main

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1 Image Classification

1.1 Overview

This assignment explores image classification in Keras. It uses a sequential model to evaluate the test data. This is repeated with different architectures such as RNN and CNN for evaluation. Finally, a pretrained model is used for classification. This portfolio component will test our understanding on the concept of deep learning and allow us to use images to tp understand various patterns.

1.2 Dataset

The dataset utilized is the Animal Crossing vs Doom image classification dataset. Doom and Animal Crossing are video games with different art styles in that Animal Crossing is a relaxing game where you design an island and Doom is a First Person Shooter where you slay hordes of demons.

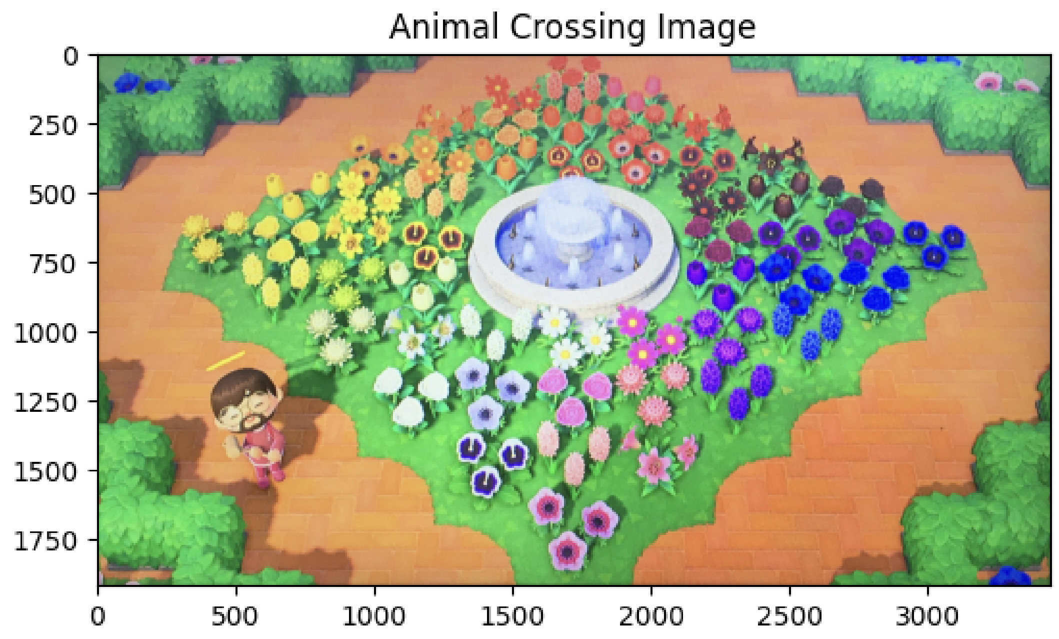
In this instance, we will use classification so that

- Doom - 0
- Animal Crossing - 1

source: https://www.kaggle.com/datasets/andrewmvd/doom-crossing?resource=download&select=animal_crossi

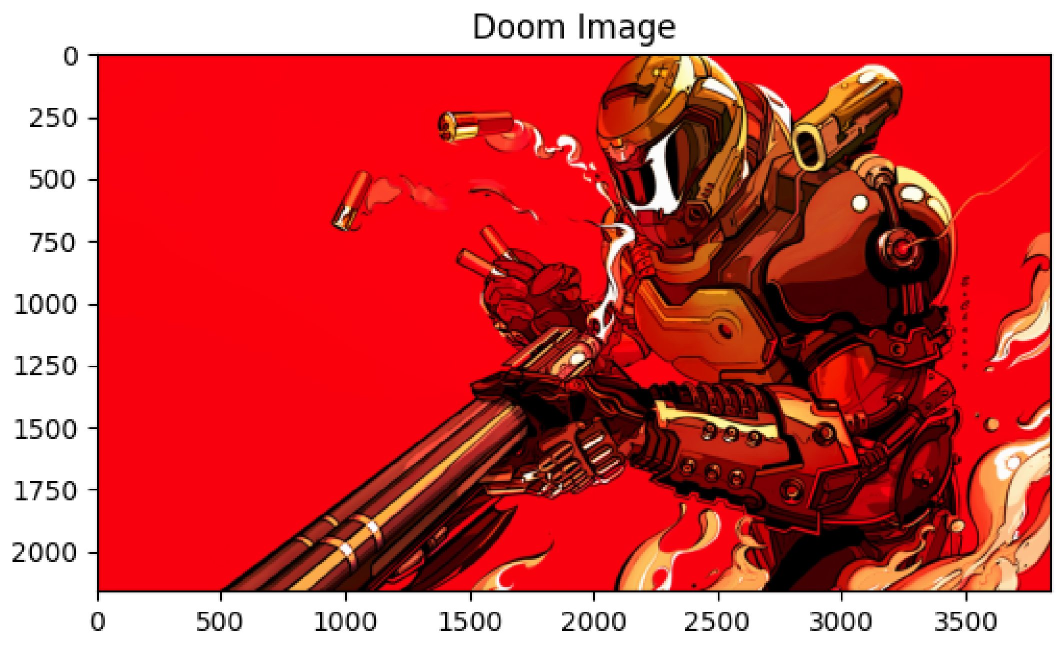
1.2.1 Example of an Animal Crossing image.

