```
!mkdir -p ~/.kaggle
!cp kaggle.json ~/.kaggle/
```

```
!kaggle datasets download -d umairshahpirzada/birds-20-species-image-classification
```

```
Warning: Your Kaggle API key is readable by other users on this system! To fix this, you can run 'chmod 600 /root/.kaggle/kaggle.js
Downloading birds-20-species-image-classification.zip to /content
 82% 57.0M/69.3M [00:00<00:00, 74.4MB/s]
100% 69.3M/69.3M [00:00<00:00, 79.4MB/s]
```

```
import zipfile
zip_ref = zipfile.ZipFile('/content/birds-20-species-image-classification.zip', 'r')
zip_ref.extractall('/content')
zip_ref.close()
```

```
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras import layers,models
from keras import Sequential
from keras.layers import Dense,Conv2D,MaxPooling2D,Flatten,BatchNormalization,Dropout
import matplotlib.pyplot as plt
from keras.callbacks import EarlyStopping
early_stop=EarlyStopping(monitor="val_loss",mode='min',verbose=1,patience=25)
```

```
 # generators
train_ds=keras.utils.image_dataset_from_directory(directory='/content/train',labels='inferred',label_mode="int",
                                          batch_size=32,image_size=(256, 256))

validation_ds=keras.utils.image_dataset_from_directory(directory='/content/valid',labels='inferred',label_mode="int",
                                       batch_size=32,image_size=(256, 256))
test_ds=keras.utils.image_dataset_from_directory(directory='/content/test',labels='inferred',label_mode="int",
                                          batch_size=32,image_size=(256, 256))
```

```
Found 3208 files belonging to 20 classes.
Found 100 files belonging to 20 classes.
Found 100 files belonging to 20 classes.
```

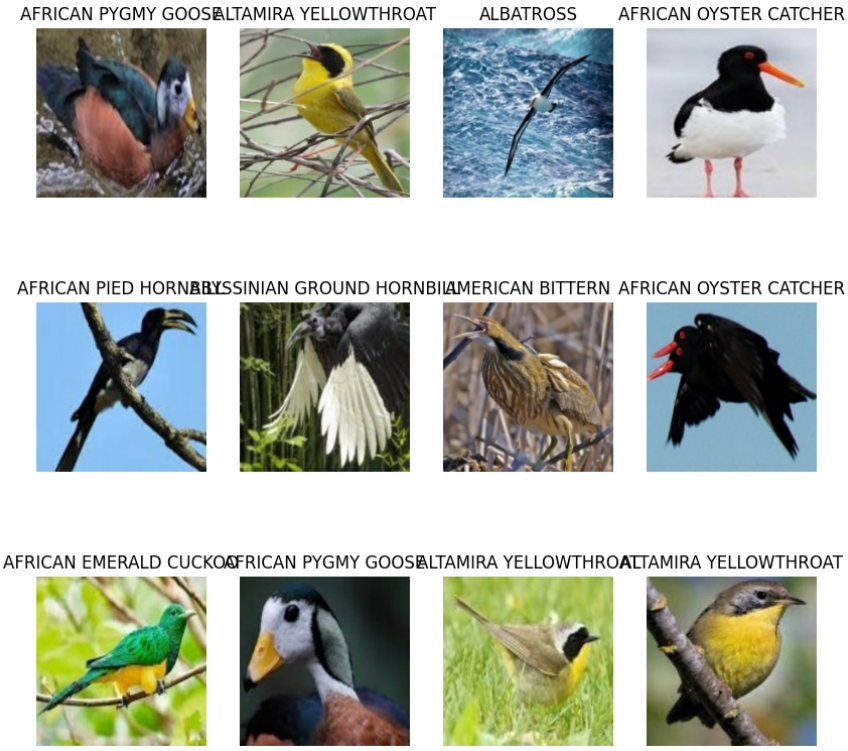
```
class_names=train_ds.class_names
class_names
```

```
['ABBOTTS BABBLER',
 'ABBOTTS BOOBY',
 'ABYSSINIAN GROUND HORNBILL',
 'AFRICAN CROWNED CRANE',
 'AFRICAN EMERALD CUCKOO',
 'AFRICAN FIREFINCH',
 'AFRICAN OYSTER CATCHER',
 'AFRICAN PIED HORNBILL',
 'AFRICAN PYGMY GOOSE',
 'ALBATROSS',
 'ALBERTS TOWHEE',
 'ALEXANDRINE PARAKEET',
 'ALPINE CHOUGH',
 'ALTAMIRA YELLOWTHROAT',
 'AMERICAN AVOCET',
 'AMERICAN BITTERN',
 'AMERICAN COOT',
 'AMERICAN FLAMINGO',
 'AMERICAN GOLDFINCH',
 'AMERICAN KESTREL']
```

```
for image,label in train_ds.take(1):
  print (image.shape)
  print (label.numpy())
```

```
(32, 256, 256, 3)
[ 2 10 11  4 15 19  1 15  7  5 13  4  8 15  0  6  1  9 12 11 12 16 15  9
  4 11 15 14  7  4 19  9]
```

```
plt.figure(figsize=(10,10))
for image,label in train_ds.take(1):
  for i in range(12):
    ax=plt.subplot(3,4,i+1)
    plt.imshow(image[i].numpy().astype("uint8"))
    plt.title(class_names[label[i]])
    plt.axis("off")
```




```
train_ds=train_ds.cache().shuffle(1000).prefetch(buffer_size=tf.data.AUTOTUNE)
validation_ds=validation_ds.cache().shuffle(1000).prefetch(buffer_size=tf.data.AUTOTUNE)
test_ds=test_ds.cache().shuffle(1000).prefetch(buffer_size=tf.data.AUTOTUNE)


#normalize
def process(image,label):
  image=tf.cast(image/255.,tf.float32)
  return image,label

train_ds=train_ds.map(process)
validation_ds=validation_ds.map(process)
test_ds=test_ds.map(process)


#create CNN MODEL
model=Sequential()
#model.add(resize_and_rescale)
#model.add(data_augmentation)
model.add(Conv2D(32,kernel_size=(3,3),padding='valid',activation='relu',input_shape=(256,256,3)))
model.add(BatchNormalization())
model.add(MaxPooling2D(pool_size=(2,2),strides=2,padding='valid'))

model.add(Conv2D(64,kernel_size=(3,3),padding='valid',activation='relu'))
model.add(BatchNormalization())
model.add(MaxPooling2D(pool_size=(2,2),strides=2,padding='valid'))

model.add(Conv2D(128,kernel_size=(3,3),padding='valid',activation='relu'))
model.add(BatchNormalization())
model.add(MaxPooling2D(pool_size=(2,2),strides=2,padding='valid'))

model.add(Flatten())
```

