Classifying Indian denomiation

Importing libraries

In [1]:

```
import matplotlib.pyplot as plt
import numpy as np
import os
import PIL
import tensorflow as tf

from tensorflow import keras
from tensorflow.keras import layers
from tensorflow.keras.models import Sequential
```

Setting the path to the dataset

In [2]:

```
import pathlib
data_dir = '/home/glitch101/Downloads/CURRENCY_DATASET'
data_dir  = pathlib.Path(data_dir)
```

Checking the number of images in the dataset

In [3]:

```
image_count = len(list(data_dir.glob('*/*.png')))
print(image_count)
```

```
400
```

Samples of each class

In [4]:

```
ten = list(data_dir.glob('10/*'))
PIL.Image.open(str(ten[0]))
```

In [5]:

```
PIL.Image.open(str(ten[1]))
```

In [6]:

```
twenty = list(data_dir.glob('20/*'))
PIL.Image.open(str(twenty[0]))
```

In [7]:

```
PIL.Image.open(str(twenty[1]))
```

In [8]:

```
hundred = list(data_dir.glob('100/*'))
PIL.Image.open(str(hundred[0]))
```

In [9]:

```
PIL.Image.open(str(hundred[1]))
```

In [10]:

```
two_hundred = list(data_dir.glob('200/*'))
PIL.Image.open(str(two_hundred[0]))
```

In [11]:

```
PIL.Image.open(str(two_hundred[1]))
```

Defining some parameters for the loader

In [12]:

```
batch_size = 32
img_height = 180
img_width = 180
```

I have used a 80-20 ratio for training and testing images

In [13]:

```
train_ds = tf.keras.preprocessing.image_dataset_from_directory(
  data_dir,
  validation_split=0.2,
  subset="training",
  seed=123,
  image_size=(img_height, img_width),
  batch_size=batch_size)
```

```
Found 556 files belonging to 4 classes.
Using 445 files for training.
```

In [14]:

```
val_ds = tf.keras.preprocessing.image_dataset_from_directory(
  data_dir,
  validation_split=0.2,
  subset="validation",
  seed=123,
  image_size=(img_height, img_width),
  batch_size=batch_size)
```

```
Found 556 files belonging to 4 classes.
Using 111 files for validation.
```

We have four classes 10, 100, 20, 200

In [15]:

```
class_names = train_ds.class_names
print(class_names)
```

```
['10', '100', '20', '200']
```

Visualizing the data

In [16]:

```
import matplotlib.pyplot as plt

plt.figure(figsize=(10, 10))
for images, labels in train_ds.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("off")
```

Creating a batch

In [17]:

```
for image_batch, labels_batch in train_ds:
  print(image_batch.shape)
  print(labels_batch.shape)
  break
```

```
(32, 180, 180, 3)
(32,)
```

Configuration

In [18]:

```
AUTOTUNE = tf.data.experimental.AUTOTUNE

train_ds = train_ds.cache().shuffle(1000).prefetch(buffer_size=AUTOTUNE)
val_ds = val_ds.cache().prefetch(buffer_size=AUTOTUNE)
```

Rescaling the rgb channels from [0, 255] to [0, 1]

In [19]:

```
normalization_layer = layers.experimental.preprocessing.Rescaling(1./255)
```

In [20]:

```
normalized_ds = train_ds.map(lambda x, y: (normalization_layer(x), y))
image_batch, labels_batch = next(iter(normalized_ds))
first_image = image_batch[0]
# Notice the pixels values are now in `[0,1]`.
print(np.min(first_image), np.max(first_image))
```

```
0.0028860057 1.0
```

Creating the model

In [21]:

```
num_classes = 4

model = Sequential([
  layers.experimental.preprocessing.Rescaling(1./255, input_shape=(img_heig
  layers.Conv2D(16, 3, padding='same', activation='relu'),
  layers.MaxPooling2D(),
  layers.Conv2D(32, 3, padding='same', activation='relu'),
  layers.MaxPooling2D(),
  layers.Conv2D(64, 3, padding='same', activation='relu'),
  layers.MaxPooling2D(),
  layers.Flatten(),
  layers.Dense(128, activation='relu'),
  layers.Dense(num_classes)
])
```

Compiling the model

In [22]:

```
model.compile(optimizer='adam',
              loss=tf.keras.losses.SparseCategoricalCrossentropy(from_logit
              metrics=['accuracy'])
```