[17]:
```python
# An example of Animal Crossing
import matplotlib.pyplot as plt

img = plt.imread('data/animal_crossing/0czcmw8rmsz41.jpg')

plt.title("Animal Crossing Image")
plt.imshow(img)
plt.show()
```



1.2.2 Example of a Doom image.

[18]:
```python
# An example of Doom
img = plt.imread('data/doom/a46ep8c89jq41.jpg')

plt.title("Doom Image")
plt.imshow(img)
plt.show()
```



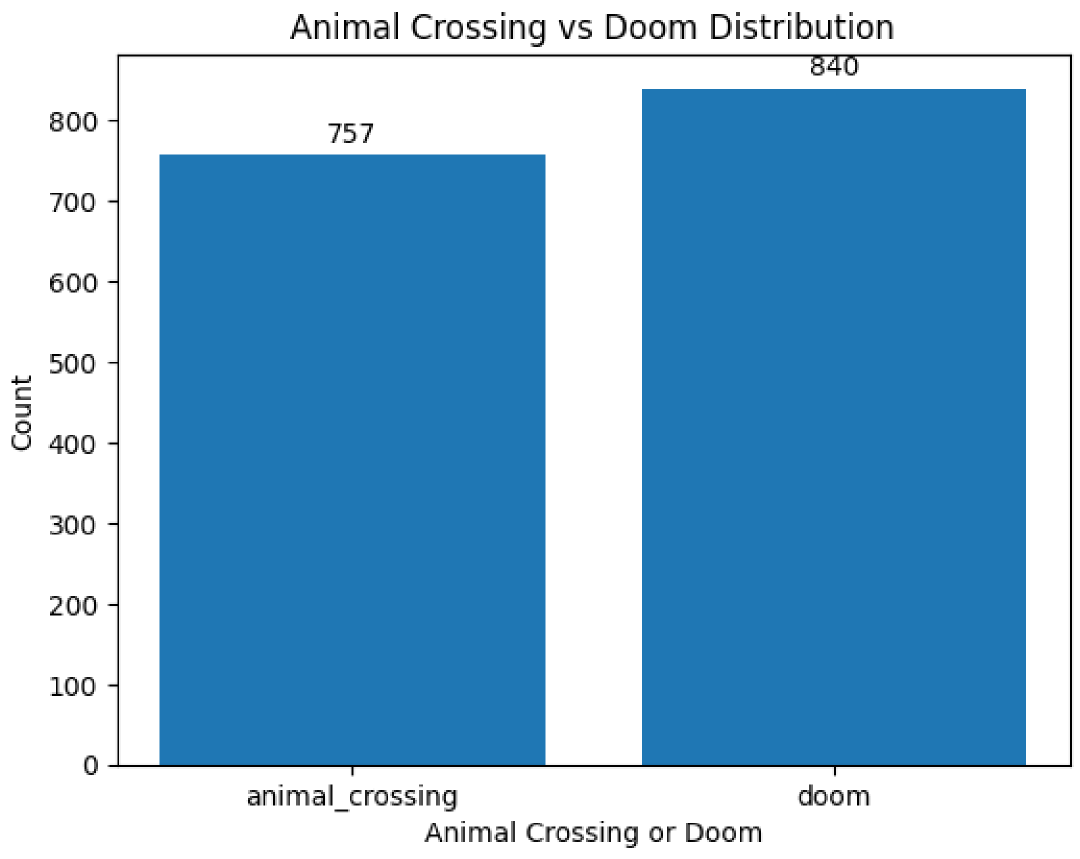
1.3 Preparing the dataset for training and testing.

Here we are importing the dataset and splitting it into train and test sets.

[19]:
```
# Prepare the dataset
import os
import pandas as pd
import cv2


animal_crossing_csv = pd.read_csv('./data/animal_crossing_dataset.xls')
doom_csv = pd.read_csv('./data/doom_dataset.xls')

# Prepare x-axis for images and y-axis for labels
x = []
y = []

# Gather images from directories
animal_crossing_images = os.listdir('data/animal_crossing')
doom_images = os.listdir('data/doom')

# Prepare all Animal Crossing images
for file_name in animal_crossing_images:
    image_path = 'data/animal_crossing/' + file_name
    try:
        # Use OpenCV to read the image
        img_arr = cv2.imread(image_path)
        # Convert the image to greyscale
        grayscale_arr = cv2.cvtColor(img_arr, cv2.COLOR_BGR2GRAY)
        # Resize the array
        resized_arr = cv2.resize(grayscale_arr, (224, 224))
        x.append(resized_arr)
        y.append('animal_crossing')
    except Exception:
        pass

# Prepare all Doom images
for file_name in doom_images:
    image_path = 'data/doom/' + file_name
    try:
        # Use OpenCV to read the image
        img_arr = cv2.imread(image_path)
        # Convert the image to greyscale
        grayscale_arr = cv2.cvtColor(img_arr, cv2.COLOR_BGR2GRAY)
        # Resize the array
        resized_arr = cv2.resize(grayscale_arr, (224, 224))
        x.append(resized_arr)
        y.append('doom')
    except Exception:
        pass
```

1.4 Class Distribution

[20]:
```
# Create a counter of each of the labels
y_counter = {}

for label in y:
    if label not in y_counter:
        y_counter[label] = 1
    else:
        y_counter[label] += 1

# Create a bar graph of each of the counts
figure, bar_graph = plt.subplots()
bars = bar_graph.bar(['animal_crossing', 'doom'],␣
 ↪[y_counter['animal_crossing'], y_counter['doom']])
bar_graph.set_xlabel('Animal Crossing or Doom')
bar_graph.set_ylabel('Count')
bar_graph.set_title('Animal Crossing vs Doom Distribution')

# Create the labels above the bar graphs
for bar in bars:
    height = bar.get_height()
    bar_graph.annotate(str(height), xy=(bar.get_x() + bar.get_width() / 2,␣
↪height),
                    xytext=(0, 3), textcoords="offset points", ha='center',␣
↪va='bottom')

plt.show()
```



According to the graph, we have a total of 757 Animal Crossing images and 840 Doom images.