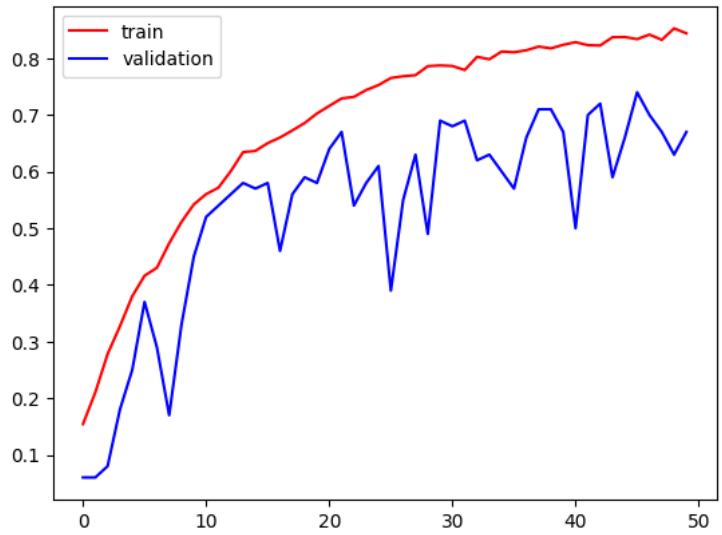
```
model.add(Dense(128,activation='relu'))
model.add(Dropout(0.1))
model.add(Dense(64,activation='relu'))
model.add(Dropout(0.1))
model.add(Dense(20,activation='softmax'))


model.summary()
```

```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 254, 254, 32)      896

 batch_normalization (BatchN  (None, 254, 254, 32)     128
 ormalization)

 max_pooling2d (MaxPooling2D  (None, 127, 127, 32)     0
 )

 conv2d_1 (Conv2D)           (None, 125, 125, 64)      18496

 batch_normalization_1 (Batc  (None, 125, 125, 64)     256
 hNormalization)

 max_pooling2d_1 (MaxPooling  (None, 62, 62, 64)       0
 2D)

 conv2d_2 (Conv2D)           (None, 60, 60, 128)       73856

 batch_normalization_2 (Batc  (None, 60, 60, 128)      512
 hNormalization)

 max_pooling2d_2 (MaxPooling  (None, 30, 30, 128)      0
 2D)

 flatten (Flatten)           (None, 115200)            0

 dense (Dense)               (None, 128)               14745728

 dropout (Dropout)           (None, 128)               0

 dense_1 (Dense)             (None, 64)                8256

 dropout_1 (Dropout)         (None, 64)                0

 dense_2 (Dense)             (None, 20)                1300

=================================================================
Total params: 14,849,428
Trainable params: 14,848,980
Non-trainable params: 448
_________________________________________________________________
```

