 394ms/step - loss: 0.9640 - accuracy: 0.6733
Epoch 80/100
27/27 [=====] - 11s 394ms/step - loss: 0.9717 - accuracy: 0.6849
Epoch 81/100
27/27 [=====] - 11s 394ms/step - loss: 0.9484 - accuracy: 0.7023
Epoch 82/100
27/27 [=====] - 11s 394ms/step - loss: 0.9472 - accuracy: 0.6779
Epoch 83/100
27/27 [=====] - 11s 393ms/step - loss: 0.9878 - accuracy: 0.6814
Epoch 84/100
27/27 [=====] - 11s 395ms/step - loss: 0.9136 - accuracy: 0.6977
Epoch 85/100
27/27 [=====] - 11s 394ms/step - loss: 0.9648 - accuracy: 0.6686
Epoch 86/100
27/27 [=====] - 11s 394ms/step - loss: 0.9383 - accuracy: 0.6919
Epoch 87/100
27/27 [=====] - 11s 394ms/step - loss: 0.9338 - accuracy: 0.6826
Epoch 88/100
27/27 [=====] - 11s 394ms/step - loss: 0.9585 - accuracy: 0.6977

```

```

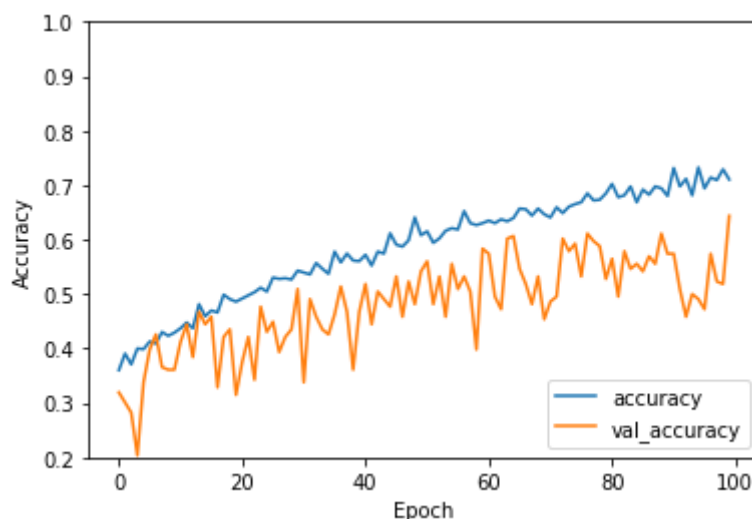
Epoch 89/100
27/27 [=====] - 11s 394ms/step - loss: 0.9167 - accuracy: 0.6942
Epoch 90/100
27/27 [=====] - 11s 395ms/step - loss: 0.9497 - accuracy: 0.6802
Epoch 91/100
27/27 [=====] - 11s 394ms/step - loss: 0.8567 - accuracy: 0.7314
Epoch 92/100
27/27 [=====] - 11s 394ms/step - loss: 0.9376 - accuracy: 0.6977
Epoch 93/100
27/27 [=====] - 11s 412ms/step - loss: 0.8621 - accuracy: 0.7116
Epoch 94/100
27/27 [=====] - 11s 394ms/step - loss: 0.9052 - accuracy: 0.6814
Epoch 95/100
27/27 [=====] - 11s 395ms/step - loss: 0.8507 - accuracy: 0.7326
Epoch 96/100
27/27 [=====] - 11s 394ms/step - loss: 0.9625 - accuracy: 0.6942
Epoch 97/100
27/27 [=====] - 11s 412ms/step - loss: 0.8630 - accuracy: 0.7140
Epoch 98/100
27/27 [=====] - 11s 395ms/step - loss: 0.8917 - accuracy: 0.7093
Epoch 99/100
27/27 [=====] - 11s 393ms/step - loss: 0.8383 - accuracy: 0.7291
Epoch 100/100
27/27 [=====] - 11s 394ms/step - loss: 0.8822 - accuracy: 0.7105

```