1.5 Data Preparation

This section will split the data into training and testing, transform the values into floating-point data, and convert the labels into categorical sections.

[21]:
```
import tensorflow as tf
import numpy as np
from sklearn.model_selection import train_test_split

# Split the data into train and test
```

```
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2,␣
 ↪random_state=1234)

# Convert the data into floating-point data
x_train = np.divide(x_train, 255.)
x_test = np.divide(x_test, 255.)

# Convert y into 0 or Doom and 1 for Animal Crossing
y_train = [0 if label == 'doom' else 1 for label in y_train]
y_test = [0 if label == 'doom' else 1 for label in y_test]

# Convert the class vectors into binary class matrices
y_train = tf.keras.utils.to_categorical(y_train, len(set(y)))
y_test = tf.keras.utils.to_categorical(y_test, len(set(y)))
```

1.6 Sequential Model

This section will create a Sequential model utilizing Keras.

[22]:
```
model = tf.keras.models.Sequential([
tf.keras.layers.Flatten(input_shape=(224, 224)),
tf.keras.layers.Dense(512, activation='relu'),
tf.keras.layers.Dropout(0.2),
tf.keras.layers.Dense(512, activation='relu'),
tf.keras.layers.Dropout(0.2),
tf.keras.layers.Dense(len(set(y)), activation='softmax'),
])

model.summary()

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

```
Model: "sequential_4"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 flatten_3 (Flatten)         (None, 50176)             0

 dense_8 (Dense)             (None, 512)               25690624

 dropout_6 (Dropout)         (None, 512)               0

 dense_9 (Dense)             (None, 512)               262656

 dropout_7 (Dropout)         (None, 512)               0
 dense_10 (Dense)            (None, 2)                 1026

=================================================================
Total params: 25,954,306
Trainable params: 25,954,306
Non-trainable params: 0
_________________________________________________________________
```

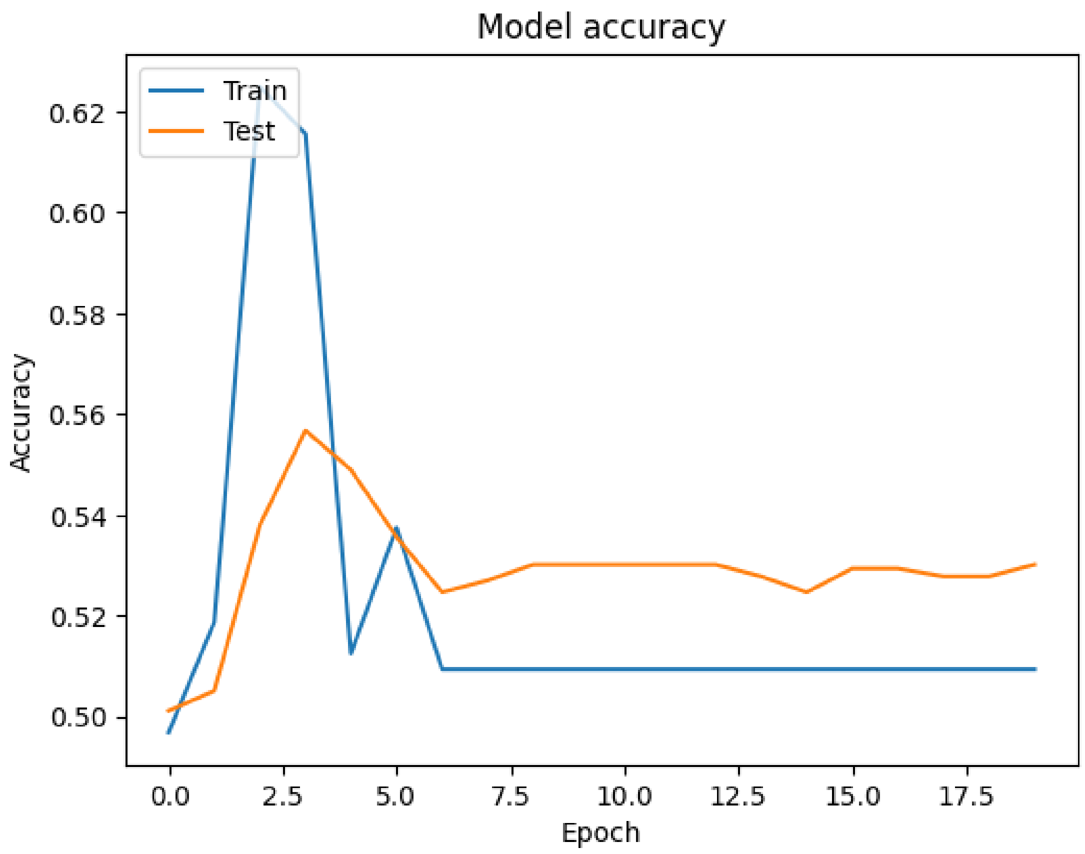
[23]:
```
history = model.fit(x_train, y_train,
    batch_size=128,
    epochs=20,
    verbose=1,
    validation_data=(x_test, y_test))

score = model.evaluate(x_test, y_test, verbose=0)