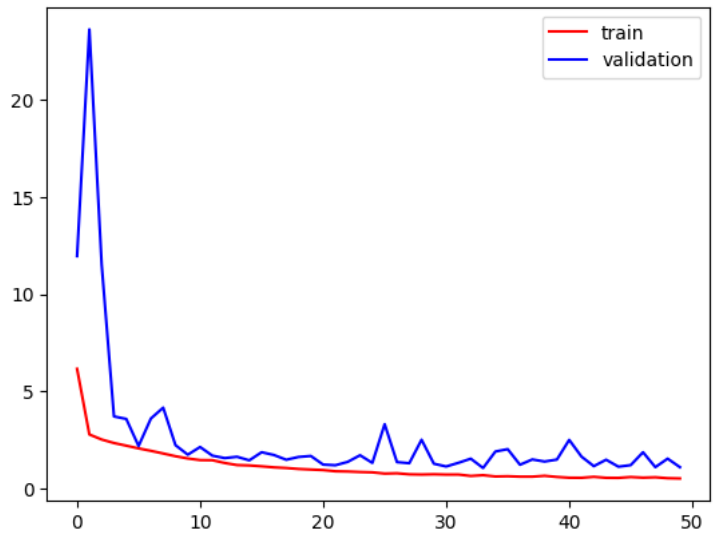
```
model.compile(optimizer='adam',loss='sparse_categorical_crossentropy',metrics=['accuracy'])
history=model.fit(train_ds,epochs=50,validation_data=validation_ds,callbacks=[early_stop])
```

```
Epoch 38/50
101/101 [==============================] - 9s 84ms/step - loss: 0.6098 - accuracy: 0.8208 - val_loss: 1.4957 - val_accuracy: 0.7
Epoch 39/50
101/101 [==============================] - 9s 86ms/step - loss: 0.6543 - accuracy: 0.8176 - val_loss: 1.3883 - val_accuracy: 0.7
Epoch 40/50
101/101 [==============================] - 9s 86ms/step - loss: 0.5953 - accuracy: 0.8239 - val_loss: 1.4895 - val_accuracy: 0.6
Epoch 41/50
101/101 [==============================] - 9s 86ms/step - loss: 0.5552 - accuracy: 0.8286 - val_loss: 2.5017 - val_accuracy: 0.5
Epoch 42/50
101/101 [==============================] - 9s 85ms/step - loss: 0.5518 - accuracy: 0.8233 - val_loss: 1.6406 - val_accuracy: 0.7
Epoch 43/50
101/101 [==============================] - 9s 86ms/step - loss: 0.6006 - accuracy: 0.8226 - val_loss: 1.1497 - val_accuracy: 0.7
Epoch 44/50
101/101 [==============================] - 9s 86ms/step - loss: 0.5509 - accuracy: 0.8373 - val_loss: 1.4812 - val_accuracy: 0.5
Epoch 45/50
101/101 [==============================] - 9s 86ms/step - loss: 0.5469 - accuracy: 0.8376 - val_loss: 1.1231 - val_accuracy: 0.6
Epoch 46/50
101/101 [==============================] - 9s 86ms/step - loss: 0.5907 - accuracy: 0.8339 - val_loss: 1.2030 - val_accuracy: 0.7
Epoch 47/50
101/101 [==============================] - 9s 85ms/step - loss: 0.5587 - accuracy: 0.8420 - val_loss: 1.8672 - val_accuracy: 0.7
Epoch 48/50
101/101 [==============================] - 9s 87ms/step - loss: 0.5777 - accuracy: 0.8326 - val_loss: 1.0988 - val_accuracy: 0.6
Epoch 49/50
101/101 [==============================] - 9s 86ms/step - loss: 0.5306 - accuracy: 0.8529 - val_loss: 1.5375 - val_accuracy: 0.6
Epoch 50/50
101/101 [==============================] - 9s 87ms/step - loss: 0.5168 - accuracy: 0.8441 - val_loss: 1.0967 - val_accuracy: 0.6
```

```
plt.plot(history.history['accuracy'],color='red',label='train')
plt.plot(history.history['val_accuracy'],color='blue',label='validation')
plt.legend()
plt.show()
```




```
plt.plot(history.history['loss'],color='red',label='train')
plt.plot(history.history['val_loss'],color='blue',label='validation')
plt.legend()
plt.show()
```



```
scores=model.evaluate(test_ds)
```

```
4/4 [==============================] - 0s 26ms/step - loss: 1.3557 - accuracy: 0.7000
```

```
scores
```

```
[1.3557260036468506, 0.699999988079071]
```

```
for image,label in test_ds.take(1):
  print (image.shape)
  print (label.numpy())
```