In [23]:

```
1 model.summary()
```

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
rescaling_1 (Rescaling)      (None, 180, 180, 3)       0
_________________________________________________________________
conv2d (Conv2D)              (None, 180, 180, 16)      448
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 90, 90, 16)        0
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 90, 90, 32)        4640
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 45, 45, 32)        0
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 45, 45, 64)        18496
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 22, 22, 64)        0
_________________________________________________________________
flatten (Flatten)            (None, 30976)             0
_________________________________________________________________
dense (Dense)                (None, 128)               3965056
_________________________________________________________________
dense_1 (Dense)              (None, 4)                 516
=================================================================
Total params: 3,989,156
Trainable params: 3,989,156
Non-trainable params: 0
_________________________________________________________________
```

Training

In [24]:

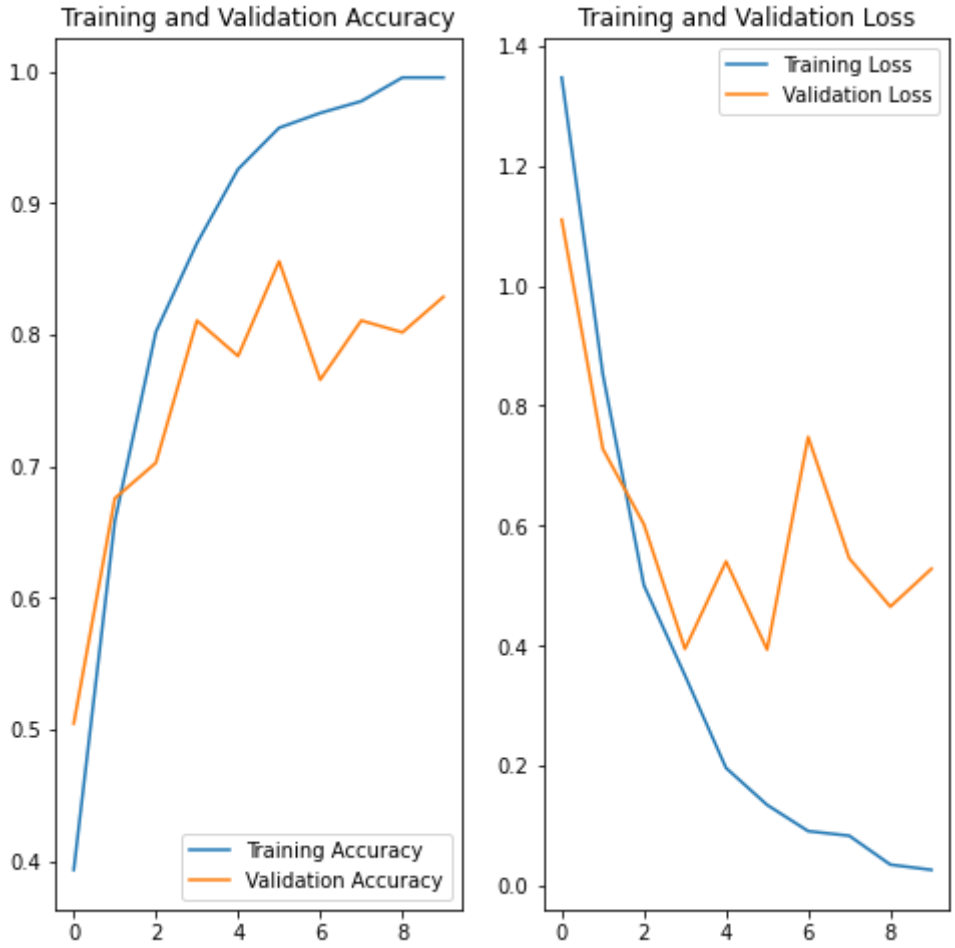
```
epochs=10
history = model.fit(
  train_ds,
  validation_data=val_ds,
  epochs=epochs
)
```

```
Epoch 1/10
14/14 [==============================] - 7s 493ms/step - loss: 1.3468 - accuracy: 0.3933 - val_loss:
0.5045
Epoch 2/10
14/14 [==============================] - 5s 341ms/step - loss: 0.8527 - accuracy: 0.6584 - val_loss:
0.6757
Epoch 3/10
14/14 [==============================] - 5s 352ms/step - loss: 0.5009 - accuracy: 0.8022 - val_loss:
0.7027
Epoch 4/10
14/14 [==============================] - 5s 383ms/step - loss: 0.3507 - accuracy: 0.8697 - val_loss:
0.8108
Epoch 5/10
14/14 [==============================] - 5s 325ms/step - loss: 0.1965 - accuracy: 0.9258 - val_loss:
0.7838
Epoch 6/10
14/14 [==============================] - 7s 489ms/step - loss: 0.1350 - accuracy: 0.9573 - val_loss:
0.8559
Epoch 7/10
14/14 [==============================] - 6s 456ms/step - loss: 0.0913 - accuracy: 0.9685 - val_loss:
0.7658
Epoch 8/10
14/14 [==============================] - 7s 481ms/step - loss: 0.0836 - accuracy: 0.9775 - val_loss:
0.8108
Epoch 9/10
14/14 [==============================] - 7s 474ms/step - loss: 0.0355 - accuracy: 0.9955 - val_loss:
0.8018
Epoch 10/10
14/14 [==============================] - 6s 440ms/step - loss: 0.0267 - accuracy: 0.9955 - val_loss:
0.8288
```

Training results

In [25]:

```
acc = history.history['accuracy']
val_acc = history.history['val_accuracy']

loss = history.history['loss']
val_loss = history.history['val_loss']

epochs_range = range(epochs)

plt.figure(figsize=(8, 8))
plt.subplot(1, 2, 1)
plt.plot(epochs_range, acc, label='Training Accuracy')
plt.plot(epochs_range, val_acc, label='Validation Accuracy')
plt.legend(loc='lower right')
plt.title('Training and Validation Accuracy')

plt.subplot(1, 2, 2)
plt.plot(epochs_range, loss, label='Training Loss')
plt.plot(epochs_range, val_loss, label='Validation Loss')
plt.legend(loc='upper right')
plt.title('Training and Validation Loss')
plt.show()
```



Augmenting the dataset to improvise for small training samples

In [26]:

```
data_augmentation = keras.Sequential(
  [
    layers.experimental.preprocessing.RandomFlip("horizontal",
                                                 input_shape=(img_height,
                                                              img_width,
                                                              3)),
    layers.experimental.preprocessing.RandomRotation(0.1),
    layers.experimental.preprocessing.RandomZoom(0.1),
  ]
)
```

Few augmentaiton examples

In [27]:

```
plt.figure(figsize=(10, 10))
for images, _ in train_ds.take(1):
  for i in range(9):
    augmented_images = data_augmentation(images)
    ax = plt.subplot(3, 3, i + 1)
    plt.imshow(augmented_images[0].numpy().astype("uint8"))
    plt.axis("off")
```

Using Dropout to reduce overfitting of the model

In [28]:

```
model = Sequential([
  data_augmentation,
  layers.experimental.preprocessing.Rescaling(1./255),
  layers.Conv2D(16, 3, padding='same', activation='relu'),
  layers.MaxPooling2D(),
  layers.Conv2D(32, 3, padding='same', activation='relu'),
  layers.MaxPooling2D(),
  layers.Conv2D(64, 3, padding='same', activation='relu'),
  layers.MaxPooling2D(),
  layers.Dropout(0.2),
  layers.Flatten(),
  layers.Dense(128, activation='relu'),
  layers.Dense(num_classes)
])
```

Compiling the model

In [29]:

```
model.compile(optimizer='adam',
              loss=tf.keras.losses.SparseCategoricalCrossentropy(from_logit
              metrics=['accuracy'])
```

In [30]:

```
model.summary()
```

```
Model: "sequential_2"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
sequential_1 (Sequential)    (None, 180, 180, 3)       0
_________________________________________________________________
rescaling_2 (Rescaling)      (None, 180, 180, 3)       0
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 180, 180, 16)      448
_________________________________________________________________
max_pooling2d_3 (MaxPooling2 (None, 90, 90, 16)        0
_________________________________________________________________
conv2d_4 (Conv2D)            (None, 90, 90, 32)        4640
_________________________________________________________________
max_pooling2d_4 (MaxPooling2 (None, 45, 45, 32)        0
_________________________________________________________________
conv2d_5 (Conv2D)            (None, 45, 45, 64)        18496
_________________________________________________________________
max_pooling2d_5 (MaxPooling2 (None, 22, 22, 64)        0
_________________________________________________________________
dropout (Dropout)            (None, 22, 22, 64)        0
_________________________________________________________________
flatten_1 (Flatten)          (None, 30976)             0
_________________________________________________________________
dense_2 (Dense)              (None, 128)               3965056
_________________________________________________________________
dense_3 (Dense)              (None, 4)                 516
=================================================================
Total params: 3,989,156
Trainable params: 3,989,156
Non-trainable params: 0
_________________________________________________________________
```

Training the model

In [31]:

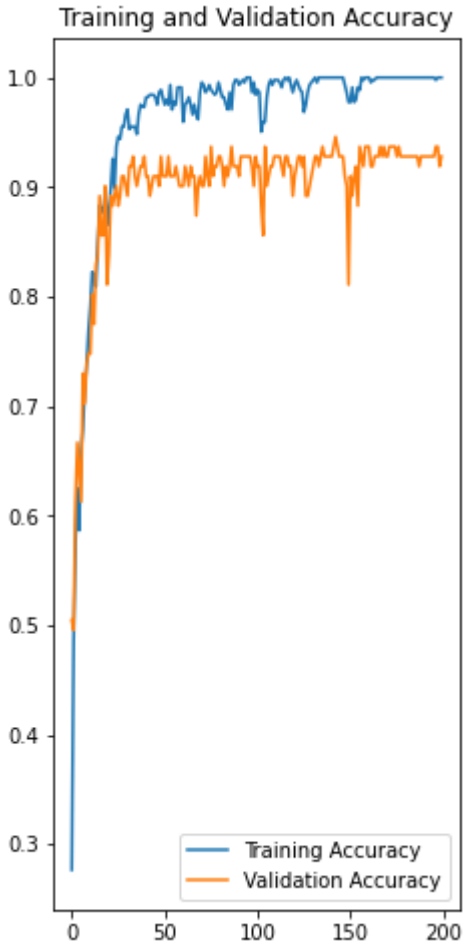
```
epochs = 200
history = model.fit(
  train_ds,
  validation_data=val_ds,
  epochs=epochs
)
```

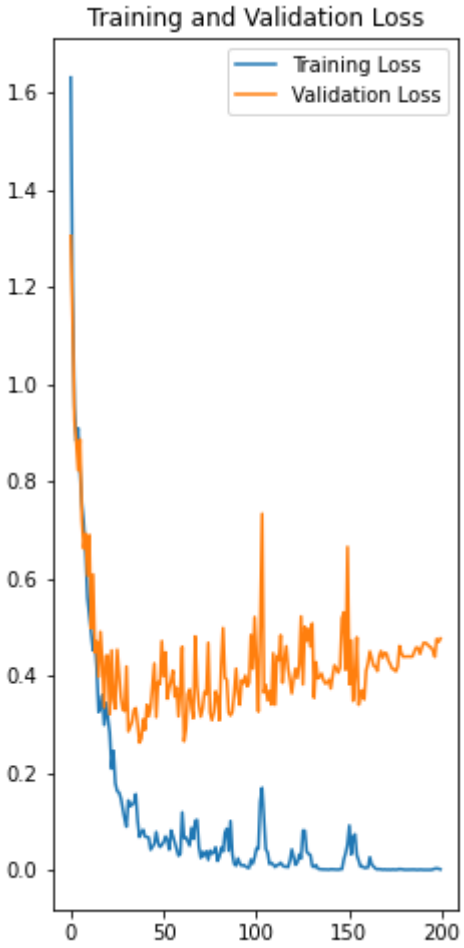
```
14/14 [==============================] - 5s 367ms/step - loss: 0.0012 - accuracy: 1.0000 - val_loss:
0.9279
Epoch 167/200
14/14 [==============================] - 5s 365ms/step - loss: 0.0019 - accuracy: 1.0000 - val_loss:
0.9369
Epoch 168/200
14/14 [==============================] - 5s 377ms/step - loss: 0.0011 - accuracy: 1.0000 - val_loss:
0.9279
Epoch 169/200
14/14 [==============================] - 5s 368ms/step - loss: 5.6975e-04 - accuracy: 1.0000 - val_lo
cy: 0.9369
Epoch 170/200
14/14 [==============================] - 5s 368ms/step - loss: 0.0011 - accuracy: 1.0000 - val_loss:
0.9279
Epoch 171/200
```

Training results

In [35]:

```
acc = history.history['accuracy']
val_acc = history.history['val_accuracy']

loss = history.history['loss']
val_loss = history.history['val_loss']

epochs_range = range(epochs)

plt.figure(figsize=(8, 8))
plt.subplot(1, 2, 1)
plt.plot(epochs_range, acc, label='Training Accuracy')
plt.plot(epochs_range, val_acc, label='Validation Accuracy')
plt.legend(loc='lower right')
plt.title('Training and Validation Accuracy')

plt.subplot(1, 2, 2)
plt.plot(epochs_range, loss, label='Training Loss')
plt.plot(epochs_range, val_loss, label='Validation Loss')
plt.legend(loc='upper right')
plt.title('Training and Validation Loss')
plt.show()
```





Testing on new data

In [36]:

```
test_image_path = '/home/glitch101/Downloads/20_rupee.jpg'

img = keras.preprocessing.image.load_img(
    test_image_path, target_size=(img_height, img_width)
)
img_array = keras.preprocessing.image.img_to_array(img)
img_array = tf.expand_dims(img_array, 0) # Create a batch

predictions = model.predict(img_array)
score = tf.nn.softmax(predictions[0])

print(
    "This image most likely belongs to {} with a {:.2f} percent confidence.
    .format(class_names[np.argmax(score)], 100 * np.max(score))
)

print(score)
```

```
This image most likely belongs to 20 with a 100.00 percent confidence.
tf.Tensor([5.7689140e-06 1.9313859e-10 9.9999404e-01 2.7660934e-07], shape=(4,), dtype=float32)
```

Saving the model for use with our python script

In [37]:

```
model.save('/home/glitch101/Downloads/CURRENCY_MODEL/')
```

```
INFO:tensorflow:Assets written to: /home/glitch101/Downloads/CURRENCY_MODEL/assets
```