print('Test loss:', score[0])
print('Test accuracy:', score[1])
```

```
Epoch 1/20
10/10 [==============================] - 3s 205ms/step - loss: 52.6469 -
accuracy: 0.5012 - val_loss: 1.6078 - val_accuracy: 0.4969
Epoch 2/20
10/10 [==============================] - 2s 189ms/step - loss: 2.0523 -
accuracy: 0.5051 - val_loss: 0.6840 - val_accuracy: 0.5188
Epoch 3/20
10/10 [==============================] - 2s 190ms/step - loss: 1.0315 -
accuracy: 0.5380 - val_loss: 0.6702 - val_accuracy: 0.6250
Epoch 4/20
10/10 [==============================] - 2s 189ms/step - loss: 0.6810 -
accuracy: 0.5568 - val_loss: 0.6763 - val_accuracy: 0.6156
Epoch 5/20
10/10 [==============================] - 2s 191ms/step - loss: 0.7454 -
accuracy: 0.5489 - val_loss: 0.6852 - val_accuracy: 0.5125
Epoch 6/20
10/10 [==============================] - 2s 193ms/step - loss: 0.6984 -
accuracy: 0.5356 - val_loss: 0.6902 - val_accuracy: 0.5375
Epoch 7/20
10/10 [==============================] - 2s 191ms/step - loss: 0.7264 -
accuracy: 0.5247 - val_loss: 0.6935 - val_accuracy: 0.5094
Epoch 8/20
10/10 [==============================] - 2s 188ms/step - loss: 1.2580 -
accuracy: 0.5270 - val_loss: 0.6874 - val_accuracy: 0.5094
Epoch 9/20
10/10 [==============================] - 2s 185ms/step - loss: 1.3566 -
accuracy: 0.5301 - val_loss: 0.6924 - val_accuracy: 0.5094
Epoch 10/20
```

```
10/10 [==============================] - 2s 191ms/step - loss: 0.6908 -
accuracy: 0.5301 - val_loss: 0.6923 - val_accuracy: 0.5094
Epoch 11/20
10/10 [==============================] - 2s 192ms/step - loss: 0.6910 -
accuracy: 0.5301 - val_loss: 0.6925 - val_accuracy: 0.5094
Epoch 12/20
10/10 [==============================] - 2s 190ms/step - loss: 0.6905 -
accuracy: 0.5301 - val_loss: 0.6926 - val_accuracy: 0.5094
Epoch 13/20
10/10 [==============================] - 2s 187ms/step - loss: 0.6892 -
accuracy: 0.5301 - val_loss: 0.6969 - val_accuracy: 0.5094
Epoch 14/20
10/10 [==============================] - 2s 189ms/step - loss: 0.7372 -
accuracy: 0.5278 - val_loss: 0.6925 - val_accuracy: 0.5094
Epoch 15/20
10/10 [==============================] - 2s 189ms/step - loss: 0.6894 -
accuracy: 0.5247 - val_loss: 0.6940 - val_accuracy: 0.5094
Epoch 16/20
10/10 [==============================] - 2s 190ms/step - loss: 0.6884 -
accuracy: 0.5294 - val_loss: 0.6861 - val_accuracy: 0.5094
Epoch 17/20
10/10 [==============================] - 2s 187ms/step - loss: 0.6711 -
accuracy: 0.5294 - val_loss: 0.7275 - val_accuracy: 0.5094
Epoch 18/20
10/10 [==============================] - 2s 191ms/step - loss: 0.6795 -
accuracy: 0.5278 - val_loss: 0.6826 - val_accuracy: 0.5094
Epoch 19/20
10/10 [==============================] - 2s 198ms/step - loss: 0.8586 -
accuracy: 0.5278 - val_loss: 0.6870 - val_accuracy: 0.5094
Epoch 20/20
10/10 [==============================] - 2s 191ms/step - loss: 0.6847 -
accuracy: 0.5301 - val_loss: 0.6812 - val_accuracy: 0.5094
Test loss: 0.6811737418174744
Test accuracy: 0.5093749761581421
```

The model has returned a Loss of 69% and an Accuracy of 51.2%. There is about a 69% error rate between the predicted output and the true output. The model is only correct about 51% of the time as well.

[24]:
```
# Plot training & validation accuracy values
plt.plot(history.history['val_accuracy'])
plt.plot(history.history['accuracy'])
plt.title('Model accuracy')
plt.ylabel('Accuracy')
plt.xlabel('Epoch')
plt.legend(['Train', 'Test'], loc='upper left')
plt.show()
```



1.7 RNN Architecture

RNN's are recurrent neural networks. These models are generally used for time series or natural languages. An RNN layer utilizes a for loop to iterate over the timesteps in a sequence. It maintains an internal state that encodes information about the timesteps it's had so far.

[25]:
```
model = tf.keras.models.Sequential([
tf.keras.layers.SimpleRNN(64, input_shape=(224,224)),
tf.keras.layers.Dense(512, activation='relu'),
tf.keras.layers.Dropout(0.2),
tf.keras.layers.Dense(512, activation='relu'),
tf.keras.layers.Dropout(0.2),
tf.keras.layers.Dense(len(set(y)), activation='softmax'),
])

model.summary()

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

```
Model: "sequential_5"

_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 simple_rnn_1 (SimpleRNN)    (None, 64)                18496

 dense_11 (Dense)            (None, 512)               33280

 dropout_8 (Dropout)         (None, 512)               0

 dense_12 (Dense)            (None, 512)               262656

 dropout_9 (Dropout)         (None, 512)               0

 dense_13 (Dense)            (None, 2)                 1026

=================================================================
Total params: 315,458
Trainable params: 315,458
Non-trainable params: 0
_________________________________________________________________
```