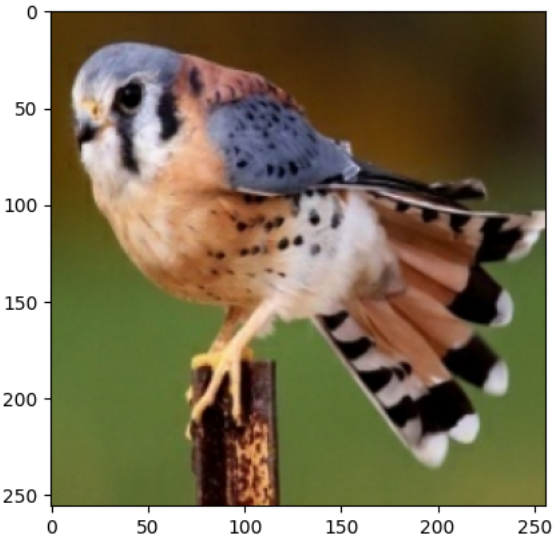
```
(32, 256, 256, 3)
[10  3  9  1 16  2 17  3  5 11  4  3  1 11 13  1 19  2  1 18 13  1 13  7
 11  8  3  7 15  8 12 10]
```

```
plt.figure(figsize=(10,10))
for image,label in train_ds.take(1):
  for i in range(12):
    ax=plt.subplot(3,4,i+1)
    plt.imshow(image[i].numpy())
    plt.title(class_names[label[i]])
    plt.axis("off")
```


```
for image,label in test_ds.take(1):
  plt.imshow(image[0].numpy())
```

```
import numpy as np
for image,label in test_ds.take(1):
  first_image=image[0].numpy()
  first_label=label[0].numpy()

  print('first image to predict')
  plt.imshow(first_image)
  print('actual_label',class_names[first_label])

  batch_prediction=model.predict(image)
  print('predicted_label',class_names[np.argmax(batch_prediction[0])])
```

```
first image to predict
actual_label AMERICAN KESTREL
1/1 [==============================] - 0s 34ms/step
predicted_label AMERICAN KESTREL
```



```
def predict(model,img):
  img_array=tf.keras.preprocessing.image.img_to_array(images[i].numpy())
  img_array=tf.expand_dims(img_array,0)   # create a batch

  predictions=model.predict(img_array)

  predicted_class=class_names[np.argmax(predictions[0])]
  confidence=round(100 * (np.max(predictions[0])),2)
  return predicted_class,confidence


plt.figure(figsize=(15,15))
for images,labels in test_ds.take(1):
  for i in range(9):
    ax=plt.subplot(3,3,i+1)
    plt.imshow(images[i].numpy())

    predicted_class, confidence=predict(model,images[i].numpy())
    actual_class=class_names[labels[i]]

    plt.title(f'Actual: {actual_class},\n Predicted: {predicted_class}.\n Confidence:{confidence}')

    plt.axis("off")
```

```
1/1 [==============================] - 0s 25ms/step
1/1 [==============================] - 0s 23ms/step
1/1 [==============================] - 0s 24ms/step
1/1 [==============================] - 0s 19ms/step
1/1 [==============================] - 0s 22ms/step
1/1 [==============================] - 0s 21ms/step
1/1 [==============================] - 0s 20ms/step
1/1 [==============================] - 0s 21ms/step
1/1 [==============================] - 0s 23ms/step
```

Actual: AMERICAN KESTREL,
Predicted: AMERICAN KESTREL.
Confidence:55.69

Actual: AMERICAN GOLDFINCH,
Predicted: AMERICAN GOLDFINCH.
Confidence:100.0

Actual: AMERICAN BITTERN,
Predicted: AMERICAN BITTERN.
Confidence:63.63

Actual: AFRICAN EMERALD CUCKOO,
Predicted: AFRICAN EMERALD CUCKOO.
Confidence:100.0

Actual: AMERICAN FLAMINGO,
Predicted: AMERICAN FLAMINGO.
Confidence:99.91

Actual: AFRICAN EMERALD CUCKOO,
Predicted: AFRICAN EMERALD CUCKOO.
Confidence:100.0

Actual: AMERICAN AVOCET,
Predicted: ABBOTTS BABBLER.
Confidence:24.94

Actual: AMERICAN GOLDFINCH,
Predicted: AMERICAN GOLDFINCH.
Confidence:100.0

Actual: ALBATROSS,
Predicted: ALBATROSS.
Confidence:100.0