```

plt.plot(history.history['accuracy'], label='accuracy')
plt.plot(history.history['val_accuracy'], label = 'val_accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.ylim([0.2, 1])
plt.legend(loc='lower right')
plt.show()

```

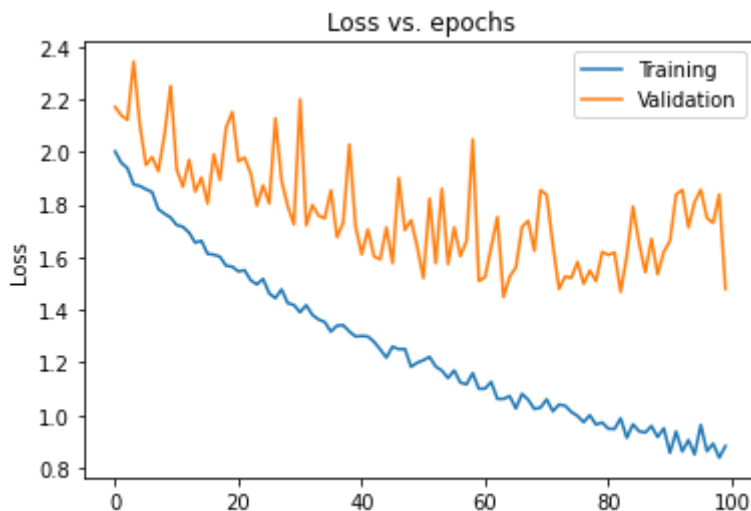


```

plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('Loss vs. epochs')
plt.ylabel('Loss')
plt.xlabel('Epoch')

```

```
plt.legend(['Training', 'Validation'], loc='upper right')
plt.show()
```



```
# Save the weights
model.save_weights('./checkpoints/my_checkpoint')

inputs = Input(shape = (256, 256, 3))
x = conv_base(inputs)
x = GlobalAveragePooling2D()(x)
x = Flatten()(x)
# Add a fully connected layer with 512 hidden units and ReLU activation
x = Dense(512, activation='relu')(x)
# Add a final sigmoid layer for classification
output = Dense(len(class_names), activation='softmax')(x)

model2 = Model(inputs, output)

# Restore the weights
model2.load_weights('./checkpoints/my_checkpoint')

<tensorflow.python.training.tracking.util.CheckpointLoadStatus at 0x7f0df7d63390>

with open("test.npy", "rb") as f:
    X_val = np.load(f)
    y_val = np.load(f)

X_val = X_val / 255.0

X_val[1].shape

(256, 256, 3)

classif_prob = model.predict(X_val)
print(classif_prob)

[[9.9079680e-01 1.8352343e-13 9.2491671e-04 ... 1.1319467e-07
```

```

4.0909299e-08 7.9312094e-06]
[5.9418303e-01 1.6796980e-09 4.7567502e-02 ... 6.5906934e-05
5.9400845e-05 6.4122584e-03]
[7.9076058e-01 4.1297371e-10 2.2103989e-02 ... 4.8845042e-05
2.8628907e-05 3.1372164e-03]
...
[8.1754662e-03 2.6119809e-04 3.2341129e-06 ... 3.5841912e-01
2.4187183e-01 5.2144378e-02]
[4.6716304e-04 7.2954346e-05 2.0611715e-02 ... 3.0913332e-04
1.4982893e-01 4.7001913e-01]
[1.3893687e-03 6.4356675e-05 1.4540068e-02 ... 5.2434229e-03
9.7010687e-02 3.4245518e-01]]

```

```
pred_classes_argmax = np.argmax(classif_prob,axis=-1)
```

```

predicted_cls = pred_classes_argmax[0]
print("Predicted class:", predicted_cls)
print()

```

```
Predicted class: 0
```

```

values = model.evaluate(X_val, y_val)
print("{}: {}, {}: {}".format(model.metrics_names[0], values[0], model.metrics_names[1], values[1]))

```

```

9/9 [=====] - 4s 301ms/step - loss: 3.2318 - accuracy: 0.4167
loss:3.231823444366455, accuracy:0.4166666567325592.

```