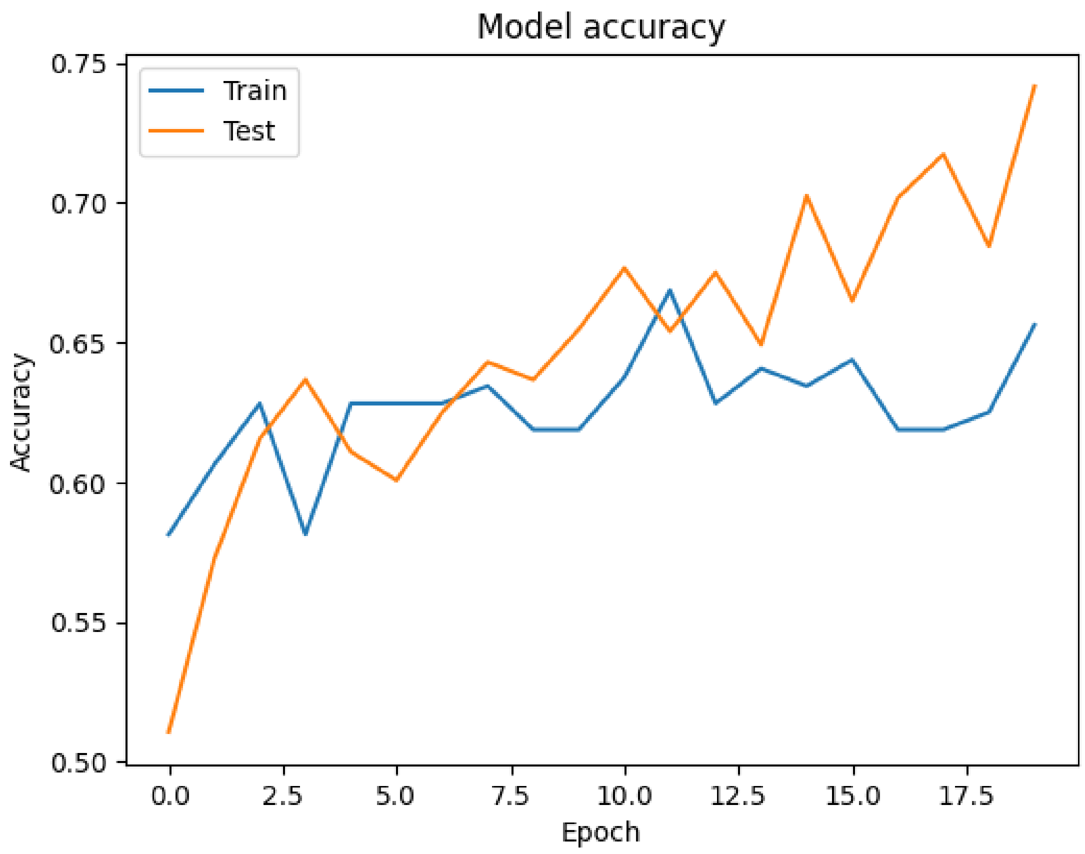
[26]:
```
history = model.fit(x_train, y_train,
    batch_size=128,
    epochs=20,
    verbose=1,
    validation_data=(x_test, y_test))

score = model.evaluate(x_test, y_test, verbose=0)

print('Test loss:', score[0])
print('Test accuracy:', score[1])
```

```
Epoch 1/20
10/10 [==============================] - 2s 106ms/step - loss: 0.7928 -
accuracy: 0.5106 - val_loss: 0.6743 - val_accuracy: 0.5813
Epoch 2/20
10/10 [==============================] - 1s 72ms/step - loss: 0.6721 - accuracy:
0.5724 - val_loss: 0.6516 - val_accuracy: 0.6062
Epoch 3/20
10/10 [==============================] - 1s 72ms/step - loss: 0.6801 - accuracy:
0.6155 - val_loss: 0.6490 - val_accuracy: 0.6281
Epoch 4/20
10/10 [==============================] - 1s 72ms/step - loss: 0.6377 - accuracy:
0.6366 - val_loss: 0.6982 - val_accuracy: 0.5813
Epoch 5/20
10/10 [==============================] - 1s 71ms/step - loss: 0.6552 - accuracy:
0.6108 - val_loss: 0.6461 - val_accuracy: 0.6281
```

```
Epoch 6/20
10/10 [==============================] - 1s 71ms/step - loss: 0.6780 - accuracy:
0.6006 - val_loss: 0.6596 - val_accuracy: 0.6281
Epoch 7/20
10/10 [==============================] - 1s 70ms/step - loss: 0.6326 - accuracy:
0.6249 - val_loss: 0.6386 - val_accuracy: 0.6281
Epoch 8/20
10/10 [==============================] - 1s 70ms/step - loss: 0.6219 - accuracy:
0.6429 - val_loss: 0.6434 - val_accuracy: 0.6344
Epoch 9/20
10/10 [==============================] - 1s 70ms/step - loss: 0.6227 - accuracy:
0.6366 - val_loss: 0.6492 - val_accuracy: 0.6187
Epoch 10/20
10/10 [==============================] - 1s 73ms/step - loss: 0.6103 - accuracy:
0.6547 - val_loss: 0.6419 - val_accuracy: 0.6187
Epoch 11/20
10/10 [==============================] - 1s 71ms/step - loss: 0.6053 - accuracy:
0.6766 - val_loss: 0.6353 - val_accuracy: 0.6375
Epoch 12/20
10/10 [==============================] - 1s 70ms/step - loss: 0.6194 - accuracy:
0.6539 - val_loss: 0.6574 - val_accuracy: 0.6687
Epoch 13/20
10/10 [==============================] - 1s 71ms/step - loss: 0.5744 - accuracy:
0.6750 - val_loss: 0.6648 - val_accuracy: 0.6281
Epoch 14/20
10/10 [==============================] - 1s 72ms/step - loss: 0.5782 - accuracy:
0.6492 - val_loss: 0.6658 - val_accuracy: 0.6406
Epoch 15/20
10/10 [==============================] - 1s 71ms/step - loss: 0.5570 - accuracy:
0.7024 - val_loss: 0.6625 - val_accuracy: 0.6344
Epoch 16/20
10/10 [==============================] - 1s 73ms/step - loss: 0.5789 - accuracy:
0.6648 - val_loss: 0.6531 - val_accuracy: 0.6438
Epoch 17/20
10/10 [==============================] - 1s 74ms/step - loss: 0.5302 - accuracy:
0.7016 - val_loss: 0.6704 - val_accuracy: 0.6187
Epoch 18/20
10/10 [==============================] - 1s 76ms/step - loss: 0.5249 - accuracy:
0.7173 - val_loss: 0.6960 - val_accuracy: 0.6187
Epoch 19/20
10/10 [==============================] - 1s 73ms/step - loss: 0.5875 - accuracy:
0.6844 - val_loss: 0.6981 - val_accuracy: 0.6250
Epoch 20/20
10/10 [==============================] - 1s 76ms/step - loss: 0.4928 - accuracy:
0.7416 - val_loss: 0.6679 - val_accuracy: 0.6562
Test loss: 0.6678863763809204
Test accuracy: 0.65625
```

The test loss 67% and has an accuracy of 65%. This shows that there is about a 67% error rate between the predicted output and the true output, and that the model is only correct 65% of the time. This shows a significant increase from the previous test results.

[27]:
```
# Plot training & validation accuracy values
plt.plot(history.history['val_accuracy'])
plt.plot(history.history['accuracy'])
plt.title('Model accuracy')
plt.ylabel('Accuracy')
plt.xlabel('Epoch')
plt.legend(['Train', 'Test'], loc='upper left')
plt.show()
```



Here is what the model accuracy graph shows.

1.8 CNN Architecture

[28]:
```
model = tf.keras.models.Sequential([
tf.keras.Input(shape=(224,224,1)),
tf.keras.layers.Conv2D(32, kernel_size=(3, 3), activation="relu"),
tf.keras.layers.MaxPooling2D(pool_size=(2, 2)),
tf.keras.layers.Conv2D(64, kernel_size=(3, 3), activation="relu"),
tf.keras.layers.MaxPooling2D(pool_size=(2, 2)),
tf.keras.layers.Flatten(),
tf.keras.layers.Dropout(0.5),
tf.keras.layers.Dense(2, activation="softmax"),
])

model.summary()

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

```
Model: "sequential_6"

_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d_4 (Conv2D)           (None, 222, 222, 32)      320

 max_pooling2d_4 (MaxPooling  (None, 111, 111, 32)     0
 2D)

 conv2d_5 (Conv2D)           (None, 109, 109, 64)      18496

 max_pooling2d_5 (MaxPooling  (None, 54, 54, 64)       0
 2D)

 flatten_4 (Flatten)         (None, 186624)            0

 dropout_10 (Dropout)        (None, 186624)            0

 dense_14 (Dense)            (None, 2)                 373250

=================================================================
Total params: 392,066
Trainable params: 392,066
Non-trainable params: 0
_________________________________________________________________
```

[29]:
```
history = model.fit(x_train, y_train,
    batch_size=128,
    epochs=20,
    verbose=1,
    validation_data=(x_test, y_test))

score = model.evaluate(x_test, y_test, verbose=0)
```

```python
print('Test loss:', score[0])
print('Test accuracy:', score[1])
```

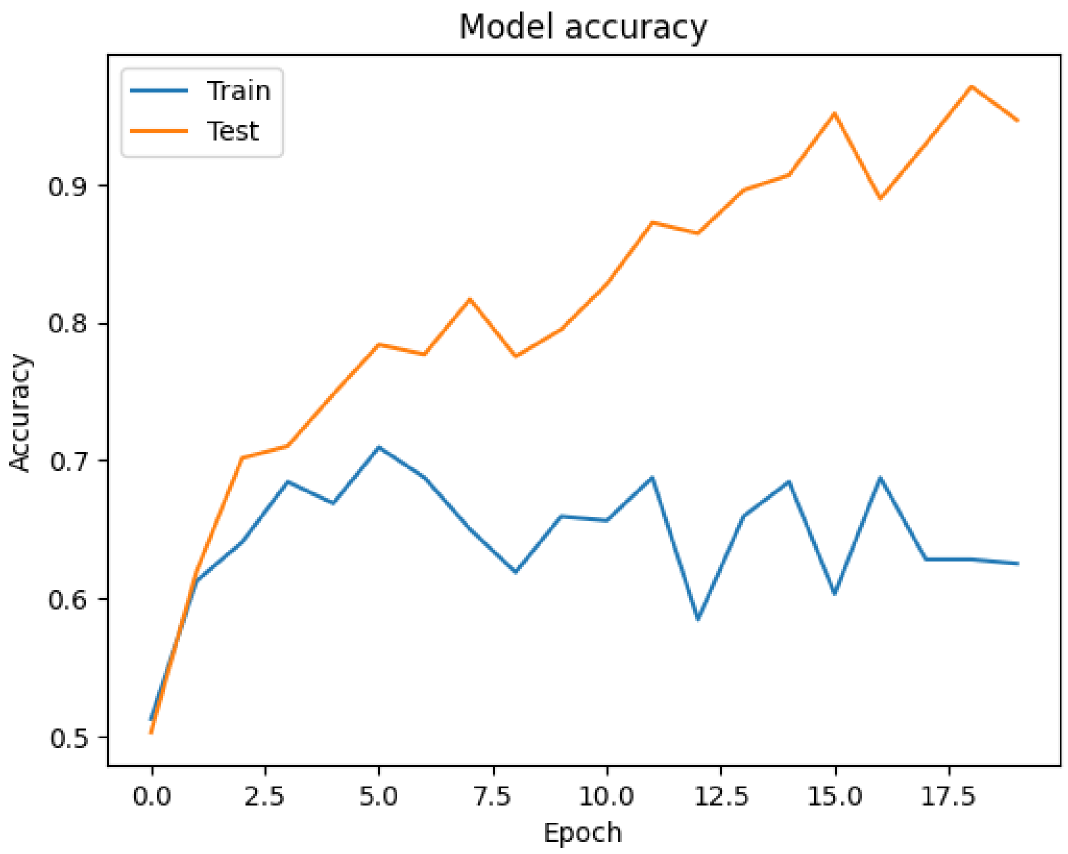
```
Epoch 1/20
10/10 [==============================] - 21s 2s/step - loss: 2.5655 - accuracy:
0.5027 - val_loss: 0.7150 - val_accuracy: 0.5125
Epoch 2/20
10/10 [==============================] - 20s 2s/step - loss: 0.6503 - accuracy:
0.6194 - val_loss: 0.6837 - val_accuracy: 0.6125
Epoch 3/20
10/10 [==============================] - 20s 2s/step - loss: 0.6288 - accuracy:
0.7016 - val_loss: 0.6504 - val_accuracy: 0.6406
Epoch 4/20
10/10 [==============================] - 20s 2s/step - loss: 0.6061 - accuracy:
0.7103 - val_loss: 0.6400 - val_accuracy: 0.6844
Epoch 5/20
10/10 [==============================] - 20s 2s/step - loss: 0.6266 - accuracy:
0.7478 - val_loss: 0.6475 - val_accuracy: 0.6687
Epoch 6/20
10/10 [==============================] - 20s 2s/step - loss: 0.4997 - accuracy:
0.7839 - val_loss: 0.6219 - val_accuracy: 0.7094
Epoch 7/20
10/10 [==============================] - 20s 2s/step - loss: 0.5040 - accuracy:
0.7768 - val_loss: 0.6249 - val_accuracy: 0.6875
Epoch 8/20
10/10 [==============================] - 20s 2s/step - loss: 0.4324 - accuracy:
0.8168 - val_loss: 0.6513 - val_accuracy: 0.6500
Epoch 9/20
10/10 [==============================] - 20s 2s/step - loss: 0.4744 - accuracy:
0.7753 - val_loss: 1.0839 - val_accuracy: 0.6187
Epoch 10/20
10/10 [==============================] - 20s 2s/step - loss: 0.4460 - accuracy:
0.7948 - val_loss: 0.7030 - val_accuracy: 0.6594
Epoch 11/20
10/10 [==============================] - 20s 2s/step - loss: 0.3826 - accuracy:
0.8277 - val_loss: 0.6211 - val_accuracy: 0.6562
Epoch 12/20
10/10 [==============================] - 21s 2s/step - loss: 0.3532 - accuracy:
0.8724 - val_loss: 0.6525 - val_accuracy: 0.6875
Epoch 13/20
10/10 [==============================] - 20s 2s/step - loss: 0.3608 - accuracy:
0.8645 - val_loss: 0.8581 - val_accuracy: 0.5844
Epoch 14/20
10/10 [==============================] - 20s 2s/step - loss: 0.3095 - accuracy:
0.8958 - val_loss: 0.8850 - val_accuracy: 0.6594
Epoch 15/20
10/10 [==============================] - 20s 2s/step - loss: 0.2665 - accuracy:
```

```
0.9068 - val_loss: 0.7266 - val_accuracy: 0.6844
Epoch 16/20
10/10 [==============================] - 20s 2s/step - loss: 0.1760 - accuracy:
0.9514 - val_loss: 1.2839 - val_accuracy: 0.6031
Epoch 17/20
10/10 [==============================] - 20s 2s/step - loss: 0.3151 - accuracy:
0.8896 - val_loss: 0.7798 - val_accuracy: 0.6875
Epoch 18/20
10/10 [==============================] - 20s 2s/step - loss: 0.2416 - accuracy:
0.9295 - val_loss: 0.7385 - val_accuracy: 0.6281
Epoch 19/20
10/10 [==============================] - 20s 2s/step - loss: 0.1496 - accuracy:
0.9710 - val_loss: 0.9173 - val_accuracy: 0.6281
Epoch 20/20
10/10 [==============================] - 20s 2s/step - loss: 0.1565 - accuracy:
0.9468 - val_loss: 1.1546 - val_accuracy: 0.6250
Test loss: 1.1545612812042236
Test accuracy: 0.625
```

The test loss is substantially high at around 115%, which a drastic difference from the other tests. The accuracy of this test is around 63%.

The history graph shows:

[30]:
```
# Plot training & validation accuracy values
plt.plot(history.history['val_accuracy'])
plt.plot(history.history['accuracy'])
plt.title('Model accuracy')
plt.ylabel('Accuracy')
plt.xlabel('Epoch')
plt.legend(['Train', 'Test'], loc='upper left')
plt.show()
```



1.9 Pretrained Model (VGG-16)

VGG-16 was developed at the University of Oxford and is one of the most popular models used. Here we will use VGG-16 to attempt to predict a completely different video game, Minecraft.

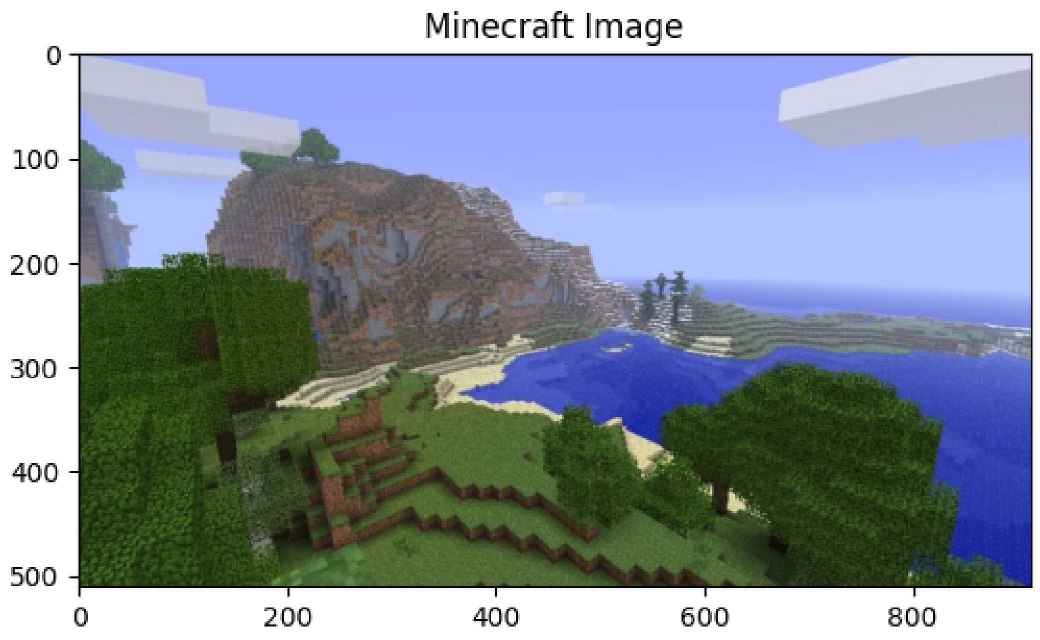
[31]:
```python
from keras.applications.vgg16 import VGG16

model = VGG16()
model.summary()
```

```
Downloading data from https://storage.googleapis.com/tensorflow/keras-
applications/vgg16/vgg16_weights_tf_dim_ordering_tf_kernels.h5
553467096/553467096 [==============================] - 11s 0us/step
Model: "vgg16"

_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_4 (InputLayer)        [(None, 224, 224, 3)]     0


 block1_conv1 (Conv2D)       (None, 224, 224, 64)      1792
 block1_conv2 (Conv2D)       (None, 224, 224, 64)      36928

 block1_pool (MaxPooling2D)  (None, 112, 112, 64)      0

 block2_conv1 (Conv2D)       (None, 112, 112, 128)     73856

 block2_conv2 (Conv2D)       (None, 112, 112, 128)     147584

 block2_pool (MaxPooling2D)  (None, 56, 56, 128)       0

 block3_conv1 (Conv2D)       (None, 56, 56, 256)       295168

 block3_conv2 (Conv2D)       (None, 56, 56, 256)       590080

 block3_conv3 (Conv2D)       (None, 56, 56, 256)       590080

 block3_pool (MaxPooling2D)  (None, 28, 28, 256)       0

 block4_conv1 (Conv2D)       (None, 28, 28, 512)       1180160

 block4_conv2 (Conv2D)       (None, 28, 28, 512)       2359808

 block4_conv3 (Conv2D)       (None, 28, 28, 512)       2359808

 block4_pool (MaxPooling2D)  (None, 14, 14, 512)       0

 block5_conv1 (Conv2D)       (None, 14, 14, 512)       2359808

 block5_conv2 (Conv2D)       (None, 14, 14, 512)       2359808

 block5_conv3 (Conv2D)       (None, 14, 14, 512)       2359808

 block5_pool (MaxPooling2D)  (None, 7, 7, 512)         0

 flatten (Flatten)           (None, 25088)             0

 fc1 (Dense)                 (None, 4096)              102764544

 fc2 (Dense)                 (None, 4096)              16781312

 predictions (Dense)         (None, 1000)              4097000

=================================================================
Total params: 138,357,544
Trainable params: 138,357,544
Non-trainable params: 0
_________________________________________________________________
```

1.9.1 An Example of Minecraft

This will be the image of Minecraft that VG16 will attempt to predict.

[33]:
```
img = plt.imread('data/minecraft_image.jpg')

plt.title("Minecraft Image")
plt.imshow(img)
plt.show()
```



[38]:
```
# load an image
image = tf.keras.utils.load_img('data/minecraft_image.jpg', target_size=(224,␣
 ↪224))

# convert the image pixels to a numpy array
input_arr = tf.keras.utils.img_to_array(image)
input_arr = np.array([input_arr])

# Predict what the image is
predictions = model.predict(input_arr)

image_prediction = tf.keras.applications.vgg16.decode_predictions(predictions,␣
 ↪top=5)
image_prediction
```

```
1/1 [==============================] - 0s 144ms/step
Downloading data from https://storage.googleapis.com/download.tensorflow.org/dat
```

```
a/imagenet_class_index.json
35363/35363 [==============================] - 0s 0us/step
```

[38]:
```
[[('n03598930', 'jigsaw_puzzle', 0.16339023),
  ('n09193705', 'alp', 0.13127784),
  ('n09246464', 'cliff', 0.09332522),
  ('n03781244', 'monastery', 0.06552275),
  ('n04346328', 'stupa', 0.06209536)]]
```

According to VGG16, the top 5 predictions of the Minecraft image are jigsaw_puzzle, alp, cliff, monastery, and stupa.

1.10 Analysis of the Performance of Different Approaches

From what is shown from the results, each test provided results that were in a general ballpark. The most successful of the approaches was the RNN test which yielded the lowest tet loss percentage and the highest accuracy and 67% and 65% respectively. The test that showed the biggest error was the CNN test which yielded a very high test loss of 1.15. Despite all this, all the tests had an accuracy in the ball park or around 50%-60%, which shows that the variable that these tests varied drastically in were the loss statistics. One thing we did notice was how long the tests took to execute, which shows how complex some of the tests truly were. We deduced that the reason for this was due to the massive amount of images used and how analyzing images was very GPU/CPU intensive.